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Essais sur la liquidité, les interconnections et la contagion bancaire

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Jury

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To my Parents,

my Husband,

my Brother ...

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Résumé

Compte-tenu du degré de complexité des interconnexions au sein du système financier mondial, mis en avant pendant la crise financière 2007-2009, l'adoption des modèles de réseaux, comme paradigme d'analyse et d'amélioration de la robustesse du système, paraît particulièrement pertinent, sinon nécessaire. Les institutions financières sont vues comme des noeuds d'un réseau où les transactions interbancaires constituent les liens au travers desquels la propagation des chocs se matérialise. En outre, la crise a également mis en évidence le rôle d'un rationnement de la liquidité comme canal majeur de transmission des chocs. Cette thèse examine les interactions entre les tensions sur le marché monétaire, la contagion interbancaire et la structure du réseau, avec une application au marché interbancaire européen et au système de paiement. La contribution de cette étude à la littérature sur les réseaux financiers s'articule autour de trois axes. Le premier est un modèle intégrant trois canaux de propagation des chocs, à l'oeuvre durant la crise 2007-2009, à savoir les expositions à un facteur de risque commun, aux risques de contrepartie et, enfin, au risque de liquidité. Le deuxième axe est une application de ce modèle étudiant les expositions interbancaires dans le système financier européen entre 2008 et 2012, et ce, au niveau individuel des agents, i.e. de banque à banque; constituant ainsi, et à notre connaissance, l'unique contribution académique dans ce domaine. Cette étude souligne notamment le rôle de la structure du réseau dans la propagation des chocs et reproduit la fragmentation du marché européen observée en 2011-2012. Enfin, la troisième contribution porte sur la propension des banques à retarder leurs transactions sur la base des données du système de paiement TARGET2. Cette étude souligne une divergence des comportements des banques au niveau de leur gestion de la liquidité intra-journalière. En effet, deux types de comportements se distinguent à cet égard : le premier consiste à fixer un niveau de liquidité initiale suffisant pour répondre aux besoins de la journée et un second qui a tendance à gérer cette liquidité en flux tendus. Les banques adoptant ce deuxième type de comportement sont à l'origine de la majorité des retards de paiements constatés au niveau du système financier. L'ampleur des retards de paiement est par ailleurs fortement corrélée au niveau des tensions sur le marché, constituant de ce fait un indicateur avancé d'une éventuelle crise à venir.

Mots-clés: Risque Systémique, Contagion, Réseaux, Marché Interbancaire, Risque de Liquidité, Risque de Contrepartie, Système de Paiement, Retards de Paiements.

Essays on liquidity, interconnectedness and interbank contagion

Abstract

Given the extent and importance of financial interconnectedness in recent years that were particularly underlined by the 2007-2009 financial crisis, the adoption of the network paradigm to analyze and improve robustness of a financial system appears to be fully relevant. Financial institutions are viewed as nodes of a network and their short- or long-term loans extended to each other as links or exposures through which a shock may propagate. Moreover, the same crisis accentuated the role of funding shortage as a channel of shock transmission. This dissertation focuses on the interplay of liquidity stress, interbank contagion and a network structure with application to the European interbank market and payment system. The contribution of this research to the literature on financial networks is threefold. The first develops a model that allows analyzing three contagion channels that happened to be at play during the financial crisis: exposures to a common risk factor; exposures to credit and counterparty risk in the interbank market; exposures to short-term liquidity risk. The second contribution is the unique analysis of cross-border contagion in the European banking system from 2008 to 2012 at the bank level using the developed model. Overall, the study finds the importance of the network structure for the extent of contagion propagation and captures the fragmentation of the market observed in 2011-2012. The third contribution consists of analysis of payment delays in the European payment system TARGET2. More specifically, this chapter provides evidence that banks differ in the way they manage their daily liquidity and can be split into two groups in this regard: those which put enough initial liquidity into the system, and those which economize on liquidity and rely on incoming payments to make outgoing transactions. The second group is responsible for the majority of the delayed payments, particularly during the period of low liquidity in the market, which constitutes an early warning indicator of stress.

Keywords: Systemic Risk, Contagion, Networks, Interbank Market, Liquidity Risk, Counterparty Risk, Payment Systems, Payment Delays.

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Introduction

La crise financière de 2007-2009 a mis en exergue deux faits caractéristiques du système financier actuel. Tout d'abord, elle a montré que le système financier international est intrinsèquement fragile. Ensuite, elle a souligné qu'aussi bien sa taille que son degré d'interdépendance avec l'économie réelle constituent une véritable menace pour la stabilité de cette dernière. Dans les années qui ont précédé la crise financière, les banques centrales et les superviseurs bancaires ont largement sous-estimé l'importance de la stabilité du système dans son ensemble en se concentrant essentiellement sur la santé financière de chaque établissement indépendamment des autres. Ils ont en effet été grandement séduits par la sophistication de l'ingénierie financière et notamment sa capacité à valoriser les risques des actifs et à fluidifier les marchés, faisant ainsi abstraction des vulnérabilités financières cachées du système existant à l'origine de la crise systémique de 2007-2009.

A contrario, la notion du risque systémique s'articule autour de deux propriétés : i) sa nature endogène, à savoir, outre le fait de créer le risque lui-même, les actions des agents financiers sont également susceptibles d'en accentuer l'ampleur; ii) sa nature de système, à savoir que les agents sont à la fois interconnectés et interdépendants. Cette dernière caractéristique a été largement délaissée dans les différentes études et notamment la littérature académique du fait, entre autres raisons, de l'opacité du système dans son ensemble et du manque d'informations sur la réalité des expositions des institutions financières des unes vis-à-vis des autres. Cette ignorance coûteuse a été à la source d'un gel total des marchés interbancaires mondiaux qui a conduit à la faillite de deux des plus grandes et plus anciennes banques d'investissement américaines, entretenant de ce fait la suspicion et la défiance sur les marchés financiers.

Le but de la réunion du G20 en 2009, qui s'est tenue à Pittsburg, a justement été de promouvoir la stabilité financière mondiale en recommandant, entre autre, la collecte des informations sur les transactions de gré à gré afin d'améliorer la transparence du système et de mieux appréhender le degré d'interconnectivité des institutions financières. Nombre de chercheurs universitaires et de décideurs ont attiré l'attention sur la complexité de la structure en réseau du système financier et ont promu l'utilisation des modèles de réseaux comme paradigme d'étude du système financier. Ainsi, dans son discours "Repenser le réseau financier" en 2009, Andrew Haldane, directeur général du département de la stabilité financière à la Banque d'Angleterre, s'est longuement attardé sur la capacité des modèles de réseaux à, d'un côté, "fournir une vue différente sur les vulnérabilités structurelles qui ont caractérisé le système financier au cours de la dernière décennie", et, de l'autre côté, à "proposer des moyens d'améliorer la robustesse du système dans la période à venir".[1]

Sans surprise, la crise financière a été à l'origine d'un fort regain d'intérêt pour les questions relatives au risque systémique et à la stabilité du système financier. En effet, comme l'a souligné J. Yellen, présidente de la Reserve Fédérale Américaine, dans son discours sur l'interconnexion et le risque systémique (Yellen (2013)), le nombre de publications depuis 2007 portant sur ces deux questions a plus que doublé par rapport à ce qui avait été recensé durant les 20 années précédant la crise.[2] Cependant, et malgré cette prolifération d'articles de recherche, beaucoup de questions restent en suspens et continuent d'alimenter nombre de nouvelles études. Le chapitre 1 se présente comme une revue structurée de la littérature qui met l'accent sur la richesse des liens financiers ainsi que la capacité des modèles de réseaux à analyser et à améliorer la stabilité financière. Cette section couvre l'analyse des réseaux financiers réels et leur propension à propager des chocs dans un cadre aussi bien statique que dynamique; l'étude économétrique de la corrélation entre les caractéristiques financières des noeuds et leurs positions dans le réseau et la pertinence de l'utilisation de données de marchés ou incomplètes appliquées aux marchés financiers.

L'ensemble de ces études éclairent sur la structure des différents réseaux financiers qu'ils soient basés sur les crédits interbancaires et les titres, les contrats de CDS ou encore les flux de paiement. Un des résultats clés et qui est partagé par une majorité de ces études, est le fait que ces réseaux présentent, malgré leur grande diversité, des propriétés similaires qui se retrouvent également dans tous les réseaux complexes examinés dans d'autres disciplines (informatique, microbiologie, etc.).[3] En effet, les réseaux complexes sont généralement caractérisés par : 1) une faible densité dans le sens où le maillage bancaire est clairsemé, 2) des distributions de degrés des noeuds suivant une loi de puissance : la majorité des connexions est concentrée autour de quelques noeuds centraux, 3) un coefficient de "clustering"

[1] Haldane (2009)

[2] Selon la base de données Econlit, le nombre d'articles académiques mentionnant les termes "'interconnexion" ou "risque systémique" dans leurs résumés s'élève à 311 entre la période 1988-2006, ce nombre atteint à 624 sur la seule période allant de 2007 à 2013. En limitant la recherche aux seuls articles publiés dans des revues à comité de lecture, ces chiffres s'élèvent à, respectivement, 186 et 375

[3] Entre autre, Barabasi (2002)

du réseau relativement bas et 4) le phénomène dit de "petit monde" : le chemin le plus court moyen entre deux noeuds du réseau ("degré de séparation") est faible. Ces interactions interbancaires utiles, voire nécessaires, car permettant une fluidification des marchés et un partage des risques, peuvent être à l'origine de troubles susceptibles de menacer l'existence même d'un ou plusieurs noeuds du réseau voire l'ensemble du système lui-même. Par ailleurs, et comme le démontrent plusieurs études, des structures de réseaux différentes engendrent des propriétés de stabilités différentes. Ainsi et s'agissant des réseaux financiers, les banquiers centraux, à l'instar des milieux académiques, sont particulièrement intéressés de savoir dans quelle mesure la structure du réseau est susceptible d'influer sur sa stabilité et sa résilience face à un choc, mais aussi par quels moyens réglementaires aboutir à cette stabilité: renforcement des noeuds eux-mêmes (exigences supplémentaires en fonds propres et en liquidité) ou amendement des liaisons entre les noeuds (instauration de seuils ou de taxes sur les expositions individuelles).

La notion de stabilité du système financier soulève la question cruciale des canaux de transmission de chocs, et ce d'autant plus qu'en raison de la complexité du système, les agents financiers sont capables d'activer plusieurs canaux simultanément, multipliant ainsi les vecteurs de propagation et donc l'amplitude du choc initial. Le rôle de la liquidité ainsi que la question de la confiance dans le marché a de ce point de vue été longtemps ignoré. Cependant, la grande incertitude qui a marqué les marchés durant la dernière crise financière, a été le principal canal de la paralysie de l'activité sur le marché interbancaire qui a conduit, par la suite, à la faillite de plusieurs institutions financières à court de liquidité, à la nécessité de renflouement de plusieurs autres et aux injections massives de liquidités par les banques centrales. Cela incite à développer un modèle de réseau qui permet d'analyser la façon dont la stabilité du système financier peut être compromise à la fois par le risque de crédit mais aussi par le risque de liquidité en cas d'une exposition excessive aux marchés interbancaires.

Le chapitre 2 propose, à ce titre, un modèle d'analyse de trois canaux de contagion qui se sont révélés particulièrement puissants pendant la crise, à savoir les expositions à un facteur de risque commun (par ex. au prix de marché de certains actifs), au risque de contrepartie sur le marché interbancaire et enfin les expositions au risque de refinancement de court terme (par ex. l'impossibilité de renouveler un emprunt interbancaire au jour le jour ou à une semaine). La méthodologie développée est suffisamment parcimonieuse et flexible pour être facilement incluse dans les exercices de *stress-tests* des banques centrales afin de tenir compte des effets, généralement négligés, de second tour des chocs macroéconomiques ou des chocs de marché. En outre, nous développons une nouvelle méthodologie permettant de simuler des chocs de marchés basés sur des données détaillés des actifs bancaires. Nous utilisons ensuite ce modèle afin d'évaluer la résistance du système financier français à la fin de l'année 2011. Ainsi, et en nous appuyant sur des données bancaires arrêtées au 31 décembre 2011, le système financier français ressort généralement robuste face à des chocs de marché d'amplitude standard ainsi qu'aux effets de contagion, les pertes en capital dues aux effets de contagion demeurant relativement modestes. Par ailleurs, et bien que les pertes dues à la contagion de solvabilité ou de liquidité soient d'ampleurs similaires, les chocs de liquidité ont la particularité de pouvoir engendrer des pertes en capital même en absence d'effet de contagion de solvabilité, appuyant de ce fait la pertinence voire la nécessité d'une modélisation des deux canaux simultanément. Cependant, et à l'instar de la majorité des études s'intéressant aux systèmes bancaires nationaux, notre approche fait l'hypothèse restrictive que le système bancaire français évolue dans un système fermé.

Le chapitre 3 se présente comme une extension du chapitre précédent en tenant compte des expositions des banques françaises aux marchés internationaux, mais aussi en augmentant le modèle pour couvrir 73 groupes bancaires issus de 21 pays européens. La nécessité de la prise en compte du système financier au niveau européen s'explique notamment par le processus d'intégration bancaire qui a été fortement encouragé à l'aune de l'intégration économique et financière du début des années 90. En France, la moitié des banques sont devenues de grands acteurs européens avec une activité transfrontalière significative et de relativement, faibles expositions au secteur bancaire national. Cependant, cette nécessité d'intégrer les expositions transfrontalières se retrouve vite confrontée au problème de la disponibilité des données. En effet, même les autorités nationales de surveillance financière n'ont, au mieux, accès qu'à une vue très partielle des expositions internationales des banques sous leurs contrôles[4]. Ainsi, certains articles s'intéressant à la question des externalités transfrontalières, à l'instar de Degryse et al. (2009) et de Halaj and Kok (2013), sont contraints de procéder à une analyse macroéconomique des effets de contagion, i.e. d'un système financier à un autre, et non au niveau des institutions individuelles.

Afin de tenir compte des fortes hétérogénéités qui caractérisent les systèmes nationaux et de dresser une représentation des expositions des banques fidèles à la réalité, nous exploitons une base de données unique des prêts interbancaires, à différentes échéances, échangés sur le marché monétaire. Cette base est estimée à partir des données issues de la plateforme de

[4]En effet, les autorités nationales de surveillance financière n'ont généralement accès qu'aux actifs dépassant un certain montant et ayant une maturité longue. À titre d'exemple, le registre de crédit allemand répertorie uniquement les expositions bilatérales - produits dérivés, actifs au bilan et hors bilan - au-dessus du seuil de 1,5 millions d'euros. En France, la base de données "grands risques" contient les expositions bilatérales trimestrielles des banques dont le montant est supérieur à 10 % de leur capital ou dépassant 300 millions d'euros.

paiement européenne TARGET2 (cf. Arciero et al. (2013)). À notre connaissance, notre étude est la seule qui mobilise une telle base de données pour examiner le potentiel de contagion transfrontalière à un niveau microéconomique, de banque à banque.

Plus précisément, nous utilisons l'ensemble des prêts interbancaires à échéance inférieure à un mois pour modéliser le réseau des liens interbancaires de court-terme et établir la carte de probabilités d'interconnexion entre banques sur le marché monétaire. En parallèle, nous établissons également une carte de probabilité des prêts de long terme en tenant compte des montants et des fréquences des titres de maturité plus longue. La combinaison de cette dernière matrice avec le montant total des expositions d'une banque vis-à-vis de l'ensemble de ses concurrentes européennes permet de simuler un grand nombre de matrices d'exposition de long-terme suivant la nouvelle méthode préconisée par Halaj and Kok (2013). Nous étendons, par ailleurs, la période d'analyse sur les 5 années allant de 2008 à 2012.

Nos différentes simulations suggèrent que les effets de la contagion, qu'elle soit due à des chocs de solvabilité ou de liquidité, constituent des risques extrêmes : la moyenne des pertes sur différents scenarios de stress, de banque initiale en defaut ou sur les réseaux simulés demeure limitée. Cette moyenne cache néanmoins des pertes excessives bien que rares. Selon nos simulations, le montant des pertes maximales aurait atteint en 2008 près du tiers du total du capital du système bancaire; cependant la résilience du système s'est grandement améliorée au fil des années.

En outre, nos résultats, issus des simulations de différents réseaux, montrent l'impact crucial de la structure du réseau sur la propagation des chocs, soulignant la nécessité de tenir compte du caractère dynamique du réseau.

L'ampleur de la crise financière de 2007-2009 a indéniablement surpris, d'autant qu'il s'agit à l'origine d'une crise des *subprime* américains censée être limitée par son ampleur et son extension géographique. En effet, comme nous le montrons dans les chapitres 2 et 3, la multiplicité des vecteurs des transmissions des chocs, conjuguée à l'intégration financière de plus en plus approfondie, augmente sensiblement la vitesse de propagation des chocs ainsi que leur ampleur; d'où la nécessité de déterminer des indicateurs avancés permettant de prévenir une éventuelle intensification de la crise. Par ailleurs, l'analyse des données de paiements interbancaires montre que lorsqu'une banque souhaite modifier son comportement, en procédant par exemple à une thésaurisation de sa liquidité, les systèmes de paiements sont susceptibles de procurer des signes précurseurs d'une éventuelle difficulté ou d'une réaction anormale des agents. Ainsi, comme le soulignent Benos et al. (2012), la faillite de Lehman Brothers a poussé plusieurs banques à retarder leurs paiements et à réévaluer leur degré d'implication dans le marché interbancaire par crainte du risque, alors élevé, de contrepartie. Le bon fonctionnement des infrastructures financières, en particulier, le système de paiement, est crucial pour la stabilité financière dans son ensemble, et peut donc servir d'indicateur avancé pour prévenir d'éventuels risques systémiques[5].

Le Chapitre 4 s'inscrit dans cette nouvelle littérature en s'intéressant particulièrement à la gestion de la liquidité intra-journalière et à sa capacité à paralyser l'ensemble du système de paiement. Nous nous focalisons plus précisément sur les retards de paiement sur le marché interbancaire, à savoir le délai qui s'écoule entre l'introduction de l'ordre de paiement dans le système et son règlement effectif, en mobilisant des données TARGET2 relatives à deux périodes distinctes : une période sous haute tension correspondant au mois de septembre 2008 et une période calme correspondant au mois de mai 2014.

A l'instar de Massarenti et al. (2013) et de Heijmans and Heuver (2011), nous constatons que les banques ont tendance à retarder leurs paiements, et plus particulièrement en période de crise. Pour expliquer ce phénomène, les articles théoriques qui utilisent une approche issue de la théorie de jeux suggèrent que les banques prennent des décisions stratégiques relatives à chaque transaction bilatérale. Or, nos résultats montrent que les banques ont tendance à prendre des décisions portant sur la gestion de l'ensemble de leur liquidité journalière. Nous distinguons ainsi deux types de banques : un premier groupe qui fixe un niveau de liquidité initiale suffisant pour répondre à ses engagements de la journée, et un deuxième groupe qui restreint systématiquement son niveau initial de liquidité et compte sur l'exécution des paiements de tiers pour traiter les siens. Bien que ce procédé, atypique, de gestion de la liquidité journalière ne soit pas nécessairement nocif au système dans son ensemble, il peut néanmoins conduire à son grippage total et plus particulièrement en période d'asséchement des marchés. La dynamique de cette divergence de comportements vis-à-vis des retards de paiement est susceptible de constituer un indicateur avancé d'éventuelles tensions sur le marché monétaire.

[5]Se référer à Manning et al. (2009) pour un résumé détaillé de la théorie ainsi que des pratiques répandues, les retards compris, dans les systèmes de paiement de grande valeur (LVPS). Rochet and Tirole (1996) fournit un éclairage supplémentaire sur les systèmes de compensation nette et l'architecture du système de paiement.

Chapter 1

Literature review

1.1 Introduction

For a long time, a banking system was represented by a representative bank without taking into account the interlinkages of the banking, and larger, financial system. However, during the 2007-2009 financial crisis, it was precisely those linkages that threatened the stability of the financial system worldwide. Financial institutions (banks from now on for simplicity) appeared to be highly interconnected, directly and indirectly, via different financial products. Direct exposures of one bank to another deplete bank's capital if its counterparty defaults on its commitments. These exposures can be through loans, equity holdings or derivative products such as CDS contracts. On the other hand, banks holding similar assets are connected indirectly since fire sales of those assets on a distressed market will impact negatively balance sheets of the banks.

Such interconnectedness is at the core of systemic risk, the risk of a collapse of the entire financial system, while a network is a natural way of representing a financial system with multiple linkages. Therefore the network approach as a tool to analyze systemic risk and test macroprudential regulations has received significant attention from both researchers and policy makers.

The analysis of complex systems through a network representation has been widely used in physics, biology and social sciences for a long time. However, researchers in economics and finance developed an interest in this approach only recently starting with the seminal paper by Allen and Gale (2000). This interest gained momentum during and after the 2007-2009 financial crisis, when the level of system interconnectedness threatened the stability of the financial system worldwide. In the past few years, the financial networks literature has boomed, and this chapter provides a survey of this vast amount of studies.

The primary question when it comes to analyzing the interconnectedness of the financial system concerns the data availability on bilateral exposures between institutions. This is not a trivial question since such data, if they exist, remain highly confidential. Therefore, I consider important to introduce the reader to the issues related to the sources of the data, a small history of their availability, as well as problems and solutions found by researchers to overcome complete absence or partial availability of the data. Particularly, this chapter will cover methods to simulate bilateral exposures given incomplete information and the use of market/public data as an alternative approach to obtain information on bilateral relationships. Additionally, I will describe the main characteristics of different real financial networks that are well documented by empirical literature and explain how these properties relate to the functioning of a system.

Seemingly the largest stream of the financial networks literature is on network stress-testing or counterfactual simulations. These models have been largely developed by central banks because they allow analyzing how resilient a banking system is to contagion at a given point in time (snapshot of a network), and especially because central banks have often an access to the data on bilateral exposures. Upper (2011) provides an excellent survey and analysis of the studies done by 2011, however, this strand has strongly developed since then. These studies are characterized primarily by: models that take the network as given; banks' behavior that is based on rules of thumb; and the major question asked is how losses due to an initial shock will propagate through the system given certain channels of propagation and behavioral rules. Two main aspects of such an analysis are particularly interesting, as I will describe below: which network structure is more vulnerable/resilient to contagion and how different banks' characteristics improve system stability.

The evolving nature of network linkages inspired researchers to move forward and analyze network formation and dynamics, more specifically why and how banks' strategic decisions on link creation can lead to the formation of the networks that we observe. Moreover, these studies address the issue of the optimality of networks created in equilibrium, therefore providing a link between banks' incentives and the created network structure that could have fruitful policy implications. Some findings of this literature show that banks tend to create too many links while others not enough which builds in dangerous asymmetry in the network structure, thus pointing out to potential for financial stability regulation.

The last stream of the financial networks literature that I survey is related to econometric models which aim at explaining banks' financial characteristics with their position in a network. The methodology developed by studies on social networks identifies peer effects well, thus allowing treating the difficult question of how the behavior of an agent is affected by others. All these studies agree that the position of a bank in a network as well as the network architecture itself are important to explain financial characteristics of a node and a system.

1.2 Data

To represent a financial system as a network, knowledge about bilateral interactions between the agents is indispensable. With few exceptions, such information is available only to the participants themselves and sometimes also to an intermediary which provides post-trade financial services such as clearing and settlement. For instance, the US company DTCC, that settled $1.7 quadrillion in value of securities transactions worldwide in 2011, is the main provider of the data on the CDS trades. Three exceptions are (*i*) the widely used anonymous intraday data on interbank lending from the e-MID interbank lending platform[1]; (*ii*) the syndicated loans data from Dealogic, and (*iii*) BIS data on exposures between banking systems in different countries.

Whereas such opacity attracts little attention during normal times, it becomes a real problem during a crisis. As a consequence banking supervisors in different countries very often started to collect information on bilateral exposures after a crisis hit their country's financial system: e.g., in Russia in 1998; in Mexico in 2004. In most European countries, almost the only reliable source of information on bilateral exposures is the quarterly reports of banks to their supervisors, so called credit registers. In the run-up to the crisis, these data were used mainly for supervision and not for systematic research and analysis of the interbank bilateral relationships, therefore the data were often of limited quality. As Upper (2011) documents in his survey, only in Hungary and Italy, were these reports fairly complete, allowing for full identification of the elements of bilateral exposures matrix; whereas in the majority of countries, they covered only the largest exposures (Netherlands, Finland, Sweden, Switzerland) or excluded off-balance sheet exposures (Belgium, Netherlands). Moreover, the data often lack information about the breakdown by instrument and maturity.

[1]Interbank trading in the e-MID platform reached its maximum of 17% of the interbank unsecured lending in 2007, however, after the beginning of the crisis its share has significantly reduced.

The 2007-2009 financial crisis emphasized at the same time the threat posed to the stability of the system by interlinkages between financial institutions and the complexity of channels through which a shock can propagate, namely the role of short-term funding and derivatives exposures. The supervisors in most of the countries were caught by surprise and did not know how much one institution was exposed to another, which led to significant bailouts in order to prevent contagion. In 2009, at the G20 Pittsburgh conference, the G20 Data Gap Initiative was taken which recommends the collection of consistent bank-level data for joint analysis and enhancements to existing sets of aggregate statistics, and the enhancement to the BIS international banking statistics. Indeed, the situation with data collection and data availability started changing: the Bank of England launched the program in 2011 to collect information about exposures of banks to different financial institutions distinguished by maturity and type of financial instruments; European Securities and Market Authority enabled the collection of the data on bilateral derivatives trades since 2014; the European Central Bank has provided access of a small group of researchers within the Eurosystem to money market loans and payment system data.

At the international level, the situation is even more difficult: whereas the world financial system is very intertwined with financial institutions investing and having their subsidiaries all over the world, the regulation and data collection remains to a great extent national. Cerutti et al. (2012) provide an interesting analysis of existing challenges to global systemic risk measurement and identify areas where enhancements to data are most needed. In the euro area, the creation of Banking Union and Single Supervisory Mechanism may soon change the situation in a positive way since the ECB, as the central prudential supervisor, should be able to have access to the entirety of the data on national banking systems including their mutual exposures.

Whatever data on bilateral exposures are concerned, national or international, the problem is always twofold. First, supervisory agencies lack good quality data themselves and fail to assess systemic risk in a financial system coming from the interlinkages. Second, these data are confidential and not available to academics and the public. The first problem is getting partly solved thanks to the crisis and the ensuing renewed interest in the network approach as a tool to analyze the stability of a financial system.[2] However, it is difficult to foresee that the data on interbank bilateral exposures will become less confidential. This limited access to real network data gave birth to two particular streams of the network literature: first, methods allowing for a reconstruction of exposures matrices from partial

[2]pioneered by the Bank of England and Andrew Haldane, many central banks have in their agenda the analysis of systemic risk using a network toolkit.

publicly available data, such as banks balance sheet data (Section 1.3); second, the estimation of bilateral relationships between listed financial institutions using public data on equity prices (Section 1.8).

1.3 Incomplete data

In the absence of direct information on bilateral exposures, researchers looked for alternatives, namely to find a way to reconstruct a network from partial data. It turned out to be a challenging task due to the very particular structure of real financial networks (discussed in section 1.4). Moreover, the way a network is reconstructed may bias results of network stability analysis. In this section, I will focus on methods allowing reconstruction of networks from partial data, and biases that these estimated interconnections may introduce in the analysis of contagion propagation.

The most easily available information is banks' balance sheets published on a regular basis. Among other items, banks report their total interbank assets and liabilities. This information is the starting point for all the methods reconstructing a network. The key assumption regards how banks allocate their interbank lending across potential counterparties, and existing methods differ by the assumptions they make. The first and most widely used assumption is that banks spread their lending as evenly as possible given the assets and liabilities reported in the balance sheets of all other banks. This method is known as the maximum entropy method. This concept originating from physics was first introduced in the contagion literature by Sheldon and Maurer (1998) and has been often used in the stress-testing literature. This methodology, however, tends to create complete networks, thus failing to account for several stylized facts of interbank networks such as sparseness and power-law degree distribution. Moreover, several studies showed that maximum entropy leads to biased estimations of the severity of contagion (Mistrulli (2011); Degryse et al. (2009)). Figure 1.1 from Batiz-Zuk et al. (2013) shows the difference between a network generated under the ME principle and one built using real exposures data.

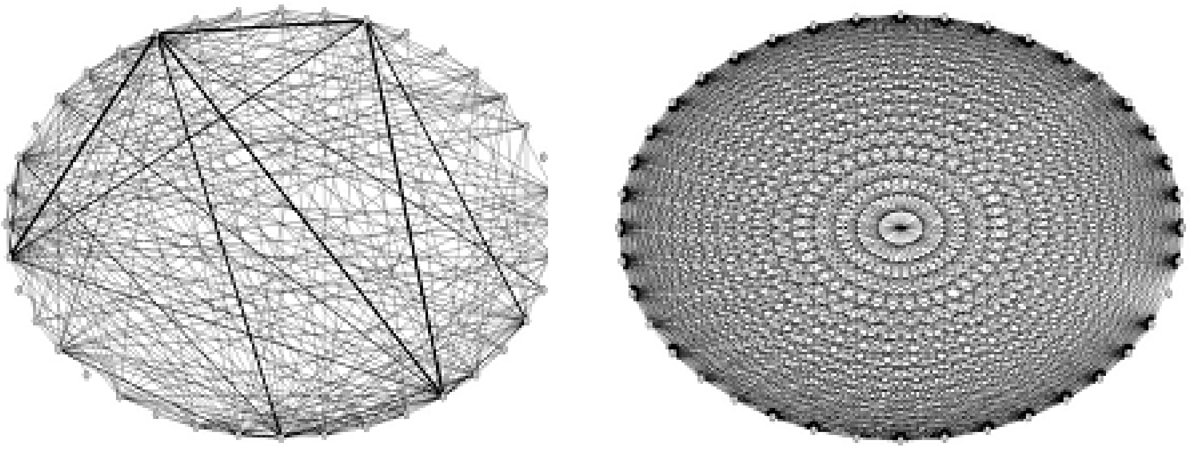


Figure 1.1: Figure from Batiz-Zuk et al. (2013). Two networks: one generated with real exposures (on the left) and the one under the maximum entropy principle (on the right)

Recently, many other approaches have been proposed in order to overcome the limitations of the maximum entropy approach. These studies can be split into two main groups: the first ones look for additional information to be used as a prior for a distribution of interbank aggregate assets and liabilities; and the others exploit statistical properties of observed financial networks as prior information. In the first group, Halaj and Kok (2013) use a probability map to define the probability that two given banks are connected and then run an iterative procedure to generate interbank networks by randomly picking a link between banks and accepting it with a probability taken from the probability map. The authors recognize that the method does not necessarily generate core-periphery structures. However, this may very well depend on the assumptions used to construct the probability map.[3] In their other paper, Halaj and Kok (2014) undertake a very different approach which belongs rather to Section 1.6 where banks allocate interbank exposures while optimizing their portfolio with respect to risk and return. Along with the information to define a probability map, this method requires quite a lot of other market information. The method proposed in Musmeci et al. (2013) is at the border of the two groups: on the one hand, the authors aim at reconstructing global topological properties of complex networks (network density and k-core structure), on the other hand, they assume to know the degree for a subset of the nodes in the network. The authors use a fitness model, calibrated on the

[3]In chapter 3 based on the paper "Cross-border interbank contagion in the European Banking System", we use interbank long-term loans (from 3 months to 1 year) from TARGET2 payment system to construct a probability map which allows us to obtain simulated networks with core-periphery structure.

subset of nodes for which degrees are known, in order to generate a set of networks. They find that a subset of 10% of nodes can be enough to estimate the properties of the network.

In other words, the maximum entropy (ME) method reallocates interbank lending given no prior information on the distribution. However, from the empirical studies (see Section 1.4), we know that real financial networks exhibit several well-documented properties, namely sparsity (low density) and heterogeneity (power-law degree distribution). The second group of methods uses the statistical properties of these findings in order to reconstruct an interbank network. Moussa (2011) proposes a method which is very similar to the maximum entropy with the only difference that the relative entropy is minimized not with the non-informative uniform prior but with a sparse prior reflecting the belief on the scale-free structure of a network. The author states that this approach reproduces the observed degree heterogeneities of interbank networks. Anand et al. (2014), unlike the maximum entropy principle which has no economic meaning, proceed from an economic assumption that banks' networks are sparse because interbank activity is based on relationships and link creation is costly. This assumption corresponds well to the theoretical literature on endogenous network formation which shows that given that links are costly, banks optimally choose a star network structure.[4] Moreover, Craig and von Peter (2010) show that real interbank networks tend to have core-periphery structure that is small banks interact with money center banks. Therefore, Anand et al. (2014) follow an approach that minimizes the density, called the "minimum density" (MD) approach, where the most probable links are identified and loaded with the largest possible exposures, while ensuring consistency with the aggregate lending and borrowing limits for each bank. The authors confront the two methods (ME and MD) with the true German interbank network and find that minimum density solution preserves some of the network's structural features better than maximum entropy does. Baral and Fique (2012) use copula in order to reconstruct an interbank network given aggregated assets and liabilities. The method exploits the fact that copula allows capturing asymmetries of a matrix in two dimensions and therefore having different types of blocks such as core-periphery blocks defined in Craig and von Peter (2010): core-core block is characterized by intense relationships; periphery-periphery almost zero connections; and core-periphery, periphery-core by regular links. The authors compare copula methodology with ME and document that as long as the data are asymmetric and a network is far from being complete (the case of real networks), the copula method outperforms the ME one. Mastromatteo et al. (2012) propose a message-passing algorithm to explore the space of possible network structures producing worst-case configurations in terms of contagion risk.

[4]More about findings of the theoretical literature in Section 1.6

The authors show that ME severely underestimates the risk of contagion, whereas their algorithm is able to produce maximally fragile structures, providing a practical upper bound for the risk of contagion when the actual network structure is unknown.

Almost all the aforementioned studies explicitly compare their performance with the results given by the maximum entropy approach or with the real networks. Some of them also analyze how the way a network is reconstructed can bias contagion risk. All find that their respective methods perform better than ME in obtaining networks that reproduce some of the stylized characteristics of real networks, and that the ME approach tends to underestimate the risk of contagion. However, given the differences in the underlying assumptions and the information required, it is difficult to say which method is better, and there have not yet been any studies that compare these approaches to each other. To fill this gap, a group of researchers from the Basel Committee research task force has undertaken a big effort in order to compare these methods by using them on the same set of different exposures data and computing the same set of network statistics and contagion indicators.[5] It can be foreseen that this exercise is not going to find an outcome "one size fits all", the performance of the methods will depend to a great extent on the particular data structure. However, these results will provide important insights into how an interbank exposures matrix can be reconstructed and bias each method introduces. The results are forthcoming in a BIS working paper.

1.4 Empirical networks

In this section, I summarize the main findings of studies analyzing the characteristics of the real financial networks. I provide an economical interpretation of those characteristics and show how they are linked with systemic risk and financial fragility of the system.

The main findings of this literature are that financial networks have similar characteristics whatever financial system and data sources are used. Boss et al. (2004) are one of the first who analyzed the topological properties of an interbank market using the credit exposures data of Austrian banking system. The authors show that the banking network shares typical structural features known in numerous complex real world networks: low density, meaning that interbank networks are highly sparse; degree distributions following a power law; a low clustering coefficient of the network, and the so called small world phenomenon, meaning that the average shortest path between any two vertices ("degrees of

[5] I was a part of this group since May 2014.

separation") in the network are surprisingly small. Many other studies documented similar stylized facts for different data sets: Bech and Atalay (2008) for the overnight federal funds market; Cont et al. (2010) for Brazilian interbank exposures; Gabrieli (2011) for the e-MID interbank market; Peltonen et al. (2014) for worldwide CDS network and Clerc et al. (2014) for European interbank CDS exposures among others.

A financial network consists of a set of banks (nodes) and a set of relationships (edges) between the banks. These relationships can be of different nature: interbank overnight loans, e.g., Bech and Atalay (2008) and Gabrieli (2011); exposures in derivatives such as CDS contracts or short-term foreign exchange swap contracts, e.g., Clerc et al. (2014); Peltonen et al. (2014) and Banai et al. (2013) correspondingly; interbank credit exposures, e.g., Boss et al. (2004); Cont et al. (2010). All these relationships are important for the analysis of different aspects of interbank activity, however, due to the data availability, most of the studies focus on relationships that stem from interbank credit exposures, therefore from now on, I will always refer to a network of credit exposures if not specified otherwise.

Some topology characteristics of graphs are very helpful for the network analysis.

Definition 1.1. A (un)directed graph $G = (V, E)$ consists of a nonempty set V of vertices (nodes), and a set of (un)ordered pairs of vertices E called edges.

An interbank network is characterized by the exposures (assets) matrix E. The lending bank provides a loan and holds it as an asset, while the borrowing bank holds this loan as a liability. In a matrix form, the entries E_{ij} are the loans (exposures) of bank i to bank j.

Definition 1.2. The matrix of bilateral exposures $E(G) = [E_{ij}]$ of an interbank market G with n banks is the $n \times n$ matrix whose entries E_{ij} denote bank i's exposure to bank j. The assets a_i and liabilities l_i of bank i are given by $a_i = \sum_{j=1}^{n} E_{ij}$ and $l_i = \sum_{j=1}^{n} E_{ji}$.

To describe a network, one would start by looking at the number of nodes and the number of existing links relative to the number of possible links in the graph. The latter one is called the *density* of a network or the measure of completeness of a network. While the number of banks can vary significantly from one banking system to another, the network density lies in the interval between 0 (no connections) and 1 (complete network), and it is usually very low in financial networks: Gabrieli (2011) documents that in 2007, e-MID interbank network consisted of around 120 banks with density of 2.22%; according to Bech and Atalay (2008), in 2006, around 500 banks were active on the federal fund market with density of 0.66%. The few exceptions for which network density is close to 1 are small concentrated banking systems: the Canadian banking system is a complete network consisting of 6 banks (Gauthier et al. (2010)); the French banking system represented by 11 banking holding companies forms an almost complete network with density being equal to 80% (Fourel et al. (2013)).

The interconnectedness of a node can be defined as the in- and out- degree of the node.

Definition 1.3. The adjacency matrix of bilateral exposures $A(G) = [a_{ij}]$ of a network G with n banks is the $n \times n$ matrix whose entries a_{ij} are equal to 1 if there exists a link between bank i and bank j and 0 otherwise. The in-degree $d_{in}(i)$ and out-degree $d_{out}(i)$ of node i are defined as: $d_{in}(i) = \sum_{j=1}^{n} a_{ji}$, $d_{out}(i) = \sum_{j=1}^{n} a_{ij}$ and give a measure of the interconnectedness of the node i in a directed graph $G(V, E)$.

Not all nodes in a network have the same node degree or number of edges. Dispersion of node degrees is characterized by a distribution function $P(k)$, which gives the probability that a randomly selected node has exactly k edges. And not all networks have the same distributions of node degrees, therefore, an important concept that allows distinguishing two different networks is the degree distribution. A class of graphs that has been widely studied and which serves as a standard for comparison to is random networks, in which edges are placed randomly with the same probability of having a link between any two nodes. A majority of the nodes in such graphs have approximately the same degree, close to the average degree $< k >$, and the degree distribution follows a Poisson distribution with a peak at $P(< k >)$. However, a well-established result is that for most large networks, including financial networks, the degree distribution significantly deviates from a Poisson distribution and has a power law tail $P(k) \sim k^{-\gamma}$. Such networks are called scale-free (Barabasi and Albert (1999)).

The scale-free property of real networks describes the substantial heterogeneity of the node degrees: Bech and Atalay (2008) documents that on average banks lent to (or borrowed from) 3.3 other banks in 2006, whereas maximum in-degree (out-degree) in the network was 127.6 (48.8). Many other papers obtain similar findings for different data sets, to name but few, Cont et al. (2010) for a Brazilian network of credit exposures and Clerc et al. (2014) for the European CDS market, who both document the persistence of this property over time.

Another important concept of complex networks is the small world property which means that despite the large size of financial networks, most of them are characterized by a relatively short path between any two nodes. The average path length of a network is defined as the average length of the shortest paths for all pairs of nodes $i, j \in V$. Boss et al. (2004) show that in Austrian banking system with 900 banks, the average path length is about three degrees of separation; Gabrieli (2011) and Bech and Atalay (2008) document similar findings: about two and three degrees of separation with more than 100 banks in e-MID data and more than 450 banks in Fed Funds Market correspondingly.

The last characteristics to describe a network is the clustering coefficient, introduced by Watts and Strogatz (1998). Social networks tend to form cliques, group of friends, clubs and so on. This tendency to clustering is quantified by the clustering coefficient (Watts and Strogatz (1998)). In simple words, clustering is the probability that two nodes which are the neighbors of the same node, themselves share a link.

Definition 1.4. Let node i has degree k_i. If the first neighbors of the original node were part of a clique, there would be $k_i(k_i - 1)/2$ edges between them. The ratio between the number E_i of edges that actually exist between these k_i nodes and the total number of $k_i(k_i - 1)/2$ gives the value of the clustering coefficient of node i: $C_i = \frac{2E_i}{k_i(k_i-1)}$. The clustering coefficient of the whole network is the average of all individual C_i's.

For most of the real networks and particularly social networks, the clustering coefficient is typically much larger that it is in a random network of the same characteristics as pointed out by Watts and Strogatz (1998). Indeed, it is very likely that friends of a common friend are also friends, or that two people co-writing with the third one may be co-authors themselves. Here, a link creation has only benefits and no costs, however, it is not true for financial networks due to the involved trade-off: benefits of an additional connection vs. a cost to establish a link, or benefits of lending to one more bank vs. potential shock propagation through this connection. In the Austrian banking system, (Boss et al. (2004)) finds clustering coefficient to be about 0.12; whereas Bech and Atalay (2008) demonstrate significant asymmetry of in- and out- clustering: in 2006, about 0.10 and 0.28 correspondingly.

Short average path length with low clustering coefficient highlights certain efficiency of real networks: efficient transfer of resources from one node to another with minimum number of costly links. Assuming that indirect connections (neighbors of neighbors) are also beneficial, Jackson and Wolinsky (1996) show in a game theoretic framework that given such tradeoff the most efficient[6] network is a star network with one node in the center and all other nodes connected to the central node. Real financial networks have a form very similar to a star, however, in the center there is not one bank but a small group of well

[6] A network is defined to be efficient if it maximizes the total utility to all players in the society.

connected banks, the core, and all other banks, the periphery, being mainly connected to the core banks (Craig and von Peter (2010)). Whereas seemingly efficient (the economic efficiency of such network structures will be discussed in the overview of the theoretical literature in Section 1.6), such a structure may be also very fragile, since the whole network relies on few intermediaries. And in case of attacks targeted at the central nodes, the whole system may fall apart. Albert et al. (2000) conducted a very interesting study to analyze which network structure is more resilient, and the main finding is that there is no one-size-fits-all solution: while being more vulnerable to targeted attacks, scale-free networks are more resilient to random shocks than random networks. Indeed, in a random network all the nodes have similar importance, therefore in case of a random shock a network will be equally significantly impacted whatever node is attacked. However, the probability of hitting a core node in a random strike is very low since there are only few core nodes and many periphery ones. On the contrary, if we attack any of the hubs, the damage will be much higher comparing to the attack on any of the nodes in a random network. The issue of stability of a financial system is of particular importance, and I will discuss in details the findings of the stress-testing literature in next section.

1.5 Stress-testing literature

In this section, I focus on the network stress-testing literature. The reviewed studies differ significantly in the types of data used (real or estimated exposures matrices, fully simulated networks), contagion channels and resolution models, however, they all have the same feature: the initial network is taken as given, and it is used to analyze the resilience of a network to the propagation of contagion after an initial shock.

The first studies date back to early 2000s when Allen and Gale (2000) published their seminal theoretical paper on the network contagion, and in 2001 and 2003, Eisenberg and Noe (2001) and Furfine (2003) proposed algorithms to compute the losses due to contagion in a network system.[7] This stimulated numerous papers on contagion in real-world banking systems, for which Upper (2011) provides an excellent review.[8]

[7] Working papers circulated much earlier

[8] Amundsen and Arnt (2005) in Denmark, Blavarg and Nimander (2002) in Sweden, Degryse et al. (2009) in Belgium, Elsinger et al. (2006a,b) in Austria, Frisell et al. (2007) in Sweden, Furfine (2003) in the USA, Guerrero-Gomez and Lopez-Gallo (2004) in Mexico, Lublóy (2005) in Hungary, Mistrulli (2011) in Italy, Sheldon and Maurer (1998) in Switzerland, Toivanen (2009) in Finland, Upper and Worms (2004) in Germany, Van Lelyveld and Liedorp (2006) in Netherlands, Wells (2004) in the UK

The main focus of those studies is the presence and size of the *domino effect* due to an idiosyncratic bank failure: if one bank defaults, its counterparty writes off losses and may default as well, which may lead to other defaults of its own counterparties. This channel is often called solvency contagion. In this framework, banking systems are subject to a sudden idiosyncratic default of one bank at a time with few exceptions: Elsinger et al. (2006a,b) first proposed a shock related to the market price of the assets, Lublóy (2005) grouped banks according to their FX exposures and let all banks in a given category fail jointly. No behavioral aspects were analyzed. As discussed in Upper (2011), few clear-cut results emerge due to the differences in methods and assumptions used and banking systems analyzed. Nevertheless, according to Upper (2011), the main results can be summarized in the following way: losses of a magnitude 15-20% of total assets are documented for Italian, Belgian, British and German banking systems; studies that analyze overnight transactions find little possibility for contagion (e.g., Amundsen and Arnt (2005) and Furfine (2003)) and some other studies (Lublóy (2005) and Sheldon and Maurer (1998)) find also limited potential for contagion for Hungary and for Switzerland correspondingly.

Whereas the financial world proves to be more and more interconnected across international borders[9], the lack of the data on interbank bilateral relationships prevents the analysis of the potential for cross-border contagion. Though, a few studies tried to do it using BIS banking statistics, e.g. Degryse et al. (2009) and Espinosa-Vega and Sole (2010). The interesting point of such studies is rather documentation of changes in patterns of cross-border exposures than levels of contagion since the main assumption of a shock wiping out a significant percentage of cross-border assets of a certain country remains coarse.

As aforementioned, two main algorithms are used to resolve the problems: Eisenberg and Noe (2001) and Furfine (2003). A banking system is characterized by an exposure matrix E. Bank i holds interbank assets E_{ij} and has capital C_i. When some bank j defaults, bank i writes off losses equal to bank i exposure to bank j, E_{ij}, multiplied by recovery rate R. Therefore, bank i defaults when its capital C_i is lower than $E_{ij}R$. The default of bank i may trigger defaults of its own counterparties and so on. Eisenberg and Noe (2001) solve this problem analytically using the fixed point theorem and find an endogenous repayment vector R which is proved to be the unique solution to the problem. Furfine (2003) proposes an algorithm solved numerically, where defaults follow each other sequentially. The recovery rate is set exogenously. The difference between the two algorithms is quite significant, whereas the latter looks at defaults step by step: what are the banks that default at this round due to the defaults at the previous step; the former tells us what would be the defaults

[9]see, e.g., Cetorelli and Goldberg (2014) for a discussion of measures of complexity of global banks

in equilibrium if we take into account all the mutually dependent losses and repayments. Eisenberg and Noe (2001) has an advantage of providing an analytical solution and an endogenous recovery rate, however the timing of the model is hardly realistic considering how long it takes for the resolution of a bank default.[10] In this sense, Furfine (2003) provides a more realistic approach, however different recovery rates need to be tested.[11]

The literature developed methods to analyze contagion in a more realistic way including both idiosyncratic and correlated market shocks, other channels of contagion and endogenous reactions of banks. Some studies use real exposures data, but most of the researchers performed their analysis on simulated data. The former counts very few papers, whereas the framework of simulated networks attracts a lot of researchers due to both its feasibility and flexibility, and therefore there are multiple papers with a big variety of test settings. I will start by mentioning the papers using real data. Cont et al. (2010) analyze the Brazilian banking system and propose a way to simulate a correlated market shock as a one factor model in the absence of detailed data on the banks' balance sheet. They underline the importance of having a correlated market shock vs. an idiosyncratic shock.

Solorzano-Margain et al. (2013), on the contrary, employ rich data on the Mexican interbank network and analyze the contagion within the system given well-defined macroeconomic shocks modeled through a large-scale BVAR. The authors find that some banks may indeed default due to the market shocks. The same group of researchers from the Mexican central bank has some other publications analyzing the Mexican interbank data where they consider other types of exposures (foreign exchange, derivatives and securities) and a broader financial system including additionally brokerage firms, pensions and investment funds.[12] In terms of quality of the data, coverage of the assets, institutions and time period, their data and work are unique.

Karas and Schoors (2012) investigate an impact of additional channels of contagion on the stability of the Russian banking system: funding liquidity losses, fire assets sales and active liquidity runs on infected banks. Having extremely rich data, the authors perform their analysis on monthly data from July 1998 to October 2004, thus capturing two instances of banking crises, namely 1998 and 2004. The paper tests different channels of contagion in order to be able to reproduce the severity of the crises in terms of the number of defaulted

[10] see Fleming and Sarkar (2014) for the details of the resolution process of Lehman Brothers which took several years

[11] Memmel et al. (2012) conducted a unique analysis of default contagion using stochastic loss given default, or stochastic recovery rate.

[12] see e.g. Martinez-Jaramillo et al. (2014, 2010)

banks. The main finding suggests that only when all the channels are activated, it is possible to capture both crisis periods.

Vuillemey and Peltonen (2013) analyze the impact of a sovereign credit event affecting 65 major European banks through several channels: direct losses on sovereign bond holdings, asset fire sales, direct CDS repayment triggered by the credit event, increased collateral requirements on other non-defaulted CDS reference entities and solvency default cascades. Their results suggest that losses propagate substantially through bond exposures and to a lesser extent through CDS exposures. An interesting finding is that the CDS market hardly play a mitigating role of in case of a sovereign credit event.

Alter et al. (2014) move further than simple stress-test analysis of a banking system and investigate the effect of capital rules on the German banks, which are connected through overlapping asset portfolios and interbank loans. These rules depend on both individual bank characteristics and interconnectivity measures of interbank lending and have to minimize system wide losses. The authors find that reallocation of capital based on eigenvector centrality decreases twice as many losses in the system as Opsahl, out-degrees or closeness centrality.[13]

Going back to the papers analyzing the role of the network structure in propagating and amplifying shocks to a financial system with the use of simulated networks, Chinazzi and Fagiolo (2013) provide a nice critical survey of this literature. Here I will follow the systematization proposed in the survey with which I fully agree: different factors impact the network capacity to withstand a shock such as connectivity of a network, heterogeneity of banks' size, type of the shock hitting a system and channels of propagation. The reviewed studies analyze these factors in different settings and combinations and provide multiple insights on the relationships between various characteristics and stability of a network. I summarize these findings in a concise way in Table 1.1.

Employing methods and concepts of the literature on complex networks, Gai and Kapadia (2010) provide a critical result that a financial system exhibits a *robust-yet-fragile* property. Higher connectivity improves the stability of the system by reducing the probability of contagion being triggered, however, once contagion starts, higher connectivity increases the probability of large default cascades. The probability of contagion is low, though when it happens, its impact can be disastrous. Acemoglu et al. (2013) propose

[13] Out-degree centrality is the number of links that originate from each node. Eigenvector centrality, or Bonacich centrality, is the centrality of a node given the importance of its neighbors. Closeness centrality is defined by how close a node is to all other nodes. Opsahl centrality has been recently proposed by Opsahl et al. (2010), and it combines the out degree with the strength of the outgoing links.

another source of a tipping point: the size of the initial shock which in the model is related to total excess liquidity in the system. Their main finding shows that the result of Allen and Gale (2000) about the stability of the complete network is valid only when the shock is small, however, when the shock is large, this network structure turns out to be the least resilient and the least stable. Amini et al. (2012) address the important issue of the size of the exposures with respect to the capital. They define a link to be *contagious* when the exposure it represents is larger than the capital of the lending bank. The resilience measure then links the distribution of in- and out- degrees and the proportion of contagious links. When the latter are limited, no contagion occurs, however, if the number of contagious links crosses a certain threshold, an initial shock will spread easily through the system. Therefore, the authors underline the importance to monitor that banks do not have exposures that exceed their capital. The current regulation in France limits interbank exposures weighted by their risk to 25% of capital, however non-risk-weighted exposures can be as high as capital. [14]

Iori et al. (2006) documented that heterogeneity of the system in terms of the banks' size can be an important source of fragility. They show that a system with banks of different size becomes prone to knock-on effects whereas in a homogenous banking system interbank relationships univocally stabilize the system. Amini et al. (2013) analyze instead the heterogeneity of the system in terms of the degree and exposures distribution, or in other words, number and size of connections of a bank. While keeping the average connectivity constant, they test the impact of other structures: scale free network with heterogenous exposures; scale free network with homogenous exposures; and a random graph with homogenous exposures. The main finding states that the more a system is heterogenous the less it is resilient.

Nier et al. (2008) and Caccioli et al. (2012) test both forms of heterogeneity: over assets and degrees. Nier et al. (2008) find that the effect of the degree of connectivity is non-monotonic: initially a small increase in connectivity increases the contagion effect; but after a certain threshold value, connectivity improves the ability of a banking system to absorb shocks, however, this holds only if the banking system is well-capitalized. Another finding suggests that the lower capitalization magnifies losses due to contagion in a non-linear way, namely, there is a threshold of the amount of capital in the system below which the risk of a systemic breakdown surges. Moreover, the size of interbank liabilities tends to increase the risk of knock-on default. Finally, more concentrated banking systems are shown to be more prone to systemic risk, all else equal.

[14] CCLRF (2013)

Findings by Caccioli et al. (2012) suggest existence of two different regimes: higher probability of contagion due to the failure of the most connected bank rather than the biggest one given low average connectivity; and the other way around for high average connectivity. Additionally, they find that increasing capital buffers of only the biggest banks is effective in reducing probability of contagion only when banks have heterogenous balance-sheet sizes.[15] This result confirms the one established by Cont et al. (2010). Caccioli et al. (2012) also analyze the impact of disassortative mixing property of financial networks - well-connected banks tend to connect with nodes that have few connections - on their resilience to contagion and finds that this network characteristics does indeed decrease the instability of the system.

The aforementioned papers mostly focus on solvency cascades, however, a shock can propagate through various channels. The paper by Cifuentes et al. (2005) is one of the first to analyze the effect of asset fire sales on network stability. They find that connectivity impacts the number of contagious defaults in a non-linear way. More specifically, without the price channel, higher connectivity is always beneficial, whereas when prices are marked to market, higher connectivity may imply more banks selling their illiquid assets and therefore higher impact due to this additional channel. Nier et al. (2008) also extend their model to study assets price effects, though they assume that assets are the interbank obligations of the previously defaulted institutions. The authors find increase in systemic risk in the presence of these liquidity effects.

Montagna and Kok (2013) add one more layer of contagion on top of the aforementioned two, therefore analyzing together solvency cascades, assets fire sales and banks' liquidity hoarding behavior. They find sizeable non-linearities when taking into account banks' interactions in all the three segments, namely, losses due to contagion through the three channels can be significantly larger than the sum of the channel-induced losses when considering each layer individually.

[15] According to this finding, new regulatory measures discussed at G20 Summit in Brisbane in November 2014 such as TLAC (Total loss absorbing capacity) and GLAC (Gone-concern loss absorbing capacity) should improve the resilience of the international financial system to contagion.

Table 1.1: Comparison of results found by different studies concerning the impact of the network structure and various sources of heterogeneity on the system resilience to contagion

Impact of network structure and sources of heterogeneity on the system resilience to contagion							
	Gai and Kapadia (2010)	Acemoglu et al. (2013)	Amini et al. (2012)	Iori et al. (2006)	Amini et al. (2013)	Caccioli et al. (2012)	Nier et al. (2008)
Type of network							
Scale-free network					x	x	
Erdos-Renuy random network	x	x		x	x	x	x
Sources of heterogeneity in the system							
Shock size		x	x				
Connectivity	x	x	x	x			x
Deposits size				x			
Assets heterogeneity						x	x
Node degree and exposure size					x	x	x
Disassortative mixing						x	
Conclusions							
	i) Low probability of widespread impact; *ii)* Higher connectivity lowers probability of default when contagion has not started; but higher probability of large defaults cascades when contagion begins	When a shock is small, the complete network is the most stable; when a shock is large, it is the least stable	*i)* No assumptions on the node degree distribution; *ii)* Threshold on number of contagious links, exposure is larger than the capital of the lending bank, in the system defines if contagion will spread through the network	*i)* In a homogenous system, increasing connectivity improves stability; *ii)* In heterogenous system, higher connectivity stabilizes the system only up to a certain point, but whenever default starts, it may drive widespread consequences	The higher heterogeneity, the less resilient the network is.	*i)* Heterogenous networks are more robust when a random bank fails, but more fragile to the targeted attack on the most connected banks; *ii)* A heterogenous distribution of assets increases the probability of contagion even with respect to random failures; *iii)* The property that well-connected banks tend to connect to banks with few connections decreases the probability of contagion.	*i)* Higher capital improves system stability non-monotonically; *ii)* Non-linear effect of connectivity; *iii)* Higher concentration with higher capitalization reduce significantly contagion; and otherwise for low capital levels

1.6 Endogenous networks

While the stress-testing literature takes networks as given and looks at how they will evolve under certain conditions, studies on endogenous networks aim at answering such questions as: Why do banking networks have the structure that we observe? Are real networks optimal? How different regulation policies may change banks' decisions about links creation that new network structures would be less prone to contagion risk? Will banks' endogenous decision-making under worsening conditions aggravate a crisis? These and other questions are studied in this literature from two points of view: a static one and a dynamic one. Network formation in a static setting is a more traditional approach; it has been widely used in the social networks literature to study social strategic interactions using game-theoretic techniques. The importance of the dynamics of financial networks has been underlined by 2007-2009 financial crisis when banks' own "optimal" behavior created systemic risk. Since then researchers got interested in modeling not only how networks form but also how they evolve. However, this stream is still in it infancy.

To the best of my knowledge, the first paper that incorporates an endogenous interbank network in a theoretical model of banking is Babus (2007). The author constructs a model where banks form links with each other as an insurance mechanism to reduce the risk of contagion. The link formation process follows the intuition developed in Allen and Gale (2000): better connected networks are more resilient to contagion. The model shows the existence of a connectivity threshold above which the contagion does not occur. If there were no cost associated with link creation, banks would form a complete network which would never default due to contagion. However, the implicit cost related to a link prevents banks from forming more connections than required by the connectivity threshold. The main economic trade-off is between risk-sharing and the implicit cost of having a link. Leitner (2005) considers a trade-off between risk sharing and potential for collapse. He finds that linkages creating the threat of contagion may be optimal because this can motivate banks to help one another, even if they could not precommit to do so. Whereas Babus (2007) and Leitner (2005) consider interbank links as the insurance mechanism to reduce the risk of contagion, Castiglionesi and Navarro (2007) analyze a network formation game where banks fully anticipate the trade-off between the benefits coming from the liquidity insurance and the costs (counterparty risk) of participating in the financial network. The authors find that under the planner problem, the efficient network is complete when there is sufficient amount of bank capital available in the economy, otherwise the constrained-first-best (CFB) network is characterized by a core-periphery structure. In a decentralized setup, core-periphery structure also emerges as an equilibrium outcome, and when counterparty risk is low enough the connectivity level of the network coincide with the CFB structure otherwise it has inefficiently low level of connectivity. Fique (2011) builds on the model of Castiglionesi and Navarro (2007) and studies the impact of a "network tax" on the formation of a network. The regulatory tax charges banks according to their exposure to contagion risk and changes the initial trade-off that motivates the formation of the network therefore affecting the equilibrium network structure. In a hybrid framework, where banks decide to make interbank connections in a predefined network, Acemoglu et al. (2013) confirm known results that banks fail to internalize the externality that they impose on the network therefore creating a network different from the socially optimal. The authors find that in equilibrium banks may either "overlend" or may lend to the "wrong" set of borrowers. Farboodi (2014) looks at the network formation problem from a different angle: she studies incentives of financial institutions to capture intermediation spreads through strategic borrowing and lending decisions. She finds that it is the core-periphery network that emerges endogenously in her model with risky profitable banks being in the core and playing the role of intermediaries. And she obtains a similar finding that in a constrained efficient equilibrium, risky core banks "overconnect", exposing themselves to excessive counterparty risk, while periphery banks who mainly provide funding have too few connections.

Models of static network formation are good at explaining the intuition why banks create links and why we observe these particular network structures in equilibrium, however they cannot explain and predict the dynamics of networks. The empirical studies though show that while financial networks preserve the same statistical characteristics over time they also vary quite a lot. An illustrative example is the evolution of the interbank market in the USA during the 2007-2009 financial crisis (e.g., Afonso et al. (2011)) and in Europe during the 2010-2012 sovereign debt crisis (Abbassi et al. (2013)). The first studies that were interested in reproducing network dynamics were proposed by physicists (preferential attachment by Barabasi and Albert (1999)), though they were missing an economic rationale of links formation. Following attempts used agent-based models where banks are profit-maximizers with simple rule-of-thumbs to create interbank links to lend or to borrow liquidity. Iori et al. (2006) were the first ones to use such models to simulate a dynamic interbank market. They adapt the idea of Allen and Gale (2000) in a dynamic setup where banks trade on the interbank market in order to counteract fluctuations in liquid assets and stochastic investment opportunities, and therefore expose themselves to the contagion risk. However, banks meet randomly in the interbank market forming a random graph, and the authors do not analyze the network structure explicitly. Their main finding is the role played by the heterogeneity of a banking system: in a system with homogenous banks, "an interbank market unambiguously stabilizes the system", whereas heterogeneity makes knock-on effects possible. Ladley (2013) extends the model of Iori et al. (2006) in a partial equilibrium setting where interbank interest rates and banks' portfolio choice are determined endogenously. The author obtains a result similar to the one by Acemoglu et al. (2013) that there is no one-size-fits-all optimal network structure, and the way interbank linkages impact the stability of the system depends on the shock size: when shocks are limited, the interbank connections stabilize the system whereas in a system-wide shock, interbank links propagate instability. Georg (2013) extend the two previous models by including a central bank and testing different network structures. The author uses a pre-defined network structure for an interbank market in which lenders and borrowers meet randomly. He states that a network structure starts playing an important role only during a crisis time and finds that networks with large average path length are more resilient. If a central bank intervenes it can mitigate financial distress in the short run, however, it may also cause a crowding-out effect reducing volumes on the interbank market if it accepts too many bank assets as collateral. Porter et al. (2014) build on their previous work Iori et al. (2006) enlarging the interbank model to the real economy sector and endogenizing banks' decisions about portfolio allocation, taking into account counterparty risk and regulatory requirements. As expected, they find that leverage requirements improve the stability of the banking sector but at the same time hurting the real economy. However, the authors do not focus on the role of the network structure and analyze a banking system presented by a random graph network. The network formation mechanism in Halaj and Kok (2014) is also based on a portfolio optimization model whereby banks allocate their interbank assets while balancing the return and counterparty defaults risk as well as they diversify their funding sources. The initial pre-network is defined using the methodology by the same authors (Halaj and Kok (2013)). The paper examines the impact of regulatory instruments limiting banks' risk from interbank exposures. It finds that the regulatory large exposure limits can have a more pronounced impact on contagion risks than the Credit Valuation Adjustment, a charge on the capital allocated to the interbank asset portfolios. The authors underline that macro-prudential policies can significantly alter the network formation and therefore interbank contagion risk. Cohen-Cole et al. (2011) propose a completely different setting: banks' strategic interactions are modeled as a Cournot equilibrium game at each period: banks compete in quantities of lending, and market price (interest rate) is given by the standard linear inverse market demand. To pass from one period to another, the authors use a simple diffusion process: a randomly chosen bank creates (deletes) a link with a node with the highest (lowest) Bonacich centrality with certain probability. The equilibrium of the dynamic game is defined as the equilibrium degree distribution in the interbank market when the proportion of banks with certain number of counterparties in a network stabilizes.

Baral (2012) and Fique and Page (2013) were among the first who analyzed endogenous network dynamics in an equilibrium game-theoretic framework. Both models build on the stochastic game approach proposed by Page and Wooders (2009) where Baral (2012) focuses her attention on the change of the network dynamics when it is hit by a shock while Fique and Page (2013) are interested in banks' rollover decisions (carrying on an interbank connection or dropping it when faced different market conditions). In both models, borrowing/lending opportunities arrive randomly to a couple of banks, but afterwards banks are faced with endogenous decisions to make: lenders (borrowers) are to ask for repayment (to repay) or to ask for liquidity from the central bank as in Baral (2012); lenders decide to rollover or cut the debt of a borrower. Fique and Page (2013) find a tipping point property and hysteresis: once rollover risk takes place and creditors stop lending, credit relationships between institutions can take a very long time to establish. Moreover, they show that efforts needed to restore normal lending relationships are much higher than those to destabilize. Anand et al. (2012) also study rollover risk in a dynamic network framework and come up with the same findings. The authors build a dynamic model in a global games framework of Morris and Shin (2003), therefore explaining the tipping points by coordination failure issues.

A key question in modeling network dynamics is how banks decide with which counterparty they want to create a link. A methodology that has attracted much attention due to its flexibility is a search mechanism borrowed from the labor market literature, where banks decide on the rate and value of a loan depending on their needs, and then deals are matched through the search mechanism. Afonso and Lagos (2014) develop a dynamic equilibrium model of trade in the federal funds market that provides the intraday allocation of reserves and pricing of overnight loans, while accounting for OTC characteristics of the market: search for counterparties and bilateral negotiations. Bluhm et al. (2012) build a model, considering an interbank network as a centralized market, in which dynamic adjustment results from the endogenous response to shocks of optimizing banks and of the tatonnement equilibrium process characterizing market adjustment.[16] The authors use the model to assess the evolution of the network under various prudential policy regimes and with different channels of shock propagation: solvency contagion, liquidity hoarding and asset fire-sales

[16] An equilibrium market price is reached when demand equals supply through a groping process: prices are announced; agents state how much of each good they would like to offer (supply) or purchase (demand); no transactions take place at disequilibrium prices; prices are lowered (raised) for goods with excess supply (demand) and so on until the equilibrium reached.

externalities. Blasques et al. (2014) analyze the role that credit risk uncertainty plays in the interbank lending market. Their research suggests that repeated lending between banks may significantly reduce asymmetric information and improve credit conditions due to lower credit risk uncertainty, therefore providing foundation for well-known empirical fact that banks tend to form trading relationships (Cocco et al. (2009)). Moreover, they study the impact of monetary policy (changes in the ECB interest rate corridor) on the interbank lending network. Bianchi and Bigio (2014) focus their attention on the role of banks in the transmission of monetary policy, the centerpiece of policy debates on both sides of Atlantic. They enlarge their point of view and consider banks' lending decisions as a part of banks' liquidity management, therefore the rationale for lending or not lending in the interbank market is the tradeoff between the profit on a loan and potential own liquidity needs. Using a dynamic network framework Gofman (2014) focuses on the trade-off between the stability and efficiency of different financial architectures and the implications of different pricing mechanisms on trading efficiency. He confirms the findings of Farboodi (2014) that financial markets that require intermediation are not always efficient in allocating liquidity and risks. The advantage of his methodology as well as the ones by Blasques et al. (2014), Bianchi and Bigio (2014) and Afonso and Lagos (2014) is that they allow calibrating network models on real interbank lending data.

All the aforementioned studies on dynamic networks focus on the interbank lending market. To the best of our knowledge, only two papers stand out as far as other financial markets are concerned: Vuillemey and Breton (2014) and Heam and Koch (2014). Vuillemey and Breton (2014) present a network formation model of an OTC derivatives market where the network of exposures emerges as the aggregate outcome of CDS contracts where dealers set trade-specific prices and quantities, taking as given regulatory requirements and the level of counterparty risk. Heam and Koch (2014) stress the importance of long-term interbank relationships and test the hypothesis that the latter are caused by banks' diversification goals. The authors also underline the need to consider the endogenous evolution of banks' balance sheets when studying interconnections in long-term perspective.

1.7 Econometrics approach to networks

In this section, I will talk about studies of financial networks using econometrics methods. I start by mentioning first the developments in the literature on social networks since the literature on financial networks has borrowed most of the methodologies from it. Indeed, social networks have gained a lot of attention during the last two decades due to their importance and ubiquity. At a general level, a social network represents any pattern of relationships between agents. Noticeable examples of studies on social networks include friendship networks among adolescents, coauthorship networks among scientists, networks of criminals and trade networks between countries. The empirical literature on social networks was much smaller than theoretical one but has been expanding at a rapid pace. Network econometrics is particularly useful to treat such a difficult question as how the behavior of an individual is affected by others, because it allows to well identify such peer effects.

Econometrics of social networks relies on the methods of spatial econometrics which were initially developed to analyze location and spatial interaction in regional science, urban and real estate economics and economic geography, though it also faces difficulties specific to the interaction between agents. Manski (1993) raises three main challenges to identify peer effects. First, the researcher must determine the appropriate reference groups. Who is affected by whom? Second, unobserved attributes that are correlated between peers may generate a problem of confounding variables. For instance, individuals in the same reference group may face similar environments. Self-selection may also induce the presence of such correlated effects. Similar individuals tend to interact together, which makes the formation of the network endogenous. Third, simultaneity in peer behavior may hinder identification of exogenous effects, i.e., the influence of peer attributes, from endogenous effects, i.e., the influence of peer outcomes.

In the literature on financial networks, only a few papers use this methodology in order to identify how a bank's decision is influenced by decisions of its counterparties. Cohen-Cole et al. (2010) analyze stock futures markets, such as the Dow and S&P 500, where a large number of traders exchange contracts. The process of doing so creates a network of traders that is highly susceptible to shocks. The authors demonstrate that seemingly innocuous events can cascade into market failure by showing that a shock to one trader's profits or losses cascades into the profits or losses of those in the trading network precisely along the lines of the network architecture. Moreover, the study documents that network patterns in a fully electronic market can explain more than 80% of the individual level variation in trading performance. Cohen-Cole et al. (2011) propose a simple model of banks' profitability based on competition incentives and the outcome of a strategic game. As competitors' loans change, both for closely connected ones and the whole market, banks adjust their own decisions as a result, generating a 'transmission' of shocks through the system. This theoretical model is then reformulated in a regression equation therefore allowing estimating the model using the data, the authors use e-MID transactions data for the period from

2002 to 2009. The used approach permits to measure both the degree that shocks are amplified by the network structure and the manner in which losses and gains are shared. A very similar approach is used by Denbee et al. (2013) who analyze banks' liquidity holding decisions as a simultaneous game on an interbank borrowing market. Using a sterling interbank network database from 2006 to 2010, the authors find evidence for a substantial, and time varying, network risk, where the latter is defined as the characteristics of a network to magnify an individual shock. Craig et al. (2014) analyze the German interbank market and provide evidence on significant spillover effects between banks' probabilities of distress and the financial profiles of connected peers. They show that better capitalized and managed connections reduce the banks' own risk while higher network centrality reduces the probability of distress, supporting the notion that more complete networks tend to be more stable.

Other papers that analyze networks do not focus on the effect of one bank on the network or on its counterparties, they are rather interested how banks' characteristics are explained by their position in a network. Using e-MID data for the period 2006-2008, Gabrieli (2012) shows that network centrality measures can help explain heterogenous patterns in the interest rates paid to borrow unsecured funds in the e-MID interbank market after controlling for bank size and other relevant bank and market factors. Abbassi et al. (2013) employ Target2 interbank loan data and document significant changes in network characteristics in different segments of the interbank market during the 2007-2009 crisis. Particularly, they find that the failure of Lehman Brothers provoked a shrinkage of the interbank network and that the access to liquidity in the market exhibits substantial heterogeneity, depending on a bank's position within the network. Craig et al. (2014) also study the question of liquidity in the interbank market. More precisely, they assess how the concentration of credit relationships and the position of a bank in the network influence the bank's ability to meet its liquidity demand using two data sets: quarterly data of bilateral interbank credit exposures between all German banks from 2000 to 2008 to measure interbank relationships and the network characteristics; and bids placed by the individual banks in the European Central Bank's weekly repo auctions. Their findings suggest that banks with a more diversified borrowing structure in the interbank market bid significantly less aggressively and pay a lower price for liquidity in the ECB's main refinancing operations. Peltonen et al. (2014) analyze how different characteristics of the reference entity in the CDS market influence the corresponding CDS network properties. They document that the CDS market size and activity is largely impacted by the characteristics of both the underlying bond exposure (size, collateralization) and CDS risk (volatility, commonality in returns). Whether the reference entity is European or not has little difference for the network structural properties, however, the distinction between sovereign and financial reference entities does matter a lot.

1.8 Market Data

The last interesting stream of the network literature is again driven by the lack of bilateral data, but also, by the wish to understand how prices incorporate information about interconnectedness of the financial system. These studies are also related to the theory of investment and to risk management, since they are interested in extracting relevant information from the market data. There has been a number of technical papers by the same group of physicists and mainly published in physics journals that try different methodologies to obtain a relevant network structure from public information such as returns on assets of financial institutions. In this section, I will focus only on a few of them, which I consider the most relevant from a finance perspective.

Starting from Mantegna (1998), networks were constructed using stock price correlations with vertices corresponding to stocks and the edges between them to distances, which are transformed correlation coefficients. One of the main issues when working with market data is to filter out information from noise. Onnela et al. (2004) propose to use a random graph theory to establish a null hypothesis of a totally random graph and then compare the results for empirical graphs against those of random graphs. The deviations from random behavior are then interpreted as information. In order to do it, they construct a network differently from previously widely used approach, minimum spanning tree (MST). MST builds a tree of $N - 1$ edges with the highest correlations, where N is the number of nodes. Due to the tree condition, the asset tree fails to capture the strong clustering in the financial markets. The proposed method does a better job and allows for clustering. By comparing the obtained asset graph to the random graph, the authors found a number of differences that they interpret as information, in total they conclude that only 10% of the edges appear to carry genuine information. Tumminello et al. (2007) propose a different method to construct a network with clusters, Planar Maximally Filtered Graph (PMFG), and obtain a network with nice clustering by sectors. They also document that network properties change depending on the horizon of returns, e.g. 5 minutes or one trading day. Tse et al. (2010) notice though that such methods lead to a loss of information because of the particular filtering conditions, and they propose a winner-take-all approach in establishing edges of the networks. In this approach, two entities are considered to be connected when the true value of cross correlation of their stock prices is larger than a certain threshold value. They consider almost 20000 stocks traded on New York Stock Exchange between 2005 and 2007 and show that the full networks of stock prices, price returns and volumes are scale-free. The authors therefore conclude that a small number of stocks are having a strong influence over the entire market.

All the aforementioned approaches construct networks using solely correlations between stock returns, therefore the networks are undirected by construction. Billio et al. (2012) solve this issue by using Granger-causality tests to assign directions to the correlations which are computed using principal component analysis. The authors use monthly returns of hedge funds, banks, broker/dealers, and insurance companies, and they find that linkages within and across all four sectors are highly dynamic over time. Over time, all four sectors have become even more highly interrelated. Another finding points to an important asymmetry in the connections: the returns of banks and insurers seem to have more significant impact on the returns of hedge funds and broker/dealers than vice versa. This finding underlines also the importance to study directed networks even for market data.

Two other papers also construct directed and moreover weighted networks in a completely different way. Diebold and Yilmaz (2014) propose a methodology to construct weighted directed networks based on a variance decomposition method widely used in econometrics. They also show that their constructed measures of connectedness are intimately related to key measures of connectedness in the network literature. And then the authors track average and daily-varying connectedness of major U.S. financial institutions' stock return volatilities during different periods. Muijsson (2014) builds on the method proposed by Diebold and Yilmaz (2014), but enlarges it by deepening the understanding of the forces driving the dynamics of equity returns. She aims at disentangling the impact of balance sheet exposures (asset communality and interbank deposits) from investor behavior (information contagion) in interbank contagion. Applying the methodology to the returns of a number of European SIFIs, the author finds that interbank deposits are the main channel of transmission, with a smaller importance of information contagion.

Brownlees et al. (2014) propose a method to estimate correlations between prices of listed companies, therefore constructing an undirected network. They test this methodology on 100 liquid US blue chips and find that the reconstructed network does satisfy the standard network properties such as low density and power law distribution. The authors also observe expected industry clustering. Overall their results convey that data have quite a lot of cross-sectional dependence even after controlling for a common factor, and networks can be a useful tool to synthesize such a information.

This strand of the literature is definitely very interesting and promising. However, the results can only be as good as the information is, and the hypothesis of market efficiency consistently fails. Also the application of these findings is not obvious, since even if researchers can correctly estimate what is priced by the market, the market-based network can still be significantly different from the real underlying network. In order to understand, how such networks can be used, one has to stop thinking that linkages of these networks correspond to underlying credit exposures. Such reconstructed market webs rather reflect market perception of certain dependence structure between companies, and as underlined by Brownlees et al. (2014), indeed provide a practical way to synthesize and visualize this enormous amount of information.

1.9 Conclusion

In this chapter, we have discussed studies on financial networks using different approaches from game theory to econometrics. All in all, this literature highlights that interconnectedness is a key element for the stability of a financial system. Moreover, it demonstrates the plenitude of methodologies that consider a financial system as a network and allow for an explicit analysis of interactions between agents.

The main problem faced by any application of the network approach to financial systems is the lack of data on bilateral relationships. This situation has been improving in recent years at the level of national banking systems, but there is still a long way to go to access all the required information at the international level. Moreover, such data will remain highly confidential. In this regard, studies that aim at estimating matrices of bilateral exposures from incomplete or market data look particularly promising and useful. Some advances have already been done especially with incomplete data, however, more is needed when using market data.

The stress-testing literature has obtained interesting results in identifying dependencies between network characteristics and the extent of contagious defaults in the system. More specifically, these studies find that connectivity has non-linear effects on the stability of a network and its impact interplays with other network characteristics such as heterogeneity of nodes and the size of a shock. Indeed, for a small shock and a homogenous banking system, higher interconnectedness univocally reduces the probability of contagion. However, if a shock is big and a big bank defaults, higher interconnectedness may lead to knock-on effects. Moreover, higher interconnectedness is beneficial only when banks are well-capitalized otherwise contagious defaults will surge. One more finding relates to which bank defaults first, just any (random attack) or the biggest/most interconnected (targeted attack): in the first case, the probability of contagion is higher, in the second case, it is its extent. So, the first suggestion about the network with lower contagion propensity would be a web of better capitalized banks with certain level of interconnectedness which is high enough but not complete.

Other findings in this literature suggest that contagion can spread only through contagious exposures, i.e. exposures that are larger than capital of the lending bank, therefore underlining the necessity to regulate the size of individual exposures. The current regulation moves forward in the right direction. However, existing limits on interbank bilateral exposures are based on risk-weighted approach. Taking into account that lending to certain banks, such as well-ranked OECD banks, has zero risk weight, we observe two potential negative consequences, namely, first, banks may still have individual exposures larger than their capital, and, second, such regulation forms institutions' lending incentives, encouraging a particular network structure with some some very connected banks in the middle. This observation echoes some findings of the theoretical literature suggesting that formed networks tend to have unbalanced structure with big banks having too many links than optimal and small banks too few. A next important move would be to understand which policies provide the right incentives for banks to build a more balanced and, thus, more resilient network.

Other research streams have made important attempts but more work is still needed in the analysis of other channels of contagion, other interbank segments different from the credit market such as CDS which may have different dynamics. And particularly, more understanding about the network dynamics and endogenous agents' decisions would be a great step forward in improving financial stability.

Chapter 2

Domino Effects when Banks Hoard Liquidity: the French Network[1]

2.1 Introduction

The 2008 financial crisis accentuated again the central role of liquidity and confidence in the market for the system financial stability. As a consequence of high uncertainty and low confidence level among agents, interbank market activity froze and central banks intervened massively by injecting liquidity.[2] This paper develops a model that allows analyzing the effect of funding shortage due to banks' liquidity hoarding behavior on the system stability in a stress scenario with solvency contagion.

The following observations of the crisis development motivate our model: a shock to banks' common assets weakened capital of the system therefore increasing uncertainty about banks solvability. This, coupled with already acquired high leverage and banks' heavy reliance on short-term wholesale funding, led to shortage of funding for banks and their liquidity hoarding behavior as a reaction to increased counterparty risk and uncertainty about future availability of liquidity.[3]

[1]This chapter is based on the Banque de France Working paper Fourel et al. (2013). It has been presented at several conferences: 5th Financial Risks International Forum (Paris, 2012), IFABS 2012 (Valencia), CEF 2012 (Prague), l'AFSE 2012 (Paris), PET13 (Lisbon), FEBS 2013 (Paris), ESRB ATC Workshop (ECB, 2013)

[2]For instance, ECB provided liquidity to the market in different ways: SMP and VLTRO programs through 2009 to 2012 among others, for details see, e.g., http://www.ecb.europa.eu/ecb/html/crisis.en.html

[3]See, e.g., Acharya and Skeie (2011) and Brunnermeier (2009) for more evidence on the crisis; Berrospide (2013) documents the evidence of precautionary motives for banks' liquidity hoarding.

In this paper, we enrich a standard mechanism of default cascades by incorporating banks' preemptive actions to secure their liquidity needs and to reduce counterparty risks. The model consists of three main steps. First, a stochastic common market shock affects banks' assets. This shock is calibrated on the true data: supervisory data of banks' exposures to particular asset types and historic returns of these assets, therefore it affects all banks according to their respective portfolio composition. The shock abates the system capital level and signals a state of market distress to affected banks. Second, the shock is then propagated through the interbank system via total exposures in case of solvency contagion and via short-term exposures in case of liquidity hoarding behavior (liquidity contagion). Banks default due to solvency contagion when their capital is lower than exposures to the defaulted counterparty. Liquidity contagion is transmitted through a different mechanism: banks stop rolling over short-term loans when they are in distress. Such hoarding behavior generates cash outflows for the counterparties and lead potentially to funding problems of the latter. Then, if a bank experiencing significant cash outflow cannot honor its short-term commitments, it defaults (due to illiquidity). Following the default, more losses have to be written down by bank's counterparties, thus generating more hoarding behavior and funding distress as well as solvency domino effects. Third, we propose a set of indicators in order to assess the total impact of the shock on the banking system. In our model, the total impact can be decomposed in three different components in order to evaluate the relative role of the initial shock and both solvency and liquidity contagion channels.

The main contribution of this paper is threefold. First, we deliver a framework to analyze how banks' liquidity hoarding behavior affects a system. The hoarding behavior is modeled through a reaction function which mimics banks' heuristics in a crisis time: losses in capital determine the depth of distress and therefore the amount of liquidity held; whereas counterparties' riskiness (leverage is used as a proxy) condition the reallocation of non-renewed short-term loans among counterparties.

Second, we design an operational approach to implement a market shock. Our methodology is suitable for usual stress-tests where shocks are based on scenarios. We extend the shock methodology to deal with stochastic shocks. The design includes a calibration step in order to simulate likely stochastic shocks: the actual losses depend on the portfolio structure of banks as well as the joint distribution of four (observable) common factors. The stochastic property allows us to analyze the resilience of the banking sector to a shock either affecting simultaneously all the asset classes or driven by the fall of only one asset class (such as the burst of a bubble).

Third, we apply the model to a real case study where we measure the resilience of the French banking system. On December 31, 2011, the French banking sector appears resilient to both the market shock and the contagion. We find that losses due to solvency contagion and losses due to liquidity contagion are of similar order and, moreover, liquidity hoarding behavior may induce losses to the system even in the absence of solvency contagion; thus modeling only one contagion channel (such as solvency) would underestimate contagion risk.

From a different point of view, our paper also contributes to the emerging literature on multilayer financial networks. In this framework, each layer is a network in one particular market, e.g. interbank exposures in a CDS market represent one network, whereas exposures in the interbank money market can represent another network and so on (see Barigozzi et al. (2010)). All these layers are interconnected: a shock can affect all the networks at the same time or pass from one layer to another. In our basic model, we consider two networks, namely, that of long-term interbank exposures and that of interbank short-term exposures. These two networks propagate different types of contagion. However, a deeper analysis of the possible interactions between these two networks remains beyond the scope of this paper.

The paper is organized as follows. Section 2.2 briefly introduces the literature. Section 2.3 presents the model which aims to propose a rationale to explain how solvency defaults and liquidity hoarding can occur in a banking network when the system is affected by a market shock. Section 2.4 provides an application of our model to the French banking system with a comprehensive set of results. Section 2.5 concludes and discusses avenues for future work.

2.2 Literature review

Our paper mainly builds on the literature analyzing stability of a system via a network approach. After the seminal paper of Allen and Gale (2000) that proposed a theoretical model of contagion in a banking system, applied papers by Furfine (2003) on the US data and by Upper and Worms (2004) on German data opened an avenue for contagion risk assessment of national banking systems in different countries. Upper (2011) provides an overview of the existing literature. Most of the papers[4] focus mainly on two aspects: idiosyncratic shocks, a default of each institution one at a time; and sole solvency contagion. Elsinger et al. (2006a,b) and Cont et al. (2010) refined shocks and documented the importance of having a market shock for contagion propagation. Another improvement concerns enrichment of models by additional mechanisms. Cifuentes et al. (2005) introduced fire-sale phenomenon in a framework of solvency contagion. Asset fire-sales are related to scarce market liquidity for certain assets and, thus, deterioration of the asset value, moreover, the situation aggravates by banks' high leverage and their behavior of targeting a certain solvency ratio. On the other side of the balance sheet, the funding aspect has been introduced by Gai and Kapadia (2011) and Gauthier et al. (2010). They consider funding issues the way we do but with exogenous sources of lack of liquidity: on the contrary, we regard that the main source of liquidity needs comes from banks' own actions. In other words, we propose a model where the funding issues are endogenous to the banking sector.

From another point of view, our paper is also related to the literature on liquidity aspect in finance (market liquidity, funding liquidity, fire-sales...) that proposes both an empirical and a theoretical background for hoarding phenomena. The core activity of banks involves maturity transformation, which makes them renew regularly their debt, and therefore exposes them to liquidity risk. The interaction of roll-over mechanism and bank's solvency was emphasized in a game-theoretical framework by Morris and Shin (2003). Moreover, banks rationally start hoarding liquidity during crisis times; Acharya and Skeie (2011) and Brunnermeier (2009) provide rationale for such behavior. More generally speaking, wholesale funding is an important tool for balance sheet adjustment (see Damar et al. (2013)). By modeling hoarding mechanism in a network framework, our paper clearly inherits from the strand of literature focused on the funding aspect of liquidity. Moreover, this literature mainly employs a representative agent or homogeneous agents, therefore, we expand this literature by considering several heterogeneous agents in a network perspective: agents differ by specific characteristics (in particular their balance sheets) and by their interconnections. We contribute to this literature by including liquidity-hoarding-based contagion channel, as well as an application to the French data.

[4]See among others Mistrulli (2011) for Italy, Van Lelyveld and Liedorp (2006) for the Netherlands or Toivanen (2009) for Finland.

2.3 The Model

In this section, we provide a framework to model banks' liquidity hoarding behavior together with solvency contagion employing widely used sequential default approach. We also propose a way of simulating realistic common market shocks.

We consider a set of N banks that are exposed to each other. We distinguish short-term exposures from long-term exposures. Liquidity contagion only spreads through short-term exposures whereas long-term exposures are a channel of solvency contagion. We denote E^{LT} (resp. E^{ST}) the matrix of long-term (resp. short-term) exposures, where $E^{LT}(i,j)$ ($E^{ST}(i,j)$) represents long-term (short-term) assets of bank i invested in bank j (for $(i,j) \in [1;N]^2$). Assets consist of loans and securities. The asset side of bank i is decomposed into several items: interbank exposures ($E^{LT}(i,j)$ and $E^{ST}(i,j)$ for $j \in [1;N]$), cash $CA(i)$ and other assets $OA(i)$. We denote total assets by $TA(i)$. The liability side of bank i consists of equity $C(i)$ (hereafter capital), interbank exposures ($E^{LT}(j,i)$ and $E^{ST}(j,i)$ for $j \in [1;N]$ and $j \neq i$) and all other liabilities gathered in $OL(i)$. The market shocks affect the OA component of banks' balance sheets.

Banks start hoarding liquidity when they regard a situation as distressed, and we use a shock to banks' economic capital as a signal of the distress in the system. We denote the economic capital of bank i as $EC(i)$, and we interpret it as the overall level of capital that is considered by the bank as the capital mandatory to run its business optimally in the long run. In our application, we use the required capital as a proxy of the economic capital, therefore the latter corresponds to 8% of the risk-weighted assets (RWA) of an institution as in Basel regulation framework. At the same time, bank's leverage ratio gives a public signal of bank's fragility. When a bank preemptively withdraws liquidity, it hoards more from its riskier, more leveraged, counterparties.

Lastly, as we consider an iterative approach with multiple rounds, the variables are indexed by t for the round of contagion and upper-indexed by k for the algorithmic steps.

A schematic balance sheet of bank i is represented in table 3.1, page 73.

Main elements of the model are presented in the subsequent sections by following the algorithm process step by step: first, the market shocks trigger initial losses, then the contagion spreads through solvency and liquidity contagion channels. Finally, we introduce some indicators that we compute in order to assess system fragility to contagion.

		ASSET	LIABILITY		
Long Term Interbank Assets	$\leftrightarrow$	$E_t^{LT}(i,1)$ $\vdots$ $E_t^{LT}(i,N)$	$E_t^{LT}(1,i)$ $\vdots$ $E_t^{LT}(N,i)$	$\leftrightarrow$	Long Term Interbank Liability
Short Term Interbank Assets	$\leftrightarrow$	$E_t^{ST}(i,1)$ $\vdots$ $E_t^{ST}(i,N)$	$E_t^{ST}(1,i)$ $\vdots$ $E_t^{ST}(N,i)$	$\leftrightarrow$	Short Term Interbank Liability
Cash	$\leftrightarrow$	$Ca_t(i)$	$OL_t(i)$	$\leftrightarrow$	Other Liabilities
Other Assets	$\leftrightarrow$	$OA_t(i)$	$CA_t(i)$	$\leftrightarrow$	Capital
Total asset	$\leftrightarrow$	$TA_t(i)$	$TL_t(i)$	$\leftrightarrow$	Total liability

Table 2.1: Bank i's stylised balance sheet at date t

2.3.1 Market shocks

To assess the impact of default of a particular bank on banking system resilience to contagion under adverse conditions, we define an external event that will affect the system stability. As noted in Upper (2011), contagion is likely to occur only when the entire system is under stress.

Papers differ in the types of shocks they consider. The basic premise is to envisage idiosyncratic shocks. For instance, Upper and Worms (2004) for Germany, Mistrulli (2011) for Italy, Van Lelyveld and Liedorp (2006) for the Netherlands, Toivanen (2009) for Finland, Furfine (2003) for the USA consider the effect of the default of one bank. However, as underlined in Elsinger et al. (2006a,b), a large common market shock impacting all the credit institutions of the system at the same time appears to be a necessary condition to observe contagion propagation. Several papers, e.g., Cont et al. (2010) and Elsinger et al. (2006a), analyze the resilience of the system by applying shocks with one common component affecting all the banks in the network.

In this section, we provide a methodology of implementing the common market shocks. They affect the "Other Assets" category held in the portfolio of each bank (OA) at the initial date. We define two types of common shocks corresponding to two different ways of considering stress episodes. In the first exercise, a general common shock is simulated

	Returns	Variance	Correlation			
			Equities	Sovereign	Insurance	Corporate
Equity	-0.83%	1.07%	1	-0.28	0.23	0.19
Government Bonds	1.15%	0.04%	-0.28	1	0.43	0.50
Insurance Bonds	1.28%	0.06%	0.23	0.43	1	0.86
Corporate Bonds	1.44%	0.03%	0.19	0.50	0.86	1

Table 2.2: Statistics of daily returns (02/01/2001-31/12/2011). The average daily return on equities is -0.83%, its variance is 1.07% and its correlation with Sovereign daily return is -0.28.

so that the whole banking sector is in distress. In the other exercise, we consider specific-asset-class common market shocks, where distress in the market is defined as a sudden and dramatic price drop of a particular asset class.

2.3.1.1 Common market shock

Similarly to Elsinger et al. (2006a), we define a common market shock as losses on banks' balance sheet component "other assets" (OA) due to a correlated deterioration in asset prices.

We consider that banks' other assets OA are composed of four types of assets: equities, corporate debt, insurance[5] debt and sovereign debt with given weights that each asset type represents in the banks' portfolio. We exclude retail activity from our analysis, even though retail assets represent a significant share of banks' assets. The main reason for this is that retail assets are much less volatile, for instance, the probability of default of real estate assets hardly changed during the crisis. The French real estate market has some specific features. The vast majority of retail activity corresponds to real estate loans given to households and mainly at fixed interest rates. Unlike most countries (especially the USA and the UK), French households rarely enter into mortgages. French real estate loans depend on the household solvability and not on the expected future value of the house purchased. Retail activity is therefore barely sensitive to the business cycle and unlikely to suffer from a real estate price collapse. Furthermore, French banks have mitigated their individual retail activity risk through a risk-pooling mechanism for real estate loans.[6]

We use time series of prices for each asset class for the period from 02/01/2001 to 31/12/2011: Eurostoxx 50 for equities, JPM Insurance Senior All Index for Insurance, JPM Euro Area Government Bond All Index and JPM Large Corporate Bond Index. Table 2.2, page 42 reports a standard statistical analysis of the daily returns.

[5]It includes all financial institutions except banks.
[6]For more details of the French real estate risks, see Point and Capitaine (2013)

First, we estimate marginal probability distributions of four assets classes using the kernel density method on weekly returns between 02/01/2001 and 31/12/2011.[7] The method is widely used to estimate non parametrically marginal distributions taking into account their specific fat tails. Then the four time series of asset returns are estimated jointly using a t-Student copula in order to obtain the joint distribution of the asset returns. We replicate an aggregated banking system portfolio by aggregating the "other assets" of all the banks. Afterwards, using the correlated returns of the assets and the weights of these assets in the aggregated portfolio, we compute the profit-and-loss of the system portfolio. Finally, the shocks that are employed later on to stress the system represent the 5% left tail of the profit-and-loss distribution of the entire system.

2.3.1.2 Asset-class-specific shock

Several crises were ignited by concerns arising from one particular asset type. Therefore, it is worth analyzing network resilience to contagion in a case of a significant drop in prices of a particular asset class. We adapt the framework presented for the "common market shock" methodology to this perspective.

The data and the whole estimation procedure are exactly the same as in the case of the common market shock: we take weekly returns of four asset classes (equities, corporate debt, insurance debt and sovereign debt) between 02/01/2001 and 31/12/2011 and estimate their joint distribution. However, instead of computing the profit-and-loss distribution of the aggregated portfolio, we define the shocks as the 5% worst realizations of each asset class at a time and calculate returns of other assets classes corresponding to the left tail of the class in distress using the joint distribution. Thus, we obtain four asset-class-specific shocks corresponding to the distress of each of the considered asset classes.

2.3.2 Mechanisms of contagion

The mechanisms of contagion combine solvency default cascades and defaults induced by banks' liquidity hoarding behavior. We first consider a round of pure solvency contagion occurring during the period ($t = 1$) right after the initial shock at date ($t = 0$). Then, we consider several periods ($t = 2$, $t = 3$...) during which liquidity hoarding takes place. Liquidity hoarding at period t can lead to new defaults. These defaults might involve new

[7]Weekly returns are chosen in order that asset losses were consistent with the time frame of the model, since in the framework of our model, contagion spreads quickly in a short period of time. Considering 3 or 10 days time span does not change the results.

$t = 0$	– Initial situation
$t = 1$	– An initial shock hits the system. – Banks account for the fundamental losses due to this shock.
$t = 2$	– Solvency defaults propagate through the system until there are no more defaults. – Banks record all the losses due to the solvency default contagion.
$t = 3$	– Solvent banks for which the capital requirement condition is violated start hoarding liquidity from their solvent counterparties. – This generates reallocation of resources and possible liquidity defaults, which in its turn may trigger solvency defaults contagion. – Liquidity contagion cascades stop when there are no more defaults, and banks record all the losses.
$t = 4$, ...	– New waves of liquidity contagion may take place if there are banks whose capital is lower than the required one. – And the same process as at $t = 3$ takes place. – All the rounds of $t \geq 4$ stop when liquidity hoarding leads only to reallocation of resources and no defaults because of the violation of liquidity conditions.

Table 2.3: Timing of the model

losses due to solvency contagion and a new wave of liquidity hoarding that will happen at time $t + 1$.

The timing of the model is explained in detail in Table 2.3, page 44. As for the variables characterizing the nodes of the network, they are updated at the end of each period t.

The whole process is presented schematically on Figure 2.1, page 45. We present a detailed example of contagion mechanisms for a simple network in Appendix 2.A.

2.3.2.1 Solvency contagion

There exist two strands in the literature that address the issue of solvency contagion. The first one is called the "Clearing Vector Approach" based on the seminal paper by Eisenberg and Noe (2001). This approach, extended in Gauthier et al. (2010) or in Gourieroux et al. (2012, 2013), establishes the existence and uniqueness of the debt repayment among banks: it provides the endogenous recovery rate on interbank assets. The second strand refers to the "Iterative Default Cascade" developed by Furfine (2003). This algorithm mimics domino effects: instead of looking for a joint vector of debt repayment, it writes down the losses step by step as it might happen during a default cascade. This approach is more relevant to analyze system resilience to contagion during a crisis time, since banks may not survive while waiting for months before getting reimbursed through the bankruptcy procedure.

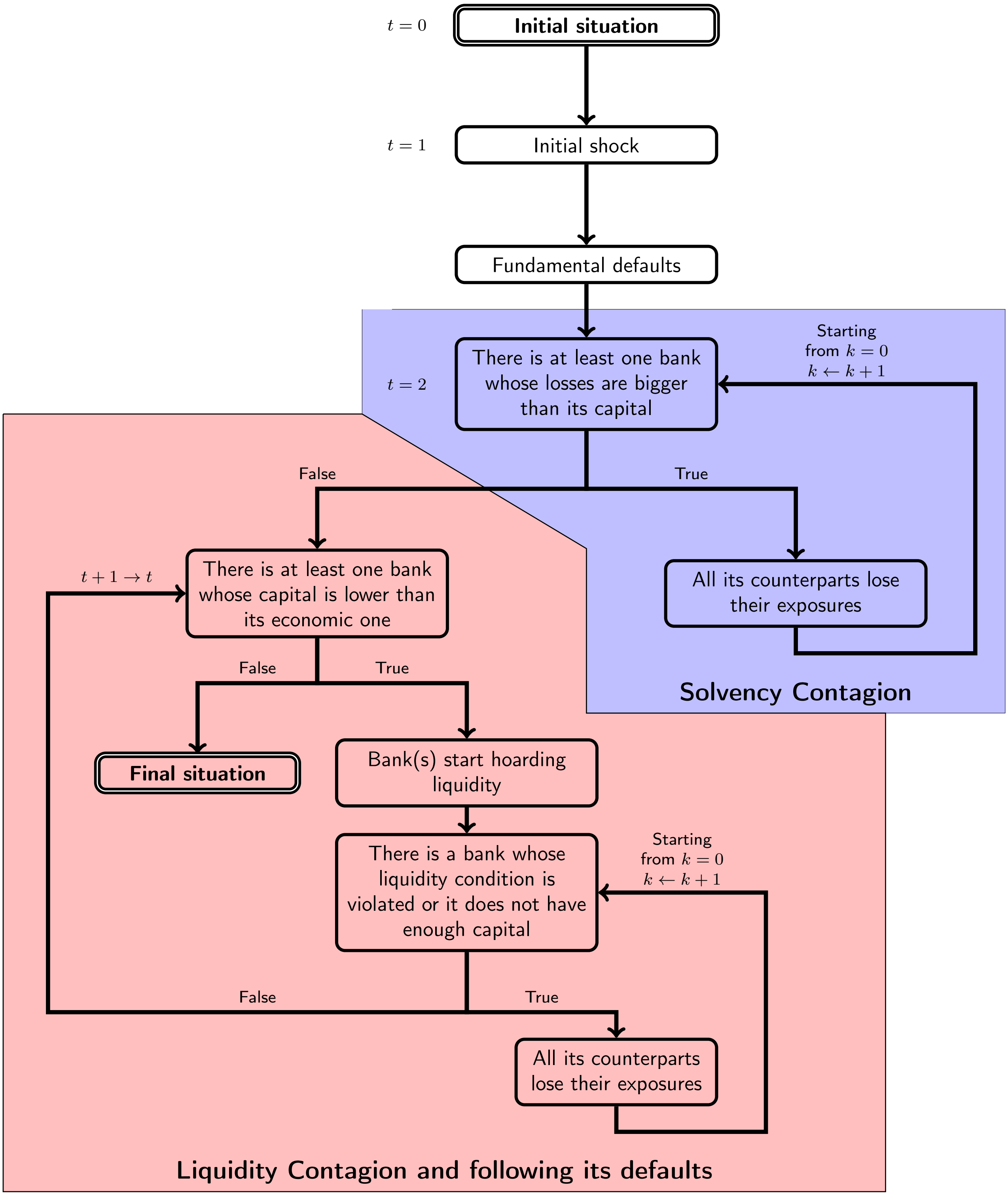


Figure 2.1: Scheme of Default Contagion.

A bank is defined to be in default when its capital falls to zero. Once a bank has failed on its commitments, all its counterparties incur losses equal to their exposure to that defaulted bank, and the losses are absorbed by capital.[8] We consider an exogenous recovery rate for solvency contagion denoted R^S. We run a case-sensitive analysis for different levels of R^S in order to ensure the robustness of our results.

At time $t = 1$, the "other assets" of the N banks are impacted by a shock according to the methodology previously described. If the initial losses are larger than bank's capital, the latter goes into bankruptcy. We can therefore define the set of all banks defaulting due to a market shock, referred to as "fundamental defaults", as

$$\begin{aligned}\mathbf{FD(C)} &= \left\{ i \in \mathbf{N} : C_0(i) + \underbrace{OA_0(i) - OA_1(i)}_{\text{initial shock}} \leq 0 \right\} \\ &= \{ i \in \mathbf{N} : C_1(i) = 0 \}, \end{aligned} \tag{2.1}$$

where $C_1(i) = (C_0(i) + OA_0(i) - OA_1(i))^+$ is the capital of bank i just after the initial shock.

From this situation, we can define a *Solvency Default cascade* (to use the terminology by Amini et al. (2013)) as a sequence of capital levels $(C_2^k(i),\ i \in \mathbf{N})_{k \geq 0}$ (where k represents the algorithmic step) occurring at time $t = 2$ and corresponding to defaults due to insolvency:

$$\begin{cases} C_2^0(i) = C_1(i) \\ C_2^k(i) = \max(C_2^0(i) - \sum_{\{j,\, C_2^{k-1}(j)=0\}} (1 - R^S) \times E_0(i,j); 0), \text{ for } k \geq 1. \end{cases} \tag{2.2}$$

The sequence converges (in at most n steps) since $(C_2^k)_k$ is a component-wise decreasing sequence of positive real numbers. Note that subscripts are used for periods of time and superscripts for rounds of cascades. By "period", we mean the sequential spread of losses through different channels. It does not refer to a time line interpretation: we consider that all the events occurred jointly within a week.

Comparison of the banks initially in default (that is $\mathbf{FD(C)}$) and the banks in default at the end of $t = 2$ corresponds to the set of institutions that defaulted only due to solvency default contagion. We label this set S_2.

[8] As soon as a bank files for bankruptcy, all the agents in the market are aware of it and immediately take an action without waiting for months of the official resolution of the bankruptcy procedure.

2.3.2.2 Liquidity hoarding mechanism

The liquidity contagion has been scarcely studied in the literature on financial networks. However, two main strands of research can be mentioned. The first channel looks at asset, or market liquidity, and losses in asset value (deterioration of the bank's balance sheet and ultimate insolvency) driven by massive sales of the asset. The studies interested in this so called fire-sales phenomenon aim to model the adverse effects of massive asset sales initiated by one or more financial institutions. For instance, banks hit by a shock will attempt to improve their leverage ratio by reducing their asset side, and thus selling some assets, which will deteriorate balance sheets of other banks holding the same assets. Cifuentes et al. (2005) model banks' reaction as a mechanical rule of selling assets in order to improve their solvency ratios. Asset prices drop with the growing volume of assets sold.

Our paper is related to the other strand of the literature, which tackles the issue of funding liquidity, problems arising on the liability side. The way we model liquidity risk is similar to the one proposed by Gai and Kapadia (2011) who build a stylized model to study how banks' hoarding behavior leads to the propagation of a liquidity shock through the system. Banks experience liquidity shortage when their counterparties call back their loans. A different approach is used by Gauthier et al. (2010) who disentangle credit and liquidity risks in a game theory framework proposed by Morris and Shin (2010).

In our model, after solvency contagion, some banks default while others have enough capital to absorb their losses. These banks will consider themselves in distress if their new level of capital no longer satisfies the supervisory requirement. As argued by Acharya and Skeie (2011) and Brunnermeier (2009), and documented by Berrospide (2013), during the crisis banks did hoard liquidity for precautionary reasons: in order to secure future liquidity needs and reduce counterparty risk.[9] In the model, we assume that banks can only stop rolling over existing short-term loans in order to get liquidity, since during a crisis - and we are only looking at periods of stress - banks will find hard to borrow from the money market for several reasons such as requirements of higher quality collateral, high interest rates and increased haircuts. We exclude central banks' policy tools from our analysis in order to study what may happen in the absence of any public intervention. The obtained liquidity is used to improve a liquidity position in view of potential future problems on the interbank market and to reimburse creditors which have started hoarding liquidity too. If a bank fails to satisfy its short-term commitments, it defaults due to illiquidity.

To model how much liquidity a bank hoards, and how much it hoards from each

[9] Note, that in our model, the only reason for hoarding is a precautionary one. In other words, we exclude any predatory behavior.

counterparty, we make the following assumptions. First of all, the total amount of liquidity withdrawn depends on the size of the shock to the bank's capital: the bigger the losses due to the market shock, the more the bank hoards liquidity. The proportion of liquidity hoarded by bank i is $\lambda(i) \in [0;1]$. It is assumed to depend on the gap between the institution's capital $C(i)$ and economic capital $EC(i)$: at time t, we denote $\lambda_t(i) = \phi_{(\theta_1,\theta_2)}\left(\frac{(EC_t(i) - C_t(i))^+}{EC(i)}\right)$, where $\phi_{(\theta_1,\theta_2)}(x)$ is the cumulative density function of a Gaussian law with mean of θ_1 and variance of θ_2.[10] We assume that bank i curtails its positions in the short-term interbank market by stopping rolling over debt for a total amount $\lambda_t(i)E_t^{ST}(i)$ where $E_t^{ST}(i) = \sum_{j\in S_{t-1}} E_{t-1}^{ST}(i,j)$ and S_{t-1} is the set of non-defaulted banks at the end of period $t-1$.

Second, the amount of liquidity the bank hoards from each counterparty depends on the market perception of counterparty risk, for which the leverage ratio can be used as a proxy. The higher the leverage, the riskier a bank is perceived to be and the more its counterparties will hoard from it.[11] Defining $\mu_t(j)$ as $\mu_t(j) = 1 - C_t(j)/TA_t(j)$, we can decompose the total amount of liquidity hoarded by bank i with respect to the counterparties:

$$\lambda_t(i)E_t^{ST,k-1}(i) = \lambda_t(i)E_t^{ST,k-1}(i) \underbrace{\sum_{j, C_t^{k-1}(j)\geq 0} \frac{\mu_t(j)E_t^{ST,k-1}(i,j)}{\Sigma_h \mu_t(k) E_t^{ST,k-1}(i,h)}}_{=1}. \tag{2.3}$$

When a bank hoards liquidity, it improves its liquidity position, whereas liquidity withdrawn by its counterparties deteriorates it. Therefore, the following liquidity condition simply says if bank i has enough liquid assets, either interbank or non-interbank, to pay its short-term debt:

$$\underbrace{CA_t(i)}_{\text{cash}} + \underbrace{\lambda_t(i)E_t^{ST,k-1}(i)}_{\text{hoarding inflows}} - \underbrace{\sum_{j, C_t^{k-1}(j)\geq 0} \lambda_t(j)E_t^{ST,k-1}(j)\frac{\mu_t(i)E_t^{ST,k-1}(j,i)}{\Sigma_l \mu_t(l) E_t^{ST,k-1}(j,l)}}_{\text{hoarding outflows}} > 0. \tag{2.4}$$

The above stated rule for modelling liquidity hoarding and the liquidity condition is a direct extension of rules applied in the literature. For instance, Gai and Kapadia (2011) assume that a constant exogenous proportion of liquidity is hoarded in case of distress. With our notations, it would be expressed as $\lambda_t(i) = \lambda$. We contribute to the literature by proposing a hoarding rule that accounts for the magnitude of liquidity hoarding (driven by a capital gap) and the distribution of it among the counterparties (driven by the respective

[10] In practice, we test a range of parameters values in order to check the robustness of our results.

[11] see, e.g., Das and Sy (2012) and Lautenschlager (2013) who discuss the use of leverage as an indicator of riskiness of a financial institution.

individual leverage ratios).

In line with the solvency contagion algorithm, we state that a bank is in default when its capital has been wiped out (solvency condition) or when it cannot satisfy its short-term commitments (liquidity condition).

$$\begin{cases} C_t^0(i) = C_{t-1}(i) \\ \text{ for } k \geq 1, \\ \textbf{Solvency condition:} \\ C_t'^k(i) = C_t^0(i) - \sum_{\{j,\, C_t^{k-1}(j)=0\}} (1-R^L) E_t^{ST}(i,j) \\ \textbf{Liquidity condition:} \\ C_t''^k(i) = \begin{cases} 0 & \text{if } CA_t(i) + \lambda_t(i) E_t^{ST,k-1}(i) - \\ & \sum_{h, C_t^{k-1}(h)\geq 0} \lambda_t(h) E_t^{ST,k-1}(h) \frac{\mu_t(i) E_t^{ST,k-1}(h,i)}{\Sigma_l \mu_t(l) E_t^{ST,k-1}(h,l)} < 0 \\ C_t'^j(i) & \text{otherwise} \end{cases} \\ \textbf{Updating equation:} \\ C_t^k(i) = max(C_t'^k(i); C_t''^k(i); 0) \end{cases} \tag{2.5}$$

We denote the recovery rate in the liquidity cascade R^L. In general, one can distinguish a recovery rate in the case of a default due to illiquidity from a recovery rate of a default due to insolvency (R^S). And one might argue that the former recovery rate should be higher since the asset side of an illiquid bank is not impaired. In the proposed algorithm, all banks that do not satisfy the liquidity condition have their total assets higher than their total debts (which makes them solvent). Thus, R^L is used to represent bankruptcy costs that do not reflect insolvency but costs associated with the liquidation of an illiquid bank.[12]

At the end of period t, the algorithm provides the status of each bank (alive or in default), their capital and their short-term exposures. Some banks may have defaulted during period t, thus some non-defaulted banks have recorded losses on their capital levels. If their capital is then lower than their economic capital, another round of liquidity hoarding dealt with in period $t+1$ will take place.

2.3.3 Indicators

We are interested in losses due to contagion corresponding to the left tail of the market shock distribution, and for this purpose we present the results using standard risk measures Value-at-Risk (VaR) and Expected Shortfall (ES) which are informative about the tail of a loss distribution. In our framework, the $VaR(q)$ is defined as loss due to contagion as a

[12] Based on a survey for U.S. banks, James (1991) establishes a bankruptcy cost of 10%.

percentage of total system capital at quantile q, while the $ES(q)$ is the average loss due to contagion as a percentage of total system capital over the worst q cases.[13] Particularly, we consider the following levels: 5%, 1%, 0.1% and 0.01%.

Moreover, we decompose the sources of losses in three terms: the effects of the "fundamental shock" (prior to any contagion), the effects of solvency contagion (subsequent to the shock and prior to liquidity contagion) and the effects of liquidity contagion (subsequent to solvency contagion). This allows us to know losses transmitted through each channel in total losses.

2.4 Application to the French banking system

In this section, we apply our model to a real network. We first introduce the data used in our framework followed by some descriptive statistics of the French banking system at the considered date. Lastly the results are presented.

2.4.1 Data

French credit institutions are required to report to the Autorité de Contrôle Prudentiel (French Prudential Supervisory Authority) a full and detailed description of their balance sheets (FINREP Report, EBSC (2009a)) and all the large bilateral exposures that they have to either other credit institutions or even a country or a company (Large Exposure Report, EBSC (2009b)). Such data allow the French Prudential Supervisory Authority to closely and continuously monitor the developments in the network and banks' counterparty risks. In the Large Exposure report, each credit institution is obliged to communicate all its exposures amounting to more than 10% of its capital or more than 300 millions of Euros. We use this unique data set on bilateral exposures and balance sheet composition to reconstruct the French banking network in December 2011.

Each bilateral exposure corresponds to the gross bilateral sum of both securities and loans that a bank holds in its portfolio with respect to a certain counterparty. Given the absence of information about the maturity of the assets held by each bank in the Large Exposure reports, we extract the ratio of short-term over long-term assets from balance

[13] for instance, "$VaR(1\%) = 0.1\%$" means that the 1% worst losses are greater than 0.1% of total capital; and "$ES(1\%) = 0.2\%$" means that over the 1% worst cases, the losses represent on average 0.2% of total capital

sheets.[14] We then apply this ratio to the amount of bilateral exposures of the corresponding bank reported in the Large Exposure dataset to obtain an estimation of long-term and short-term bilateral exposures.

The French banking system consists of more than 300 financial institutions at the solo level. Nevertheless, the French banking system is highly clustered with five major banking groups at the consolidated level accounting for more than 80% of the total assets of the system. We select the 11 largest banking groups such that our study constitutes an almost complete representation of the French banking sector, both in terms of size and business models. Indeed, it is composed of several major universal banks (either mutual banks or purely commercial banks) but also specialized banks (such as those engaged in consumer-loan activity). French banks also differ in terms of their degree of cross-border activities: some of them have intensive international activities while others operate mainly, not to say only, domestically. The sample of selected banks enables us to consider all of these heterogeneities (bank size, business model, global/local activity).[15]

Given that we study banks at the group-consolidated level, we do not consider exposures between subsidiaries within a group, since a group will try to avoid any failure of its subsidiary by reallocating profits and losses between subsidiaries and providing additional liquidity for instance. Therefore, considering the banking sector at a solo level may bias contagion analysis by counting intra-group defaults that may not occur in reality.

As documented in almost all the studies on real financial networks, the latter are usually scale-free, meaning that a few banks are connected to many other banks. This scale-free characteristic commonly observed for financial networks does not hold when we consider a small number of banks: in this sense, the network of the French banking system is rather special, since it is an almost complete one, as we can see in Figure 2.2, page 52.[16]

[14]Short-term is defined as "less than 1 month" while long-term is defined as "more than 1 month". Comparing the one-week base for a shock with this threshold of 1-month maturity for exposures introduces a conservative bias for the effect of the liquidity condition.

[15]Société Générale, Groupe Crédit Agricole, BNP Paribas, Banque Populaire-Caisse d'Epargne, La Banque Postale, Groupe Crédit Mutuel, HSBC France, PSA Finance, RCI Banque, Oséo, Laser Groupe.

[16]There are few banking systems characterized by a very limited number of banking groups, another example being Canada (see, e.g., Gauthier et al. (2010)).

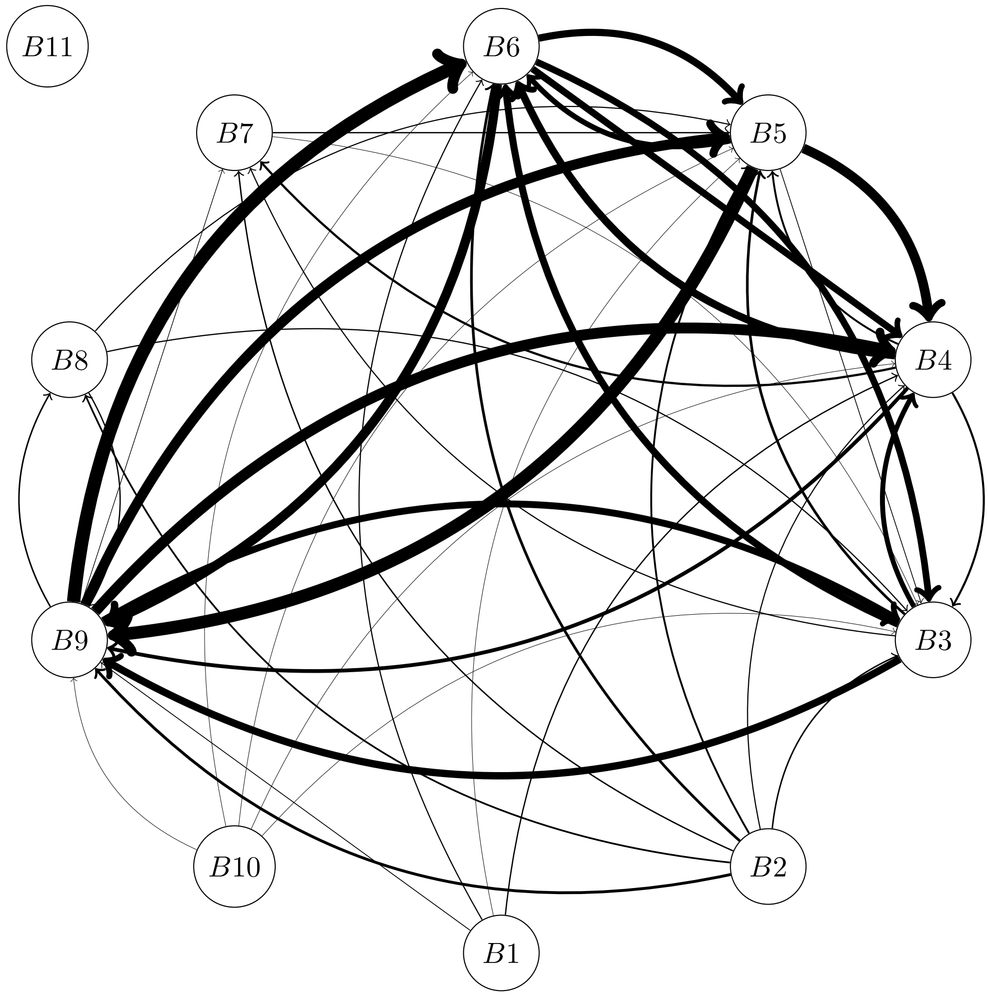


Figure 2.2: The French Banking Network in December 2011. The nodes correspond to the 11 largest French credit institutions while the edges represent the exposures (loans and securities) between the credit institutions. The widths of edges are proportional to the exposures.

2.4.2 Descriptive statistics

Table 2.4, page 52 reports some descriptive statistics on the French banking system.

Descriptive statistics			
as a %	**Mean**	**Standard Deviation**	**Median**
Interbank Exposures / TA	2.2	2.1	1.6
Interbank Exposures / Cap	34.2	28.2	27.9
Net position / Cash	171.1	557.1	0.0

Table 2.4: Descriptive statistics on the French banking network. "Exposures/TA" corresponds to the sum of all reported exposures by a bank expressed as a percentage of its total assets. "Exposures/Cap" is the sum of all reported exposures by a bank expressed as a percentage of its capital. "Net position/Cash" is the ratio of the difference between all the short-term assets owned by a bank and all its short-term liabilities vis-a-vis its lenders over its cash holdings.

The size of interbank exposures among the 11 largest French banks represents about 2.2% of their total assets. This amount may seem small, however, interbank exposures reach on average 34.2% of total capital.[17] The distribution of exposures has a heavy tail with most of the banks reporting small exposures while a few banks declaring big ones.

The ratio of total interbank assets over total capital can be an indicator of bank's sensitivity to solvency contagion, with the capital representing a safety cushion against losses. This ratio has a mean of 34.2% with a standard deviation of 28.2%. As the distribution is asymmetric, we may consider the median as a "central" indicator. With a 27.9% median for interbank exposure over capital, a generalized spread of solvency contagion seems unlikely from a very first analysis based on descriptive statistics.

In addition, another indicator that may help to measure bank's sensitivity to liquidity contagion is its net position (all credit granted minus all loans borrowed) with respect to cash.[18] Its net position defines if a bank will hoard liquidity and how well it will cope with a liquidity shock. A large amount of cash will reduce its probability of getting illiquid. The range of values observed for this indicator within the sample is ample. The greater the value, the lower the likelihood that a bank will suffer from its counterparties' liquidity hoarding behavior. Comparing a positive mean and a zero median indicates that, in general, the liquidity hoarding would not massively impact the network but that a few banks may be sensitive to this phenomenon.

2.4.3 Results

Since our model relies on several parameters, we have checked the robustness of our results by running simulations for a large set of parameters (see Appendix 2.B for details). For the sake of simplicity, we report the results for a representative set of parameters. First, we present the results for a solvency recovery rate of 40% which is conservative with respect to the EBA's stress-tests.[19] Second, as becoming illiquid does not necessarily mean that the value of its assets is subject to a large deterioration, the recovery rate for banks whose counterparty defaulted due to illiquidity issues is assumed to be equal to 80% corresponding to twice the bankruptcy cost estimated in James (1991). Third, among the

[17] These numbers are comparable to the empirical evidence documented by other studies: total exposures between the 5 Canadian banks represent on average 26.4% of Tier1 capital (see Gauthier et al. (2010)); in the USA, interbank assets represent about 5% of total assets (see, e.g., BHRPG reports provided by the Federal Financial Institutions Examination Council, www.ffiec.gov).

[18] In the model developed in Section 2.3, "cash" refers to the assets immediately available to pay short-term commitments. In the application to the French banking sector, cash corresponds to "Cash and cash balances with central banks" defined by IFRS 7.20 (see FINREP Report, EBSC (2009a)).

[19] The 2011 EBA's stress-test exercise reports that recovery rates for banks vary between 85% and 55%.

various functional forms of lambda we tested, the results displayed correspond to cases in which banks start hoarding liquidity when their capital falls below 120% of their economic capital (however, the choice of lambda does not change the results significantly).

We decompose the effect of a shock into three terms: the direct effect of a shock before any contagion mechanism takes place, the incremental effect of solvency contagion and the incremental effect of liquidity contagion.

2.4.3.1 General and Asset Class-Specific Market Shocks

In this subsection, we present the results of two exercises: the system is impacted by a common market shock and asset class-specific shocks.

The first finding is that neither of the two shocks makes any of the banks default. This finding is the direct consequence of the two facts: first, in December 2011, French banks were well capitalized and substantially above the required capital levels; second, banks' exposures to the considered asset classes are limited, and negative shocks to the value of any of these assets are not large enough to trigger the default of any of the banks. Extremely large financial market shocks are required to observe a default of at least one bank. Solvency contagion is then absent by definition. Liquidity contagion does emerge, though it is rather limited. This last result points out to the fact that banks' liquidity hoarding behavior does lead to defaults of some other banks even in the absence of solvency contagion. We could explain such small losses by the state of the banking system at the date of the analysis: as mentioned above, banks' capital is substantially above the required one and they also have enough liquid assets compared to their interbank funding. After all, it seems quite meaningful that authorities interventions have improved resilience of the system to the market shock and the spread of contagion.

The second result of such stress-test exercises is that the losses recorded are mainly if not solely caused by the initial shock, except in the extreme left tail of the distribution (see Table 2.5, page 55). In the extreme case for VaR(0.01%) of a general shock, on average a default of a bank causes 0.82% of capital loss due to liquidity hoarding phenomena. This almost 1% loss must nonetheless be compared to a shock with a magnitude of 46.31%.

We underline the fact that we obtain similar and therefore robust results for different recovery rates and for other specifications of the liquidity hoarding rule.

We also note that our results are in line with past stress-tests of French banks with respect to market risk (see, e.g., IMF (2012)), even though the performed stress-tests are much smaller in scope than in our study.

General Market Shock (Capital Loss, % of the Total Capital)						
	VaR(5%)	**VaR(1%)**	**VaR(0.1%)**	**VaR(0.01%)**	**ES(5%)**	**ES(1%)**
Shock (A)	21,91	32,93	42,97	46,31	28,29	37,37
Solvency Contagion (B)	0,00	0,00	0,00	0,00	0,00	0,00
Liquidity Contagion (C)	0,00	0,80	0,82	0,82	0,80	0,81
Total (=A+B+C)	21,91	33,73	43,79	47,13	29,09	38,18

Bubble Shock on Equity (Capital Loss, % of the Total Capital)						
	VaR(5%)	**VaR(1%)**	**VaR(0.1%)**	**VaR(0.01%)**	**ES(5%)**	**ES(1%)**
Shock (A)	20,88	32,93	42,97	46,31	27,88	37,37
Solvency Contagion (B)	0,00	0,00	0,00	0,00	0,00	0,00
Liquidity Contagion (C)	0,00	0,78	0,81	0,82	0,79	0,80
Total (=A+B+C)	20,88	33,71	43,78	47,13	28,68	38,16

Bubble Shock on Financial Institutions Bonds (Capital Loss, % of the Total Capital)						
	VaR(5%)	**VaR(1%)**	**VaR(0.1%)**	**VaR(0.01%)**	**ES(5%)**	**ES(1%)**
Shock (A)	20,51	32,05	42,97	46,31	27,37	36,93
Solvency Contagion (B)	0,00	0,00	0,00	0,00	0,00	0,00
Liquidity Contagion (C)	0,00	0,80	0,82	0,82	0,80	0,81
Total (=A+B+C)	20,51	32,85	43,79	47,13	28,17	37,74

Bubble Shock on Sovereign Bonds (Capital Loss, % of the Total Capital)						
	VaR(5%)	**VaR(1%)**	**VaR(0.1%)**	**VaR(0.01%)**	**ES(5%)**	**ES(1%)**
Shock (A)	20,65	32,93	42,97	46,31	27,63	37,37
Solvency Contagion (B)	0,00	0,00	0,00	0,00	0,00	0,00
Liquidity Contagion (C)	0,00	0,80	0,82	0,82	0,80	0,81
Total (=A+B+C)	20,65	33,73	43,79	47,13	28,43	38,18

Bubble Shock on Large Corporate Bonds (Capital Loss, % of the Total Capital)						
	VaR(5%)	**VaR(1%)**	**VaR(0.1%)**	**VaR(0.01%)**	**ES(5%)**	**ES(1%)**
Shock (A)	21,34	32,73	42,97	46,31	28,06	37,30
Solvency Contagion (B)	0,00	0,00	0,00	0,00	0,00	0,00
Liquidity Contagion (C)	0,00	0,80	0,82	0,82	0,80	0,81
Total (=A+B+C)	21,34	33,53	43,79	47,13	28,86	38,11

Table 2.5: Average (over initial default) capital loss in a French banking system (as a % of the total capital of the system) after being impacted by different market shocks (a general market shock and an asset class-specific shocks) decomposed into the source of losses: due the general market shock itself, and due to solvency and liquidity contagion. The solvency recovery rate is equal 40%; the liquidity recovery rate is equal to 80%. λ is such that banks start hoarding liquidity when their capital falls below 120% of required capital. For example, at $VaR(0.01\%)$ the system loss is 40.51% of capital, of which 39.8% is due to the general market shock. Solvency contagion is absent by definition.

2.4.3.2 Idiosyncratic shocks combined with common market shocks

We are also interested in a scenario where a common market shock follows by an exogenous default of one bank. Therefore, we perform a second set of stress-test exercises where we force one bank at a time to default in the presence of the same market shocks. The figures presented in the following tables are averages over the 11 individual idiosyncratic scenarios.

We obtain the following results: either a general shock or an asset class-specific shock, combined with an idiosyncratic default leads to no defaults due to solvency contagion, and liquidity contagion is present but limited. The absence of the domino effect when even the biggest banks default can be explained by banks' high levels of capitalization as well as by the small interbank exposures in total and, especially, to one specific counterparty. The size of losses measured as a percentage of the system's capital is entirely due to the fact that banks lose their exposures to the defaulted bank. As seen in Table 2.6, page 57, the average losses are equal to 1.18% over all types of shocks and all quantiles. The number shown is the average losses over the defaults of 11 banks, though losses vary among defaults of different banks depending on the exposure of the system to this bank.

The results of liquidity hoarding are similar to those of market shocks without idiosyncratic shocks.

The effects of solvency contagion and those of liquidity contagion are of the same magnitude, each of them triggering losses accounting for about 1.8% of total capital under the most adverse scenarios ($VaR(0.1\%)$ and $VaR(0.01\%)$). At the same time, the direct losses due to the initial shock (see Table 2.6, page 57) are 30 times larger than those occurring via each of these channels.

The robustness checks (see Appendix 2.B for more details) underline the quality and the stability of our results with respect to different specifications. When the solvency recovery rate varies from 0% to 100%, the figures keep the same approximate magnitude (see Table 2.B.1, page 68). We report results only for general market shock with and without idiosyncratic shocks, since results of asset-specific market shock are very similar and of the same order.[20]

[20] Available on demand

General Market Shock + Idiosyncratic shock (Capital Loss, % of the Total Capital)						
	VaR(5%)	**VaR(1%)**	**VaR(0.1%)**	**VaR(0.01%)**	**ES(5%)**	**ES(1%)**
Shock (A)	29,02	38,98	48,15	51,19	34,82	43,07
Solvency Contagion (B)	1,18	1,18	1,18	1,18	1,18	1,18
Liquidity Contagion (C)	0,19	0,63	0,64	0,65	0,63	0,64
Total (=A+B+C)	30,40	40,79	49,98	53,02	36,63	44,88

Bubble Shock on Equity + Idiosyncratic shock (Capital Loss, % of the Total Capital)						
	VaR(5%)	**VaR(1%)**	**VaR(0.1%)**	**VaR(0.01%)**	**ES(5%)**	**ES(1%)**
Shock (A)	28,11	38,98	48,15	51,19	34,44	43,07
Solvency Contagion (B)	1,18	1,18	1,18	1,18	1,18	1,18
Liquidity Contagion (C)	0,00	0,62	0,64	0,65	0,62	0,63
Total (=A+B+C)	29,29	40,78	49,97	53,02	36,24	44,88

Bubble Shock on Financial Institutions Bonds + Idiosyncratic shock (Capital Loss, % of the Total Capital)						
	VaR(5%)	**VaR(1%)**	**VaR(0.1%)**	**VaR(0.01%)**	**ES(5%)**	**ES(1%)**
Shock (A)	27,76	38,27	48,15	51,19	33,98	42,67
Solvency Contagion (B)	1,18	1,18	1,18	1,18	1,18	1,18
Liquidity Contagion (C)	0,26	0,63	0,64	0,65	0,63	0,64
Total (=A+B+C)	29,20	40,08	49,98	53,02	35,79	44,49

Bubble Shock on Sovereign Bonds + Idiosyncratic shock (Capital Loss, % of the Total Capital)						
	VaR(5%)	**VaR(1%)**	**VaR(0.1%)**	**VaR(0.01%)**	**ES(5%)**	**ES(1%)**
Shock (A)	27,88	38,97	48,15	51,19	34,21	43,07
Solvency Contagion (B)	1,18	1,18	1,18	1,18	1,18	1,18
Liquidity Contagion (C)	0,33	0,63	0,64	0,65	0,63	0,64
Total (=A+B+C)	29,39	40,79	49,98	53,02	36,02	44,88

Bubble Shock on Large Corporate Bonds + Idiosyncratic shock (Capital Loss, % of the Total Capital)						
	VaR(5%)	**VaR(1%)**	**VaR(0.1%)**	**VaR(0.01%)**	**ES(5%)**	**ES(1%)**
Shock (A)	28,49	38,87	48,15	51,19	34,61	43,01
Solvency Contagion (B)	1,18	1,18	1,18	1,18	1,18	1,18
Liquidity Contagion (C)	0,26	0,63	0,64	0,65	0,63	0,64
Total (=A+B+C)	29,93	40,68	49,98	53,02	36,42	44,83

Table 2.6: Capital loss (over initial default) in a French banking system (as a % of the total capital of the system) after being impacted by different market shocks (a general market shock and an asset class-specific shocks) and an idiosyncratic shock, decomposed into the source of the losses: due the general market shock itself, and due to solvency and liquidity contagion. The solvency recovery rate is equal 40%; the liquidity recovery rate is equal to 80%. λ is such that banks start hoarding liquidity when their capital falls below 120% of required capital.

2.5 Conclusion

This paper develops a model that allows us to take into account the losses of the system due to solvency and liquidity contagion after an initial correlated shock impacting the system. This is one of the first papers that makes it possible to disentangle between the losses caused by different sources of risk. We also propose a toolkit to simulate market shocks in line with liquidity hoarding phenomena. We use this model to evaluate the resilience of the French banking system to systemic market shocks.

The literature on the pure default contagion is much vaster, though the results are rather controversial. In a similar framework, Cont et al. (2010) studying Brazilian banking system find evidence of sizeable domino effects after an initial shock. At the same time, Elsinger et al. (2006a), who analyze the Austrian banking network, record rare occurrences of such effects. Other studies conducted on network contagion without any initial stress on the whole banking system document very limited consequences (Amundsen and Arnt (2005), Upper and Worms (2004)). What seems to be really essential for the existence of domino effects is not only the initial market shock, but also its magnitude.

Our results, which complement the study of pure solvency default contagion with banks' liquidity hoarding behavior, shed light on the following points. First, we clearly identify that for the French banking system on December 31, 2011, the contagion effects appear to be significantly smaller than the initial shock. Second, we find that losses due to solvency and liquidity contagion are of similar magnitude. One would therefore underestimate the losses in the system if one did not take into account the distress propagated via funding shortages.

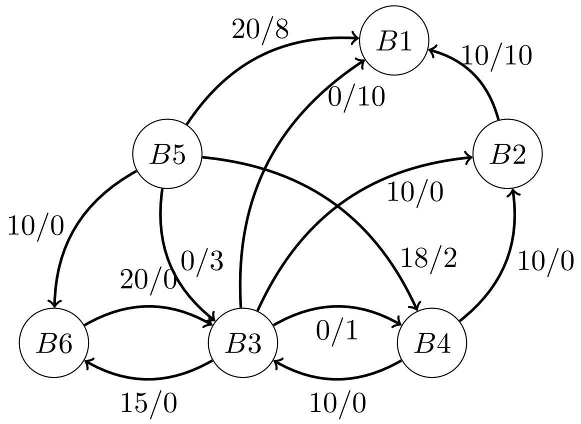
Since results of the empirical application of the model can be date-specific, in future work, it would be interesting to analyze propagation of contagion on other dates and see how contribution of different mechanisms in total losses changes over time.

Appendix

2.A Illustration of contagion mechanisms for a simple network

2.A.1 Initial network

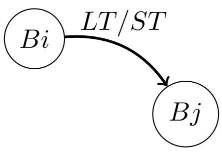
Let us consider a basic network composed of six banks as represented in Figure 2.A.1, page 59. We assume that both recovery rates, R^S and R^L, are set to 0 for simplicity.



Balance-sheet info

Bank	C	EC	$Cash$
$B1$	1	0.5	0.5
$B2$	12	10	1
$B3$	32	30	2
$B4$	22	5	1.5
$B5$	32	4	2
$B6$	22	5	2

Legend



Bank i is exposed to bank j for LT in the long term and ST in the short term.

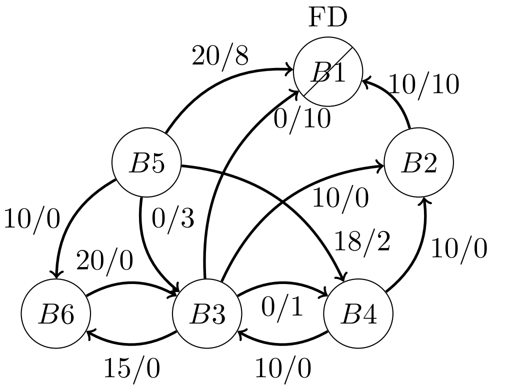
Figure 2.A.1: Initial Network

2.A.2 Round of solvency contagion

Let us consider that at $t = 0$ an initial shock erodes the capital of all the banks by the order of 2. All of the banks can absorb this shock except bank $B1$ which goes into bankruptcy. The fundamental default set is limited to bank 1. The solvency algorithm takes place and its various steps are represented in Figure 2.A.2, page 61.

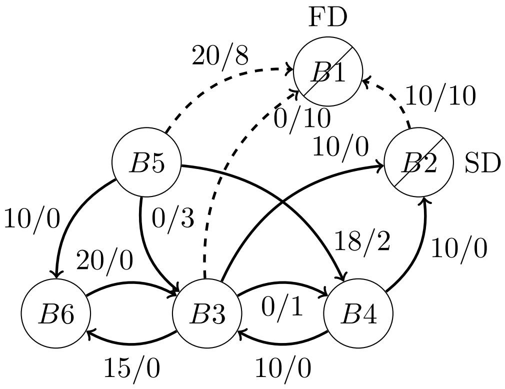
The default of bank $B1$ results in losses for its counterparties: banks $B2$, $B3$ and $B5$. For each bank in question, the losses incurred and which correspond to its total exposure to bank $B1$, are absorbed by its capital. Bank $B2$ does not have enough capital to absorb its exposures, so it goes into default. Banks $B3$ and $B5$ are sufficiently capitalized to stay alive. Bank $B2$'s default is characterized as a "solvency default".
The default of bank 2 results in losses for banks 3 and 4. This second step of solvency contagion is the last one since all the banks exposed to bank 2 have enough capital to absorb the losses.

The solvency equilibrium (the last step of this round of solvency contagion) is represented in Figure 2.A.3, page 62.



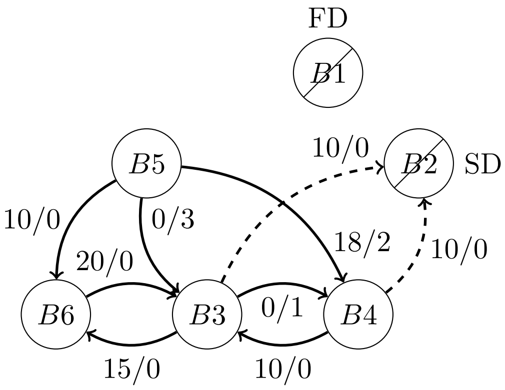
Bank	C	EC	$Cash$
$B1$	$0 = (1-2)^{+}$	0	0
$B2$	$10 = (12-2)^{+}$	10	1
$B3$	$30 = (32-2)^{+}$	30	2
$B4$	$20 = (22-2)^{+}$	5	1.5
$B5$	$30 = (32-2)^{+}$	4	2
$B6$	$20 = (22-2)^{+}$	5	2

(a) Fundamental Default



Bank	C	EC	$Cash$
$B1$	0	0	0
$B2$	$0 = (10-20)^{+}$	10	1
$B3$	$20 = (30-10)^{+}$	30	2
$B4$	20	5	1.5
$B5$	$2 = (30-28)^{+}$	4	2
$B6$	20	5	2

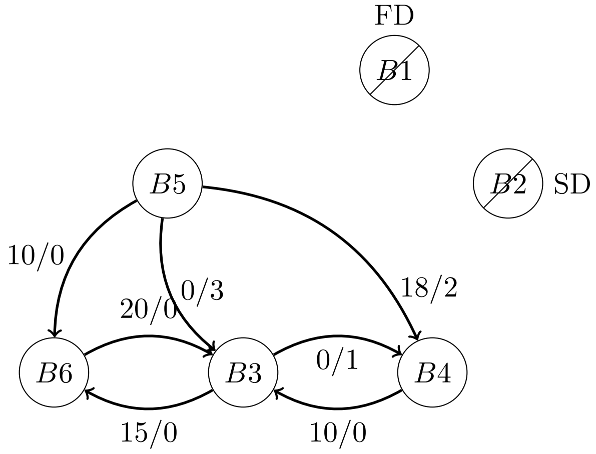
(b) Round of Solvency contagion, First step



Bank	C	EC	$Cash$
$B1$	0	0	0
$B2$	0	0	0
$B3$	$10 = (20-10)^{+}$	30	2
$B4$	$10 = (20-10)^{+}$	5	1.5
$B5$	2	4	2
$B6$	20	5	2

(c) Round of Solvency contagion, Second step

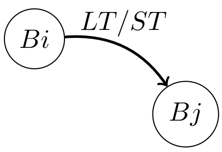
Figure 2.A.2: Solvency Contagion



Balance-sheet info

Bank	C	EC	$Cash$
$B1$	0	0	0
$B2$	0	0	0
$B3$	10	30	2
$B4$	10	5	1.5
$B5$	2	4	2
$B6$	20	5	2

Legend



Bank i is exposed to bank j for LT in long term and ST in short term.

Figure 2.A.3: Solvency Round Equilibrium Network

2.A.3 First Liquidity Contagion Round

Since the solvency contagion is over, banks $B3$, $B4$ and $B5$ are solvent. But when they compare their capital (in column C) with their economic capital (in column EC), banks $B3$ and $B5$ start hoarding liquidity whereas bank $B4$ does not modify its behavior since its capital is substantially greater than its economic capital.

In this example, we consider simply that $\lambda_i = (EC_i - C_i)^+/EC_i$ and that this proportion of liquidity hoarding is uniformly applied to all short-term exposures (or equivalently, that all banks have the same leverage ratio). Therefore, banks $B3$ and $B5$ reduce their total short-term exposures by 66% $(= (30-10)^+/30)$ and 50% $(= (4-2)^+/4))$ respectively. Consequently, the cash outflows are:

$$\begin{aligned}
\text{Cash outflow for bank } B3 = \;& 1.5 = \underbrace{0.5 \times 3}_{\text{toward bank } B5} \\
\text{Cash outflow for bank } B4 = \;& 1.66 = \underbrace{0.5 \times 2}_{\text{toward bank } B5} + \underbrace{0.66 \times 1}_{\text{toward bank } B3} \\
\text{Cash outflow for bank } B5 = \;& 0.
\end{aligned}$$

Symmetrically, the cash inflows are:

$$\begin{aligned}
\text{Cash inflow for bank } B3 = \;& 0.66 = \underbrace{0.66 \times 1}_{\text{from bank } B4} \\
\text{Cash inflow for bank } B4 = \;& 0 \\
\text{Cash inflow for bank } B5 = \;& 2.5 = \underbrace{0.5 \times 3}_{\text{from bank } B3} + \underbrace{0.5 \times 2}_{\text{from bank } B4}
\end{aligned}$$

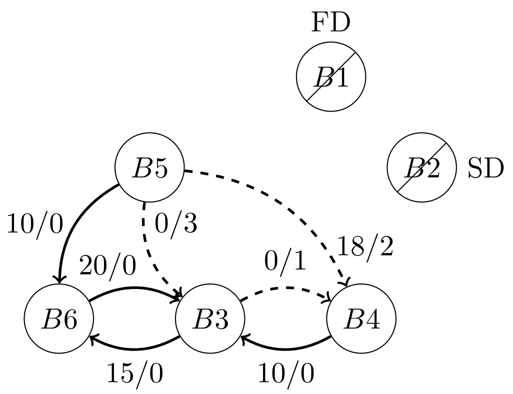
For all the steps in the liquidity hoarding phenomenon, the algorithm will consider that a bank is in default if it does not satisfy one of the two conditions (solvency and liquidity conditions) previously referred to in the theoretical model. A bank remains alive if its capital is above zero (solvency condition) and if its cash position allows it to honor its short-term commitments (liquidity condition). At each step, these two conditions are simultaneously checked for every bank. For the sake of clarity, we will consider them sequentially and first look at whether each bank satisfies its liquidity condition and then check if each bank is still solvent.

For this first step, as the network is initially in equilibrium in terms of solvency contagion, only the liquidity condition is checked. Combining the cash inflow, the cash outflow and the cash holdings of each bank, we can check if each bank fulfills its liquidity condition. For bank $B5$, we have a positive value since there is no cash outflow. Although bank $B3$ has a bigger cash outflow (1.5) than its cash inflow (0.66), its cash holding (2) can absorb the difference ($2 + 0.66 > 1.5$). By contrast, bank $B4$ is short in terms of liquidity. Its cash outflow (1.66) is higher than its cash inflow (0) and it does not have enough liquid assets (1.5) to pay back its creditors. In other words, banks $B5$ and $B3$'s behavior which consists in stopping rolling over the short-term debt issued by bank $B4$ generates a cash outflow for bank $B4$ that it cannot cope with. We consider that bank $B4$ is in default due to illiquidity. Note that in this particular case, the action of bank $B5$ or bank $B3$ alone would have not led bank $B4$ to have a liquidity shortfall since each component of the cash outflow of bank $B4$ is lower than its cash holdings. The situation after this first step of liquidity hoarding is represented in the top network of Figure 2.A.4, page 65.

In this new step, the check on whether the liquidity condition for each bank is fulfilled or not only concerns banks $B3$ and $B5$, and is represented in the middle network of Figure 2.A.4, page 65. We can easily see that bank $B5$ satisfies its liquidity condition in the sense that bank $B5$ is a pure short-term lender. For bank $B3$, the cash inflow is now 0 since $B4$, the only initial short-term debtor of bank $B3$, is in distress and its cash outflow (towards bank $B5$) is 1.5. Since bank $B3$'s cash position is 2, bank $B3$ fulfills its liquidity condition. The situation at the end of the liquidity contagion step (middle network of Figure 2.A.4, page 65) is not a solvency equilibrium since the losses due to bank $B4$'s default have not been taken into account. Thus, during this second step there is an additional check with respect to the solvency condition in the algorithm of contagion represented in the lowest plot of Figure 2.A.4, page 65. Bank $B5$ suffers a loss of 20 $(= 18 + 2)$ while bank $B3$ suffers a loss of 1 $(= 0 + 1)$. Bank $B5$ does not have enough capital to absorb this loss while $B3$ has. This fact triggers solvency contagion: bank $B6$ is able to absorb the losses incurred corresponding to its exposure to bank $B5$.

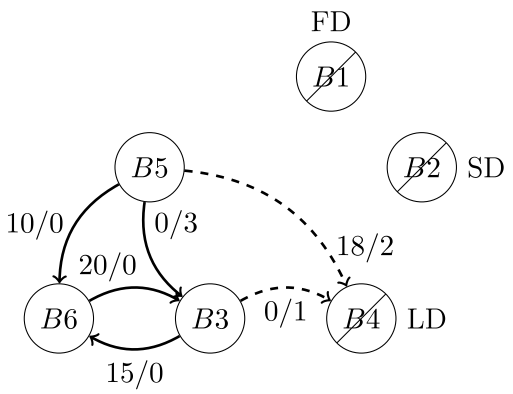
The situation after this first round of solvency contagion and this first round of liquidity contagion is stable from a solvency point of view (all remaining capital levels are strictly positive) and from a liquidity point of view (all cash holdings are sufficiently high). Note that the two remaining banks, $B3$ and $B6$, have their capital lower than their economic capital; but since they are not short-term lenders, this cannot lead them to stop short-term lending. We therefore consider that the final situation, represented in Figure 2.A.5, page 66, is the equilibrium situation reached within a week.

In this example, the equilibrium is reached with only one round of solvency contagion and one round of liquidity contagion. With more complex networks, several rounds of liquidity contagion are easily conceivable.



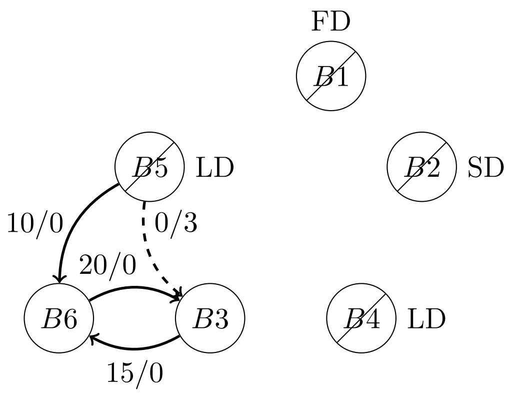
Bank	C	EC	$Cash$
$B1$	0	0	0
$B2$	0	0	0
$B3$	10	30	$2 + 0.66 - 1.5 > 0$
$B4$	10	5	$1.5 + 0 - 1.66 < 0$
$B5$	2	4	$2 + 2.5 - 0 > 0$
$B6$	20	5	2

(a) First Round of Liquidity Contagion, First step



Bank	C	EC	$Cash$
$B1$	0	0	0
$B2$	0	0	0
$B3$	10	30	2
$B4$	10	5	0
$B5$	2	4	2
$B6$	20	5	2

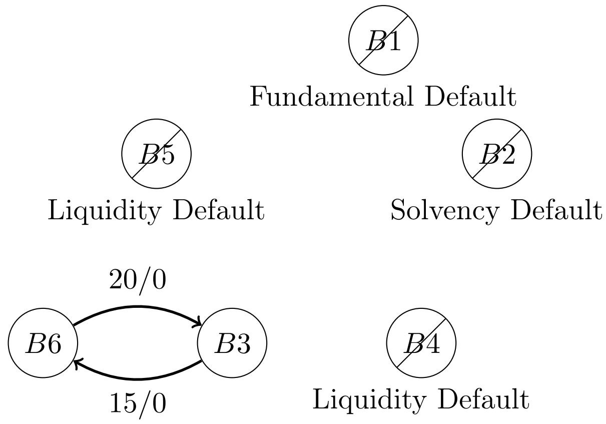
(b) First Round of Liquidity Contagion, Second step, Liquidity condition



Bank	C	EC	$Cash$
$B1$	0	0	0
$B2$	0	0	0
$B3$	$9 = (10 - 1)^+$	30	2
$B4$	0	0	0
$B5$	$0 = (2 - 20)^+$	4	2
$B6$	$10 = (20 - 10)^+$	5	2

(c) First Round of Liquidity Contagion, Second step, Solvency condition

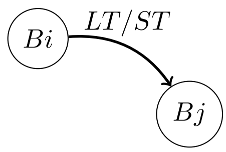
Figure 2.A.4: First Round of Liquidity Contagion



Balance-sheet info

Bank	C	EC	$Cash$
$B1$	0	0	0
$B2$	0	0	0
$B3$	9	30	2
$B4$	0	0	0
$B5$	0	0	0
$B6$	10	5	2

Legend



Bank i is exposed to bank j for LT in long term and ST in short term.

Figure 2.A.5: Final Equilibrium

2.B Robustness Checks

Running the simulation needs to define 3 mains specifications:

- The solvency recovery rate, R^S, is varying from 0.1 (only 10% of exposures it repaid) to 1 (absence of loss). Indeed, the results vary with the solvency recovery rate but keep the same approximate size, as explained in the discussion of the paper.

- The liquidity recovery rate R^L is set to 0.8: in case of default due to liquidity shortage, 20% of exposures are lost. Using another recovery rate do not change our results since the liquidity contagion spread is not overwhelming. As said before, 20% is a conservative setting since it is twice the bankruptcy cost estimated in James (1991).

- The hoarding function $\lambda(.)$ is a more sophisticated figure. We consider the inverse of a Gaussian c.d.f. as baseline shape. We run the simulations with 9 couples for the mean and the variance. The magnitudes of results are stable across specifications. However, the results are more sensitive to the mean than to the variance. In fact, the mean parameter acts as a threshold for triggering hoarding phenomena; therefore, it is logical than an easy triggering threshold leads to a more effective liquidity hoarding phenomenon.

As illustration, Table 2.B.1, page 68 reports the effect of a general market shock (with and without idiosyncratic shocks) for various solvency recovery rates.

General Market Shock, Capital Loss (% of Total Capital)

Recovery Rate		**Liquidity Hoarding: C falls below 1,2 RC**						**Liquidity Hoarding: C falls below 1,5 RC**				
	VaR(5%)	**VaR(1%)**	**VaR(0,1%)**	**VaR(0,01%)**	**ES(5%)**	**ES(1%)**	**VaR(5%)**	**VaR(1%)**	**VaR(0,1%)**	**VaR(0,01%)**	**ES(5%)**	**ES(1%)**
0,1	0,00	0,93	0,94	0,95	0,93	0,94	0,95	0,96	0,98	1,00	0,96	0,97
0,2	0,00	0,89	0,90	0,91	0,88	0,89	0,91	0,92	0,93	0,95	0,92	0,93
0,3	0,00	0,85	0,86	0,86	0,84	0,85	0,87	0,88	0,89	0,91	0,88	0,88
0,4	0,00	0,80	0,82	0,82	0,80	0,81	0,83	0,84	0,85	0,87	0,83	0,84
0,5	0,00	0,76	0,77	0,78	0,76	0,77	0,78	0,79	0,81	0,83	0,79	0,80
0,6	0,00	0,72	0,73	0,74	0,71	0,72	0,74	0,75	0,76	0,79	0,75	0,76
0,7	0,00	0,68	0,69	0,69	0,67	0,68	0,70	0,71	0,72	0,74	0,71	0,71
0,8	0,00	0,63	0,65	0,65	0,63	0,64	0,66	0,67	0,68	0,70	0,66	0,67
0,9	0,00	0,59	0,60	0,61	0,59	0,60	0,61	0,63	0,64	0,66	0,62	0,63
1	0,00	0,55	0,56	0,57	0,55	0,55	0,57	0,58	0,60	0,62	0,58	0,59

General Market Shock + Idiosyncratic Shock, Capital Loss (% of Total Capital)

Recovery Rate		**Liquidity Hoarding: C falls below 1,2 RC**						**Liquidity Hoarding: C falls below 1,5 RC**				
	VaR(5%)	**VaR(1%)**	**VaR(0,1%)**	**VaR(0,01%)**	**ES(5%)**	**ES(1%)**	**VaR(5%)**	**VaR(1%)**	**VaR(0,1%)**	**VaR(0,01%)**	**ES(5%)**	**ES(1%)**
0,1	0,38	0,72	0,73	0,74	0,72	0,73	0,75	0,76	0,77	0,78	0,75	0,76
0,2	0,36	0,69	0,70	0,71	0,69	0,70	0,72	0,73	0,73	0,75	0,72	0,73
0,3	0,27	0,66	0,67	0,68	0,66	0,67	0,69	0,69	0,70	0,72	0,69	0,70
0,4	0,19	0,63	0,64	0,65	0,63	0,64	0,66	0,66	0,67	0,69	0,66	0,67
0,5	0,12	0,60	0,61	0,62	0,60	0,61	0,62	0,63	0,64	0,66	0,63	0,64
0,6	0,12	0,57	0,58	0,59	0,56	0,57	0,59	0,60	0,61	0,63	0,60	0,61
0,7	0,00	0,54	0,55	0,56	0,53	0,54	0,56	0,57	0,58	0,60	0,57	0,57
0,8	0,00	0,51	0,52	0,53	0,51	0,51	0,53	0,54	0,55	0,56	0,54	0,54
0,9	0,00	0,48	0,49	0,50	0,48	0,48	0,50	0,51	0,52	0,53	0,50	0,51
1	0,00	0,45	0,46	0,46	0,45	0,45	0,47	0,48	0,49	0,50	0,47	0,48

Table 2.B.1: Capital loss in a French banking system (as a % of the total capital of the system) due to liquidity hoarding after being hit by a general market shock with and without an idiosyncratic shock, for different recovery rates. λ is so that banks start hoarding liquidity when their capital falls below 120% (left column) and 150 % (right column) of required capital.

Chapter 3

Cross-border interbank contagion in the European banking sector[1]

3.1 Introduction

The 2007-2009 financial crisis revealed the fragility of financial institutions worldwide. More importantly, it disclosed the major role of interconnectedness among banks in the propagation of financial distress. Interconnections, due to bilateral contractual obligations but also to exposure to common risk factors and sudden collapses in market confidence, have grown dramatically in the run-up to the crisis.[2] While higher interconnectedness is a crucial means of efficient risk transfer, it may also lead to contagious *default cascades*: an initial shock may propagate throughout the entire banking system via chains of defaults and liquidity shortages that follow highly dynamic patterns.

Direct and indirect linkages among banks arose as a key component of financial contagion in the European Union, as revealed first by the default of Lehman Brothers in September 2008, and then by the euro area sovereign debt crisis. Especially after the European Banking Authority's disclosure of the extent of European banks' common exposures to stressed sovereigns in 2011(EBA, 2011a), the potential for contagion effects through interbank transactions has taken a peculiar - geographical - dimension in the euro area, with banks reducing their exposure particularly to banks headquartered in the periphery of the euro area (see,

[1]This chapter is based on the paper co-written with S. Gabrieli and G. Vuillemey. It has been presented at several conferences: Conference on Trade and Networks (KU Leuven, 2013), CIRANO (Montreal, 2013), IFABS 2014 (Lisbon), AFSE 2014 (Lyon), MaRs (ECB, 2014), EFA 2014 (Toulouse)

[2]Total cross-border banking flows rose several-fold from 1978 to 2007 compared to their long-term average, see Minoiu and Reyes (2011).

e.g., Abascal et al. (2013) who measure fragmentation in interbank market and three other financial markets (sovereign debt, equity and the CDS market for financial institutions).

This paper is the first to investigate the scope for cross-border contagion in Europe using true exposure data at a bank-to-bank level. We analyze geographical patterns of shock propagation between 73 European banking groups from end-2008 until end-2012. Cross-border interbank exposures are generally hard to obtain. National supervisors can have at best a partial view of the largest long-term credit claims of supervised banks via credit registers.[3] To circumvent the unavailability of accurate information on domestic and cross-border interbank exposures, and obtain a realistic representation of how European banks are connected through their long- and short-term claims, we exploit for the first time a unique dataset of interbank money market transactions, with various maturities, estimated from TARGET2 payment data (see Arciero et al. (2013)). More specifically, we employ money market loans with maturities up to one month to reconstruct the network of short-term interbank linkages and a realistic probability map of short-term loans among banks; at the same time, we use information on the size and frequency of money market loans with longer maturities to construct a realistic probability map of long-term bank-to-bank exposures. These maps, together with the amount of individual banks' aggregate loans to other banks, are used to simulate a large number of long-term exposure matrices through a novel methodology proposed by Halaj and Kok (2013).

The extent of interbank contagion is assessed relying on Fourel et al. (2013) model of sequential solvency and liquidity cascades in a network setting. More specifically, we look at the distribution of simulation outcomes resulting from a common market shock on (listed) banks' capital, coupled with an exogenous bank default; the distributions are obtained over 100 different simulated networks of long- and short-term exposures. We observe the total number of defaulted banks after several rounds of solvency and liquidity contagion, and the total capital loss experienced by a certain country's banking sector when contagion is triggered by a default of a foreign or domestic bank. Heat maps are used to assess, on the one hand, which banking sectors are the most "systemic" in terms of the losses that the failure of one of their banks can impose to foreign countries' banks and, on the other, to identify which banking sectors are the most prone to cross-border contagion from European counterparties.

[3]For instance, the German credit register contains quarterly data on large bilateral exposures - derivative, on- and off-balance sheet positions - above a threshold of EUR 1.5 m. The French "grands risques" data include individual banks' quarterly bilateral exposures that represent an amount higher than 10% of their capital or above EUR 300 m. Italian banks submit to the Banca d'Italia their end-of-month bilateral exposures to all other banks.

Simulation of multiple realistic short- and long-term networks allows us to analyze the determinants of contagion using an econometric approach. Relying on five years of data and 100 pairs of simulated networks we are able to identify both bank and network characteristics that make a bank/system more fragile/resilient to contagion.

We find that both solvency and liquidity contagion are tail risks: losses averaged over stress-scenario, initial bank defaults or simulated networks are rather limited; however, averaging conceals rare extreme events. We document that losses at the tail of the distribution can reach one third of the system capital in 2008, and that the resilience of the system improves significantly over time. Under severe equity market stress and following an exogenous default of one bank, cross-border contagion can materialize in the European banking system. The overall average losses caused by a foreign bank default, however, vary remarkably over time and over different banking sectors. A foreign default has on average a small impact on most banking sectors and even less over time. However, for some banking systems, a default by a foreign bank may cause a loss as large as 15% of the capital of the impacted banking sector. Overall, our results document that the European banking system has substantially increased its capacity to withstand the same kind of adverse financial conditions that it had to face after the default of Lehman Brothers. The heat maps allow us to discern specific geographical patterns of cross-border contagion in the European Union, which vary significantly over the years. In general, the maps for 2009, 2010 and 2012 show that the potential for cross-border contagion has constantly decreased over time. This is related to a generalized reduction in the share of long-term interbank loans in bank balance sheets, on the one hand, and to an increase in banks' capitalization during those years compared to 2008.

Finally, our results show the strong impact on the domestic and cross-border propagation of losses of heterogeneity and concentration in the structure of interbank exposures. The number of defaults resulting from extreme market stress coupled with one bank's default can be five or six times larger depending on the underlying structure of interbank linkages. This is consistent with recent models of contagion in financial networks relying on simulated networks of exposures (see, Georg (2013) and Gai and Kapadia (2010)), and points to the need to account for the evolving nature of the web of interbank linkages when running contagion analysis. This is the first paper, to our knowledge, to document this feature simulating probabilistic interbank exposures based on actual bank-to-bank level data.

A large literature exists that relies on counterfactual simulations based on a network setting to estimate the potential for interbank contagion (see Upper (2011) for a comprehensive survey). Notwithstanding the increasingly international dimension of contagion, however, these simulations have so far focused essentially on national banking sectors, estimating their frailty/resilience only at one specific point in time. Moreover, only very recently have economists started to integrate behavioral foundations into their modelling frameworks, hence providing different contagion channels, and to consider the impact of common shocks on the network of interbank loan exposures, possibly resulting in concurrent losses for banks.

Our study contributes to this literature by analyzing cross-border contagion at a bank-to-bank level using realistically simulated networks from true exposure data. Up to now, a handful of papers have analyzed cross-border contagion using price data such as equity or credit default swaps, therefore relying on some form of market efficiency and not being able to identify the structural channels driving the co-movement of prices (see, Gropp et al. (2009)). Other papers focused their attention on BIS country statistics to study cross-border contagion; but this has the strong drawback that authors have to assume that the whole or a part of a country's banking system defaults and that losses propagate to other country's banking sectors (see, Degryse et al. (2009) and Espinosa-Vega and Sole (2010)).

We exploit the idea of probabilistic networks to study propagation of contagion: multiple simulated networks, drawn from real data probability maps (thanks to TARGET2 data), differ from the real existing network and, moreover, demonstrate significant heterogeneity. This allows us to analyze not only the vulnerability of one particular network realization retrieved from the real data, but plenty of potential realistic networks. All the simulated networks display well-documented properties such as a low density and a highly skewed (weighted and unweighted) degree distribution. Furthermore, we pursue the analysis one step further and econometrically identify balance sheet and network properties which drive the contagion outcome. More specifically, we investigate bank-level contagion and explain the determinants of bank fragility or systemicity with both banks' balance sheet and exposure characteristics.

The remainder of this article is structured as follows. In section 3.2, we present the theoretical model for the imputation of losses and the liquidity hoarding mechanism. In section 3.3, we describe the banks' sample, the interbank exposures data and the algorithm used to generate interbank networks. We provide descriptive evidence on both the European banking system in the period 2008-2012 and the structural properties of generated long- and short-term networks. The results of our simulations are presented and commented on in section 3.4. Section 3.5 introduces the econometric analysis of the determinants of contagion outcomes, section 3.6 concludes.

3.2 The model

Our model builds on the work by Fourel et al. (2013). In the following we expose its main theoretical blocks as well as some extensions we implement, while we refer the reader to Fourel et al. (2013) for more details.

Let us consider a system of N financial institutions indexed by i. Each of them is characterized by a stylized balance sheet presented in **Table 3.1**. The asset side of bank i is decomposed into several items: long- and short-term interbank exposures ($E^{LT}(i,j)$ and $E^{ST}(i,j)$ for $j \in [1;N]$), cash and liquid assets (cash from now on) $Ca(i)$ and other assets $OA(i)$. We denote the total assets by $TA(i)$. The liability side of bank i consists of equity $C(i)$ (hereafter capital), long- and short-term interbank exposures ($E^{LT}(j,i)$ and $E^{ST}(j,i)$ for $j \in [1;N]$) and all other liabilities gathered in $OL(i)$.

	Assets	**Liabilities**	
Long Term	$E_t^{LT}(i,1)$	$E_t^{LT}(1,i)$	Long Term
Interbank	$\vdots$	$\vdots$	Interbank
Assets	$E_t^{LT}(i,N)$	$E_t^{LT}(N,i)$	Liabilities
Short Term	$E_t^{ST}(i,1)$	$E_t^{ST}(1,i)$	Short Term
Interbank	$\vdots$	$\vdots$	Interbank
Assets	$E_t^{ST}(i,N)$	$E_t^{ST}(N,i)$	Liabilities
Cash	$Ca_t(i)$	$OL_t(i)$	Others
Others	$OA_t(i)$	$Ca_t(i)$	Capital
Total assets	$TA_t(i)$	$TL_t(i)$	Total liabilities

Table 3.1: Bank i's stylized balance sheet at date t

Banks are connected by two types of links: short-term and long-term commitments. The distinction between these links is essential within the present model as it enables defining two channels of contagion (liquidity vs. solvency contagion). Short-term exposures are represented mainly by short-term loans, e.g. with overnight or one-week maturity, and a link can be easily cut from a certain day/week to the subsequent one. This property of the link allows banks to hoard liquidity, that is, to reduce or to cut their exposures to a counterparty when needed. As explained below, liquidity contagion here propagates through the network of short-term exposures. On the contrary, long-term exposures represent a more stable source of funding and can not be cut before maturity. Therefore, only if a bank defaults do its counterparties lose all their long-term exposures to it (taking a recovery rate into account). A network of long-term exposures is the main channel for the propagation of solvency contagion.

The model consists of three parts: a common market shock, solvency contagion propagation and liquidity hoarding behavior. This section provides the main intuitions and describes the building blocks, while additional technical details can be found in Appendix 3.A.1.

Common market shock

The way a market shock is simulated is essential. The latter weakens the resilience of the system, thus revealing more plainly the potential for contagion (see Upper (2011)). In the absence of national supervisory data allowing to shock various asset classes in bank balance-sheets (as in Elsinger et al. (2006a), Elsinger et al. (2006b), or in Fourel et al. (2013)), we implement a common shock directly on all listed banks' capital using a one-factor model for equity returns (see details in Appendix 3.A.1). The same shock is consistently applied over the whole time period, 2008-2012, which allows us to make sure that contagion in the system is driven purely by the change in the network structure and banks' capitalization and liquidity levels. As depicted in figure 3.A.1, the shocks represent on average 5% of bank capital among scenarios but can reach up to 25% in extreme cases; such orders of magnitude are absolutely in line with bank capital losses observed during the recent crisis (see, e.g., BCBS (2010) and Strah et al. (2013)).

After the system is hit by a market shock, one bank at a time is exogenously pushed to default. Losses through solvency and liquidity contagion channels are then computed. The fact that only one banks fails at a time allows us to estimate losses due to the default of each bank and to rank the banks as more or less systemic.

Solvency contagion

Following Fourel et al. (2013), we define solvency contagion as follows. Let bank i default, then its counterparts lose all their exposures to this bank. If another bank or some of the banks are highly exposed to the defaulted bank, they might default as well. A general condition for a bank to default due to default contagion is as follows:

$$\underbrace{[C(j) - \epsilon(j)]}_{\text{Capital after initial shock}} - \underbrace{\sum_i R^S(i)E(j,i)}_{\text{non-recovered exposures}} < 0 \tag{3.1}$$

where $(1 - R^S(i))$ is a recovery rate. To account for all the losses due to solvency contagion, the Furfine algorithm of iterative default cascade (Furfine (2003)) is used. This algorithm allows incorporating liquidity hoarding behavior of banks in the same framework with solvency contagion.

Liquidity hoarding

Banks regularly perform liquidity management, estimating their liquidity stock, outflows and inflows for the next period. In normal times, they can foresee with some certainty how much liquidity they will need to satisfy reserve requirements or other commitments; to this end they can borrow from other banks in the interbank market as well as from the central bank (e.g. through weekly main refinancing operations). In a well functioning interbank market banks with excess liquidity can lend it to those who lack short-term funding. This situation can however radically change during times of increased uncertainty. On one hand, banks' assets become much more volatile creating liquidity outflows in terms of margin calls, higher haircuts and requirements for collateral, which are difficult to foresee. On the other hand, confidence in the market evaporates quickly, counterparty risk rises, and banks fear both their inability to get liquidity when needed as well as counterparty risk. All this can lead banks to a precautionary demand for liquidity hence to *hoarding* behavior, by which they reduce lending to each other in order to secure their own liquidity needs and to reduce exposure to counterparty risk.[4]

Banks start hoarding liquidity when there is a signal of market malfunctioning or they start experiencing problems themselves. For instance, a signal can be a drop in asset prices, high volatility or unexpectedly large losses. In our simulations we assume that a shock-related capital loss above a certain threshold represents such a signal. Therefore, banks that were impacted by a market shock and/or by solvency contagion will start hoarding liquidity, and the higher loss they experience, the more they hoard. We assume a function for liquidity hoarding depends linearly on the capital loss, $\lambda(Loss)$. The function, Figure 3.A.2, has 4 intervals: banks do not hoard liquidity in intervals 1 and 4, that is, when capital loss is below some threshold $A\%$ (no signal of crisis) or more than 100% (bank is insolvent). Banks hoard less ($a\%$) in interval 2 when the shock is moderate and more ($b\%$) in interval 3 when the shock is more adverse.

Banks will decide how much to hoard based on their own perception of market uncertainty. But they also have to decide how much and from which counterparty they will hoard. A straightforward assumption is that the riskier the counterparty is, the more a bank hoards liquidity. Provided banks have no private information about the riskiness of

[4]For the UK sterling market, Acharya and Merrouche (2013) document that riskier UK settlement banks held more reserves relative to expected payment value in the immediate aftermath of 9 August 2007, thus igniting the rise in interbank rates and the decline in traded volumes. Berrospide (2013) documents evidence for the precautionary motive of liquidity hoarding for U.S. commercial banks during the recent financial crisis.

other banks' portfolios, they can rely on leverage μ as a proxy for the riskiness of a counterparty (Das and Sy (2012), Lautenschlager (2013)). The easiest way for a bank to hoard liquidity is to stop rolling over short-term loans. After all the banks decide how much to hoard and make claims, the following condition has to be satisfied for a bank to be liquid:

$$[Cash] + [To\,Be\,Recieved] - [To\,Be\,Paid] > 0 \tag{3.2}$$

3.3 Interbank exposures and network simulation

This section presents the numerical algorithm used to generate a large number of networks of long- and short-term interbank exposures, as well as the data used to calibrate and run it. Additional balance sheet items used for the simulations and the econometric analysis are also presented. The last subsection provides descriptive evidence on the structure of simulated networks and on the domestic versus cross-border nature of the simulated national banking sectors.

3.3.1 The algorithm

We apply the algorithm proposed by Halaj and Kok (2013) to simulate a large number of interbank networks that are used to run the stress scenarios. In the absence of interbank lending and borrowing data, one common method in the literature relies on their estimation through entropy maximization (see Sheldon and Maurer (1998), Wells (2004) and Mistrulli (2011) for a comparison of this methodology with actual exposure data). We adopt an alternative methodology proposed by Halaj and Kok (2013) for different reasons. First, one essential drawback of the entropy maximization method is that the obtained matrix of bilateral exposures is such that strictly positive links are estimated between any two banks which have a strictly positive aggregate interbank exposure, i.e. the obtained network is not sparse and does not display the empirically documented core-periphery structure (averaging bias). When national banking systems are considered, such an undesirable feature may be neglected, as domestic banks within a country are typically densely interconnected. On the contrary, applying the same methodology when cross-border exposures are considered would amount to neglect either a possible home-bias in interbank exposures or the fact that financial interconnections are evenly spread nor among banks within a national banking sector neither among different countries' banking sectors. In other words, preferential banking relationships do exist, as well as strong geographical patterns. Second, the entropy maximization method yields a unique solution for the bilateral exposures matrix, and may therefore badly account for the fact that interbank exposures are likely to change quickly. In addition, performing stress scenarios on a unique exposures matrix typically fails to obtain a probability distribution over the simulation outcomes. By contrast, the methodology introduced by Halaj and Kok (2013) addresses these two issues by enabling the construction of a large number of sparse and concentrated networks that all match the aggregate exposure levels. Third, this methodology enables us to make use of additional information on actual interbank links obtained from TARGET2 payment data.[5]

The algorithm to simulate bilateral exposure matrices relies on two inputs: *(i)* a probability map and *(ii)* aggregate interbank exposures data at a bank level (i.e. the sum of the exposures of any bank i to all other banks in the system). Denote Π_t a $N \times N$ probability map at date t whose each element (i, j) is $\pi_{ij} \in [0; 1]$ with $\pi_{ii} = 0$ and $\sum_j \pi_{ij} = 1$ for all i. π_{ij} is the share of funds lent by any bank i to any bank j and is later used as the probability structure of interbank linkages.

The construction of a large number of exposure matrices at date t relies on the Π_t matrix and on the total interbank loans granted by any bank i to all its counterparties within the network, denoted L_i^t. The construction of one particular exposure matrix, i.e. of all bilateral elements L_{ij}^t, uses an "Accept-Reject" scheme. A pair (i, j) of banks is randomly drawn, with all pairs having equal probability. This link in the interbank network is kept with a probability π_{ij} and, if so, the absolute value of this exposure, denoted $\tilde{L}_{ij}$, equals L_i multiplied by a random number drawn from a uniform distribution with support $[0; 1]$. The amount of exposures left to be allocated is thus reduced. The procedure is repeated until the difference $\left(L_i - \sum_j \tilde{L}_{ij}\right)$ is below some threshold κ.

3.3.2 Data and calibration

3.3.2.1 Banks' sample

We run our contagion analysis using a sample of 73 European banking groups, whose list is provided in Table 3.A.3. Given our focus on the resilience of the European banking system, we select a subset of the banks that underwent the 2011 stress tests carried out by the European Banking Authority (EBA). In particular, our sample includes all the banking groups headquartered in Europe that are part of the list of Global Systemically Important

[5] In 2012 TARGET2 settled 92% of the total large value payments traffic in euro.

Banks (G-SIBs), while it excludes some Spanish "cajas" to avoid an over-representation of the Spanish banking sector.[6] It is worth noting that our sample also includes savings and cooperative banks, hence non-listed European institutions: differently from the extant empirical literature on contagion that relies on market data, this allows us to assess also the impact of a shock hitting relatively smaller market players.

3.3.2.2 Simulating European interbank exposures: TARGET2 data and the probability maps

Long-term interbank exposures. Information on the total interbank loans L_i granted by any bank i to all its counterparties within the network is retrieved via the balance sheet item named "Net loans to banks" available in *SNL Financials*.[7]

The probability map Π_t is obtained based on term interbank money market loans settled in TARGET2 during each year t. The money market dataset we use is the output of the Eurosystem's implementation of the Furfine (1999) methodology to TARGET2 payment data (see Arciero et al. (2013) for more details on the identification methodology). More specifically, we use loans with maturities ranging from one month and up to six months to compute shares of preferential lending. These percentages are then imputed in the simulation algorithm as *prior* probabilities about the existence and size of an interbank linkage.

For the last quarter of each year, for each lender, we bundle all term loans and compute the average amount lent to each borrower; hence based on such average amounts we look at how total credit was allocated among counterparties. Three details are worth noting in the assumptions we make to build the probability structure of interbank exposures. First, our computation includes all the banking groups participating in the interbank euro money market, i.e. not only the 73 banks belonging to our sample. Subsequently, to form the 'true' as well as the simulated networks of exposures, the shares are normalized to consider only the

[6] See EBA (2011b). The latest list of G-SIBs has been published by the Financial Stability Board in November 2012 and is available at `http://www.financialstabilityboard.org/publications/r_111104bb.pdf`.

[7] Net loans to banks are defined as *Net loans and advances made to banks after deducting any allowance for impairment*. The main difference between this item and "Loans and advances to banks" or "Deposits from banks" available e.g. in Bankscope, is that the latter also include loans to or from central banks (see Upper (2011)), which would be a major drawback for our analysis.

73 sample banks.[8] Second, we use only the term market segments in the calculations because it is for unsecured lending at such longer maturities that preferential interbank lending relationships are more likely to exist and relatively stronger geographical patterns emerge. This is especially so in periods of heightened uncertainty about counterparties' solvency. [9] Third, we consider the average size of a long-term loan traded between a lender-borrower couple independently of the frequency at which the two banks interact in the market over the quarter. An undesirable aspect of this choice is that we may turn up assigning a very high link probability to a lender-borrower couple even if they have interacted only rarely in the market. Nonetheless, we deem this choice to be the most appropriate in the context of assessing interbank contagion, since it is the actual size of exposures/links that matters for the propagation of distress (see Cont et al. (2010)), independently of whether that link was set up every month rather than just once in the whole quarter.[10]

Short-term interbank exposures. In the context of our model, liquidity contagion occurs through liquidity hoarding in the unsecured interbank money market. We take actual interbank loans, with maturities from overnight to one month, among the 73 sample banks from the dataset of Arciero et al. (2013). Notwithstanding the availability of five real networks of short-term interbank exposures from end-2008 to end-2012, we decided to simulate for each year 100 short-term interbank networks using the Halaj and Kok algorithm. This allows us to duly capture the evolving nature of short-term funding linkages and its impact on contagious losses. Moreover, we will use the large number of simulated long- and short-term networks to analyze the effect of their structural properties on the propagation of both solvency and liquidity contagion.

[8] This enables us to avoid any bias in the results related to the assignment of too large shares of interbank credit to banks that are in our sample but may represent only a small fraction of the amounts lent by a certain bank to European counterparties. Note that the 73 sample banks represent on average more than 90% of the overall euro money market turnover in the various maturity segments.

[9] See Cocco et al. (2009) and Brauning and Fecht (2012) for evidence of interbank lending relationships in the Portuguese and German money market, respectively. The second paper finds that during the 2007-08 crisis German borrowers paid on average lower interest rates to their relationship-lenders than to spot-lenders. The ECB euro money market study reports increasing market fragmentation in the euro money market in relation to the euro area sovereign debt crisis.

[10] Alternative calibrations, e.g. in which prior probabilities are based on the daily average amount lent to counterparties (thus also taking into account the frequency of bank interactions over the quarter), have been used as a robustness check. Also, note that, as reported in Arciero et al. (2013), the algorithm underestimates longer term loans at the beginning and at the end of the sample. This possibly affects our construction of the probability map for 2012 as this relies on loans traded in the last quarter of the year. We will be able to account for the underestimation as soon as new estimates of the loans are available that include TARGET2 transactions in the first months of 2013.

3.3.2.3 Additional balance sheet data

Additional year-end balance sheet information (Cash and cash equivalents, Total assets, Common equity) is retrieved from SNL Financials. [11] Table 3.A.4 reports, for each year, a set of summary statistics of banks' balance sheet ratios that are relevant for our analysis. On average, interbank exposures represent about 8% of total assets over the sample period. In 2009 banks display a reduced aggregate amount of interbank exposures (in percentage of total assets) than in 2008. The variation in the cross-section is also lower, while the ratio of common equity to total assets is on average higher, which could possibly result from the recapitalization imposed by banking supervisors after the EBA stress tests in 2009. In 2010 interbank loans continue decreasing, whereas bank liquidity deteriorates slightly and bank equity to assets ratio remains constant. In 2011 and 2012 liquidity improves, on average, while the level of common equity to total assets reduces. In fact, this is related to the negative common equity reported by various Greek and one Spanish bank for the last two years. Excluding from the sample banks with negative common equity, we can observe an increase in the average equity to assets ratio from 4.20% to 4.43% in 2011 and from 4.42% to 5% in 2012.[12]

3.3.2.4 Simulation dates

We repeat our counterfactual simulations at year-end for five dates, $t = 2008, 2009, 2010, 2011, 2012$.[13] Repeating the same stress scenario at multiple points in time allows tracking the evolution both of the financial system resilience to extreme financial distress and of the relative influence of the different contagion channels over time.

3.3.3 Descriptive evidence on simulated interbank networks

Table 3.A.5 reports summary statistics about the structure of the 100 long-term interbank networks simulated using the Halaj and Kok's algorithm and the TARGET2-based

[11] Data are exceptionally retrieved from Bankscope when not available in SNL. Consistency between the two databases has been carefully cross-checked.

[12] In 2011 and 2012 balance sheet data are not available for two Greek banks (Agricultural Bank of Greece, or ATE Bank, recapitalized in July 2011 after having failed EBA stress tests and subsequently sold to Piraeus Bank in 2012, and TT Hellenic Postbank, liquidated in August 2012), nor for Bank of Cyprus and Cyprus Popular Bank in 2012. Additionally, Eurobank Ergasias and Piraeus Bank report negative common equity in 2011 and 2012, while Alpha Bank, National Bank of Greece, and Bankia have negative common equity in 2012.

[13] Given that the TARGET2 database for unsecured interbank loans starts as of June 2008, it is not possible to run the simulation for earlier years.

probability map. The topological properties of the average simulated network are similar across the years and consistent with those observed for real interbank structures.[14] For instance, each bank is connected only with a small subset of other banks in the market (five on average across the years), so that the degree of connectivity or *density* of the networks is very small. This notwithstanding, the average length of intermediation chains is very short, i.e. banks are generally close to each other, and losses can spread from the bank in difficulty to its direct and indirect counterparties via less than three exposures, on average, and at most via four. While most of the banks have very few counterparties, there are some banks who lend to many others. The ratio between the maximum and the median number of counterparties (the *degree*), is high and increases over time: in 2012, on average across 100 networks, the most interconnected bank was about five times more connected than half of the others; for one network the ratio between maximum and median degree was as high as seven. This points to an increasing concentration of exposures over the years and to a core-periphery market structure. Table 3.A.6 reports summary statistics for the structure of the 100 short-term interbank networks obtained using the Halaj and Kok algorithm and actual short-term money market exposures. The topological properties of the average short-term simulated network are similar to those of the long-term one across the years.

Table 3.A.7 reports summary statistics of cross-country long-term exposures over 100 simulated interbank networks. The numbers displayed are the average ratios of domestic and cross-border country-level exposures in percentage of the total capital of the country. In the upper part of the table, we notice that on average during the five years banks of one country are at least 2 times more exposed to their home counterparties, with domestic exposures reaching 19% of a country's capital and foreign exposures being around 4-7%. These average figures conceal a high heterogeneity across the simulated banking sectors, which shows up clearly looking at the *maximum* ratios of domestic and foreign exposures to aggregate capital. The maximum ratios are of similar order but follow different trends over the years. Domestic interbank exposures steadily decrease from 1.89 times the country's capital in 2008 to 0.76 in 2011, with a jump to 1.48 in 2012; whereas maximum foreign exposures increase from 1.10 times the country's capital in 2008 to 2.04 in 2011, and decline slightly to 1.94 in 2012. However, it is important to keep in mind that such big ratios of domestic and cross-border interbank exposures relative to a banking sector's total capital are very rare events. The median domestic and foreign exposures ratios range between 1 to 6% of countries' capital.

[14] See for instance Soramaki et al. (2007) and Iori et al. (2008).

All in all, this evidence supports our claim about the realism of the exposure networks over which contagion simulations are run. The methodology we adopt is realistic in terms of the structural properties verified, but also because it allows capturing an evolving nature of bank interconnections. The simulated networks can be considered as probabilistic networks; networks that could be possibly formed in other realizations, however a specific simulated exposure can differ remarkably from one network to another, as well as from the actual short-term funding loan observed in the unsecured euro money market via TARGET2.

3.4 Simulation results

In this section we look at simulation outcomes resulting from several rounds of solvency and liquidity contagion triggered by 500 different realizations of the 5% worse equity market shocks, and an exogenous bank default. As widely used in the literature we impose idiosyncratic bank defaults one by one. For each year, for each shock scenario, simulation results are computed over 100 pairs of simulated networks of long-term and short-term interbank exposures. The parameters used to calibrate the common market shock and the model are given in Table 3.A.2 in Appendix 1. It is important to keep in mind that the results are three-dimensional: we compute the distributions of number of bank failures/losses in the European banking system due to an initial default of one of the 73 banks, over 500 market shock scenarios and 100 network pairs. Thus, in order to describe the results we aggregate contagion outcomes at the level of market and idiosyncratic shocks (initial bank defaults).

We start our analysis by looking at the distribution of average and maximum losses caused by the default of one bank over a set of shock scenarios. Then we compute a Value at Risk-like indicator of losses in the system, thereby synthesizing tail risks in our three-dimensional simulation framework. Thereafter, we study the extent of cross-border contagion in the European banking system and use heatmaps to visualize the more systemic or more fragile national banking sectors. Similarly, we try to exploit contagion outcomes to rank European banks as most systemic or most fragile. We conclude by describing changes in simulation results over the years, trying to identify patterns of increasing or decreasing system resilience.

3.4.1 Contagion as a tail risk

Table 3.A.8 depicts the distribution of losses in the system averaged over the shock scenarios and over the defaults of an initial bank. The part '...before liquidity hoarding' accounts for losses due to both the common market shock and solvency contagion (excluding the capital loss of the bank exogenously set into default); the part '...after liquidity hoarding & further rounds of contagion' displays total losses due to all contagion channels. The difference between the two can therefore be attributed to mere liquidity contagion. We can see that average losses are rather limited in terms of number of defaulted banks as well as in size of depleted capital (less than 2 and 5% of system capital, respectively), and that the common shock and the solvency contagion channel account for most of them. In fact, the summary statistics in table 3.A.8 show that the distributions of losses due to the shock and to solvency contagion are relatively thin-tailed across the 100 network pairs, suggesting that the underlying long-term interbank networks display only a mild variation. On the contrary, short-term interbank exposures seem to be more volatile: while in half of the network pairs average system losses (5% of overall system capital) can be explained by the initial shocks and by solvency contagion, the heavy tail of the distribution of total losses captures the variability of liquidity contagion results, with the share of depleted capital after all contagion channels reaching a maximum value of 13% in 2008 and of 10% in 2012 (corresponding to more than 4 bank failures in 2008 and more than 3 in 2012).

The relatively low dispersion of these results is easily explained: by averaging over the initial bank default, we average away the high heterogeneity of a realistic banking system. On the contrary, European interbank networks are highly heterogenous, with a handful of very large banks and numerous small ones whose default impact on the system can be markedly different. This can easily be seen by analyzing the *maximum* number of bank failures and the *maximum* share of depleted capital upon an initial bank default. Table 3.A.9 shows that the exogenous default of one bank (always coupled with a common market shock) can lead to the default of other 14 banks in 2008 and to a capital loss as large as one third of total system capital. Also in this table the common shock and solvency contagion account for most of the failures/losses. Notice that upon the default of the same bank, the maximum amount of losses is significantly larger in 2008 than afterwards.

Figures 3.A.3, 3.A.4 and 3.A.5, 3.A.6 and 3.A.7 allow us to have a more detailed view of how maximum losses (in terms of capital and number of bank failures) can vary from one network to another. Figure 3.A.3 depicts the share of depleted capital in the system over networks ordered by total losses. We can observe that losses merely due to liquidity contagion (the difference between the green and blue dots) as well as total losses (the green dots) indeed vary among the networks. Total losses (due to the market shock and both contagion channels) can represent from about 10% to 35% of total system capital in 2008, and from about 7% to 22% in other years. Interestingly, liquidity hoarding plays a very different role from one year to another, and seems to be more important in 2008 and 2010: for some networks, losses due to liquidity contagion can represent up to half of the total. The same findings are observed by comparing figures 3.A.4 and 3.A.5 with maximum losses in capital and figures 3.A.6 and 3.A.7 with maximum number of bank failures, where we present distributions in the form of box plots. In these figures, we exclude losses due to the market shock. Both distributions in terms of capital losses or number of failures have in general higher median and heavier tails after accounting for the impact of liquidity contagion, particularly in 2008 and 2010. The number of defaults resulting from the market stress coupled with one bank's default can vary significantly depending on the underlying structure of interbank linkages: from 7.5% of system's capital (or 4 banks) in one network to 30% of capital (or 14 banks) in another. Thus, consistently with recent models of contagion in financial networks relying on simulated networks of exposures (see, Georg (2013) and Arinaminpathy et al. (2012)), our results reveal the critical impact of the underlying network structure on the propagation of financial losses. Importantly, it points to the need to account for the evolving nature of the web of interbank linkages when running contagion simulations.

So far, we have averaged contagion outcomes over the market shocks and looked at how different the impact of contagion is with respect to the initial default bank and the underlying network. We have seen that maximum losses can be sizeable, whereas average losses are limited. To better investigate the likelihood of such tail risks, we analyze for each year the distribution of the Value at Risk (VaR) or $VaR(5\%)$ of our banking system. This is defined as the 95th left percentile of the distribution of losses (as a percentage of system capital) over both idiosyncratic and market shock scenarios. Figure 3.A.9 plots the distribution of $VaR(5\%)$ of losses due to contagion over 100 network pairs. We can see that the 5% worst capital loss stands on average at 8% and 5% over the networks in 2008 and all other years correspondingly, and that the loss distribution in 2008 has heavier tail. By comparing figure 3.A.9 and 3.A.5, we observe that losses in the 5% worst cases are almost half smaller than in the worst case, demonstrating the tail nature of contagion.

3.4.2 Cross-border contagion

Table 3.A.10 allows us to glance at the extent of domestic *versus* cross-border contagion in the European banking sector. It summarizes the results provided in the heat maps (figures from 3.A.10 to 3.A.14): panel A. presents the distribution of the losses on the main diagonal for each of the heat map figures, that is total losses imposed by an average bank in a banking system on its domestic counterparties; panel B. shows the distribution of the off-diagonal losses, in other words, losses imposed by an average bank in a banking system on its foreign countparties. We can immediately observe that, on average, a national banking sector imposes larger losses domestically than across the borders. However, maximum losses imposed domestically are usually smaller than losses imposed across the borders, except in years 2010 and 2012, when they are almost equal.

We plot heat maps in order to analyze the potential for cross-border contagion in the European banking sector. The cells $(A; B)$ of the map represent with colors the strength of the total capital loss experienced by country A's banking sector (as a fraction of its aggregate initial capital) given a common market shock and the default of a bank in the foreign banking system B. Examining heat maps in figures from 3.A.10 to 3.A.14, we can easily identify the most 'systemic' banking sectors, on the one hand (i.e. those resulting in a *vertical* line in which warmer-colors prevail), and the systems which are the most 'fragile', on the other (i.e. those resulting in a *horizontal* line in which warmer colors dominate). Note that a black in the color-scale of the map corresponds to a maximum country loss ranging between 7% and 14%, respectively in 2010 and in 2008, of the country's aggregate initial capital, while white cells correspond to no loss at all.[15]

In 2008 the banking sectors of countries E, H and K appear to be more systemic in terms of the total capital loss that a default of an average bank in these countries can impose on foreign banking sectors. The systems B and J follow, but the aggregate losses that the default of an average bank from these countries imposes on foreign banking sectors are much lower. The default of a bank headquartered in D, F, G or I does not have a sizeable impact on other European banks. With regard to the banking sectors that are the most

[15] Total country capital losses following the market shock and an idyosincratic foreign bank default are computed on average over 500 realizations of the market shock; over 100 different pairs of long- and short-term exposure networks; over the initially defaulting foreign banks. They have been normalized to account for the different number of banks (and hence of simulations) considered for the various national banking sectors. Heat maps have been anonymized for data confidentiality reasons, and countries for which less than 3 banks are available in the sample have been removed. Countries are ordered randomly, with the same order over time.

exposed to cross-border contagion, banks from A, B and J generally seem to experience the highest loss following a foreign default (more numerous red and/or orange cells).

The 2009 and 2010 maps show that the potential for cross-border contagion has constantly decreased over time, and that the overall potential capital loss through contagion was twice lower in 2010 than it was back to the end of 2008. More specifically, table 3.A.10 shows that the maximum loss caused by a foreign bank's default reduced from a value of 14% of foreign countries' total banking capital in 2008 to an overall loss of 10% in 2009 and of 7% in 2010. This is possibly related to a generalized reduction of long-term interbank loans and to an increase in banks' capitalization during those years (see section 3.3.2). In 2009 and 2010 we observe the geographical patterns identified persisting: E remains the most systemic banking sector; A and B the most fragile with respect to cross-border contagion stemming from a number of other European banking sectors; C and G appear vulnerable only to a few banking systems. Banks in I are relatively isolated in 2008 but become progressively more exposed to cross-border contagion in 2009 and even more in 2010. The level of vulnerability observed for most other countries changes across the years, although, as already mentioned, a generalized increase in the resilience of the system can be observed.

In 2011 and 2012 the light colors in the maps reveal a European banking system overall less vulnerable to cross-border contagion. However, the lower extent of contagion in these two years, and especially in 2012, compared to 2008 conceals important differences among national banking sectors.

All in all, we find that, under extreme equity market stress and following the exogenous default of one bank, cross-border contagion can materialize in the European banking system. The average and maximum loss caused by a foreign bank's default, however, varies remarkably over time. In particular, in 2009 and 2010 the European banking system seems to have significantly increased its capacity to withstand the same kind of adverse financial conditions that it had to face after the default of Lehman Brothers. In 2011 and 2012, banks reduce their interbank exposures (see table 3.A.4), and most notably so cross-country (see table 3.A.7), possibly as a consequence of continued sovereign-bank financial tensions in Europe. This leads to lower contagion losses overall concealing, however, a high heterogeneity across countries.

3.4.3 Systemic and fragile banks

Figure 3.A.15 depicts the systemic importance of all banks in each year from 2008 to 2012. We define a bank as 'systemic' when its default imposes more than the 85th percentile of the loss distribution over a given network pair. On the vertical axis we see the number of networks in which each bank appears to be systemic. Most of the banks are systemic in none or very few networks, however some banks turn out to be systemic in more than 60% and even 90% of the networks. Interestingly, this chart points to the same subset of banks as 'usual suspects' across the years, however there is also some variability: the subset is not identical from one year to another, only 60% of the banks appear systemic in more than 3 years.

Similarly, we try to rank banks according to the capital loss that they experience following the default of all other banks. In particular, we define a bank as 'fragile' if it suffers losses above the 85th percentile of the loss distribution over the set of shock scenarios. Figure 3.A.16 points in all the years from 2008 to 2010 some of the banks that did experience severe difficulties in 2011-2012.

3.4.4 Focusing on system resilience over time

As already highlighted, the system vulnerability to contagion differs from one year to another. The evidence presented so far points to a pattern of increasing (although not uniform) resilience to contagion from 2008 to 2012. For instance, we have seen in Table 3.A.8 and Table 3.A.9 that upon the default of the same bank, the average and maximum amount of losses are significantly larger in 2008 than in the subsequent years. The larger maximum shares of depleted capital in 2011 and 2012 are possibly related to the disappearance of 4 and 9 banks, respectively, from the sample in these years due to actual defaults. This determines both a lower total system capital and a lower diversification of interbank assets, thus resulting in a higher contagion outcome.

Figures 3.A.8 and 3.A.9 demonstrate the evolution of the system resilience to contagion over time. The year when the system was the most fragile is 2008, both with respect to solvency and liquidity contagion. In fact, in both graphs the 2008 loss distributions are characterized by a higher median and a heavier tail than those in the other years. The overall resilience of the system with respect to solvency contagion gradually improved over time, except for a small deterioration in 2011. By comparing the distributions in both figures, we can deduce that losses due to liquidity contagion do not follow the same pattern: the system seemed to be again more fragile in 2010. To statistically test this hypothesis, we perform the two-sample Kolmogorov-Smirnov test which allows us to compare the distributions of losses due solely to solvency contagion *versus* losses due to both contagion channels. This test shows that at 5% confidence level we can reject the null hypothesis of the two data sets being drawn from the same distribution for years 2008 and 2010, which means that liquidity hoarding behavior was more of an issue in those years.

Resilience to solvency contagion. The reasons behind increasing system resilience to solvency contagion are threefold. First, banks became better capitalized: average (max) common equity to total assets ratio increased from 4.18% (11.13%) in 2008 to 5% (14.82%) in 2012 with a decrease to 4.43% in 2011 (table 3.A.4). Second, the average fraction of 'Net loans to banks' to total assets gradually fell from 8.31% in 2008 to 6.81% in 2012 (table 3.A.4), and 'Net loans to banks' is the item used to reconstruct the long-term exposure networks on which solvency contagion takes place. Third, the network characteristics also changed. Namely, the network became less connected over the years (the ratio of actual to possible links reduced from 8% in 2008 to 5% in 2012); more skewed (the ratio of max to average degree jumped from 3.35 in 2008 to 4.6 in 2012); with increasing average shortest path length (in 2008, the median distance separating any two banks was of only 2.64 other institutions, whereas it reached 3.14 in 2012, and 2.77 in 2011) (table 3.A.5).

The intuition for the relationships between network measures and the results of contagion propagation goes as follows. First, less connected networks are less fragile because there are less links through which contagion may propagate. Second, more skewed networks may be more resilient to contagion, on average, since most of the banks have only few exposures, so that their default has little impact on the system. However, in those rare scenarios when a highly connected bank defaults, losses can be sizeable. This is consistent with the observation that although the system is on overage safer in 2012 than in 2008, in some extreme cases losses can reach 22% of the total system capital. Third, a higher average shortest path length has a direct explanation for the ease of losses propagation: the lower the average length of intermediation chains, the more easily losses may reach any other bank.

Resilience to liquidity contagion. As already mentioned, the system is most vulnerable to liquidity hoarding in 2008 and 2010. Given that in the algorithm liquidity contagion comes after solvency domino effects, one could expect to observe the following relationship: higher losses due to solvency contagion → weaker system → more banks hoard liquidity → higher losses due to liquidity contagion. Indeed, this mechanism does in part explain the impact of liquidity hoarding on the system, most notably in 2008; but it is not the only reason. An explanation why the system appears to be so vulnerable in 2010, for instance, comes from balance sheet statistics: banks held less cash in 2010, only 8.68% of total assets while more than 9.5% in all the other years (see table 3.A.4).

Short-term network characteristics do play a role too: banks were on average at a shorter distance from each other exactly in 2008 and 2010, and the logic behind the ease of propagation of interbank losses is the same as for solvency contagion. Moreover, the ratio of max to mean degree for short-term networks was lower in 2008 and 2010, which suggests that the relationship between the skewness of the degree distribution in short-term networks and system resilience is opposite to the one discussed above for long-term networks and solvency contagion. The intuition between the lower max to mean degree ratio figures and system stability goes as follows: the less skewed the distribution of the number of counterparties, the higher the number of banks that could hoard liquidity from many of their borrowers, thus increasing the potential for liquidity contagion. Finally, it is interesting to note that the short-term networks in 2009 and 2012 (the years displaying lower contagion) look very similar: they are the least connected (on average only 6% of all possible exposures do actually exist, against 8-9% in other years); have the longest intermediation chains (3.11 and 2.97 links separate any two banks in 2009 and 2012, respectively, against 2.55 in other years); are the most skewed (the most connected bank is exposed to a number of counterparties about 4 times larger than the average bank in 2009 and 2012, against only about 3 in other years).

3.4.5 Robustness checks

We perform a number of robustness checks to test how different model parameters impact our results. We document that changes in all the model parameters - recovery rate, availability of cash and liquidity hoarding specifications - drive our results in the expected direction. More specifically, lower recovery rates increase impact of both contagion channels, less cash as well as more aggressive liquidity hoarding drive up losses due to funding issues. The levels of the impact, though, remain perfectly reasonable, with average increase of initial losses by 10-15%.

3.5 Econometric analysis

In order to shed light on the relationship between simulation results, banks' financial ratios and network characteristics, we conduct an econometric analysis of the determinants of contagion. First, we analyze the determinants of bank-level contagion. In later subsections, we study contagion outcomes at a system level and at a country level.

3.5.1 Econometric specification

As explained below, all our dependent variables are bounded below (by zero) and above (by the number of banks in the system, or by the capital in the system) and both boundary values are likely to be observed in the data. The estimation of such a model cannot rely on OLS. A convenient way of overcoming this difficulty is by normalizing the dependent variables so that they take values on $[0;1]$. For instance, rather than using the average number of times that a bank defaults following a set of shock scenarios, we focus on the average frequency with which it defaults; rather than using the loss amount suffered by a bank, we use the average proportion of its capital that gets depleted following the shock scenarios. The estimation of models with fractional response variables relies on the methodology proposed by Papke and Woolridge (1996). It uses the generalized linear model (GLM) developed by Nelder and Wedderburn (1972) and McCullagh and Nelder (1989).

Let Y be the dependent variable. It is assumed to be generated from a distribution in the exponential family, whose mean μ depends on the independent variables X through:

$$\mathbb{E}\left[Y\right] = \mu = \Gamma^{-1}\left(X\beta\right) \tag{3.3}$$

where β is a vector of unknown parameters and Γ the p.d.f. of the link function. Furthermore, the variance of Y is a function of the mean, so that:

$$\mathrm{Var}\left[Y\right] = \mathrm{Var}\left[\Gamma^{-1}\left(X\beta\right)\right] \tag{3.4}$$

In order to model proportions, a convenient specification is that by Papke and Woolridge (1996) who assume that the dependent variable can be modeled by a binomial distribution, in combination with a logit link function Γ. The vector of parameters β is estimated by maximum likelihood.

3.5.2 Bank-level determinants of contagion

This section explains the determinants of bank fragility or vulnerability with both balance sheet and exposure characteristics.

3.5.2.1 Default outcomes

This section estimates the determinants of both bank *fragility* (i.e. average number of defaults and average amount of losses suffered following a set of shock scenarios) and bank *systemicity* (i.e. the average number of defaults and average amount of losses caused by the initial default of a bank, over a set of shock scenarios). Thus, dependent variables in the various specifications of the default model are related to default outcomes, whereas independent variables are network, exposure and balance sheet characteristics.

More specifically, for each year of results we estimate the following specification:

$$Y(i,n,t) = g^{-1}(\beta_0 + \beta_1 * X(i,n,t)) + \epsilon(i,n,t), \tag{3.5}$$

where $Y(i,n,t)$ denotes the various fragility or systemicity default outcomes for simulated (pair of) network n in year t. The vector of regressors $X(i,n,t)$ is composed of variables related to financial ratios, network position pre-shock, exposures to the weakest banks and control variables described below.

3.5.2.2 Explanatory variables and expected effects

The following regressors have been used to estimate equation 3.5 :

Financial ratios. Solvency ratio: $Common\ equity\ /\ Total\ assets$; Liquidity ratio: $Short-term\ funding\ /\ Total\ assets$. [16] Everything else equal, we expect banks that are more capitalised and more liquid to be less vulnerable to contagion due to their long and short term interbank exposures. The effect of higher financial ratios on bank systemicity is less obvious. Nonetheless, the mechanics of the model suggests that removing well capitalised and liquid banks from the system would result in a more fragile banking sector overall. Therefore, we can expect that being more leveraged and illiquid results in higher bank systemicity.

[16] The ratio of long term exposures to common equity has also been tested as proxy for bank solvability. The ratio of short term to long term funding and the so called "interbank ratio" (interbank assets divided by interbank liabilities) have been tested as proxies for bank liquidity.

(Long-term) Network position pre-shock. Closeness, betweenness or eigenvector centrality in the network of long-term interbank exposures have been alternatively tested as explanatory variables.[17] Recent literature has shown that the position occupied by a financial institution in the network of interbank connections can explain e.g. its capacity to access interbank liquidity after a shock (see Abbassi et al. (2013)), the price at which it can fund itself in the money market (see Gabrieli (2012)), or its daily liquidity holdings as a participant in a large value payment system (see Bech and Atalay (2008)). Based on this evidence, we expect *(i)* banks occupying a more central position in the interbank network in terms of being directly exposed to many counterparties (i.e. banks that are *closer* to all banks), *(ii)* banks that are more central in that they interpose themselves on many intermediation chains in the interbank network (i.e. banks with higher *betweenness*), *(iii)* banks occupying a central position because of their exposures to highly central counterparties (i.e. banks with higher *eigenvector* centrality) to be more systemic. The effect of higher centrality on bank fragility is less clear cut. On the one hand, one could expect more central banks (in terms of the three measures described) to be more exposed, hence more vulnerable, to contagion. On the other, banks that are direct lenders to many counterparties are also more diverisified in the asset side of their balance sheet, hence potentially more resilient to the propagation of interbank losses.

Exposures to weakest banks. For each bank and year, we construct the share of bank i long-term interbank lending directed to the three "riskiest" banks in the system. The latter are identified as the three *(i)* most leveraged, *(ii)* least liquid, *(iii)* most interconnected, *(iv)* most indebted European banks at the end of year t. Beyond the importance of a bank's own financial ratios, exposures to risky counterparties can have a negative effect on banks' resilience to adverse shocks. In general, we expect a bank's fragility to be higher the higher the share of its interbank loans granted to risky (more leveraged, less liquid, more indebted) counterparties. The effect of being largely exposed to very interconnected banks, however, is less straightforward. As in the case of banks with high eigenvector centrality, being exposed to banks with many counterparties in the long-term exposures network might actually lower bank fragility, because of the higher resilience of very connected (hence more diversified) counterparties. At the same time, however, exposures to banks that are highly interconnected in the short term (liquidity) networks could increase bank frailty, because a very connected counterparty could be subject to more contemporaneous liquidity withdrawals.

[17] Refer to Abbassi et al. (2013) for a description of network centrality indicators and their economic interpretation.

Control variables. To clearly identify the effect of the regressors of interest on the contagion-dependent variables, we control for the structural features of the simulated long- and short-term networks. These are notably: network *clustering*, reflecting the extent to which banks lending to each other tend to have a third common counterparty; *average shortest path length*, reflecting the length of intermediation chains; the ratio of maximum to mean degree, indicating to what extent the distribution of the number of bank counterparties is heavy tailed, with few (core) banks that are very highly interconnected, and most (peripheral) banks that have links only to few counterparties.

3.5.2.3 Results

Bank fragility. Table 3.A.11 shows the results for $Y(i,n,t)$ being successively the average number of defaults and average amount of losses suffered by bank i in network (pair) n in $t = 2008$ over a set of 500 shock scenarios. The results show that balance sheet ratios (for both solvency and liquidity) are key determinants of banks' vulnerability to contagion, especially in terms of the number of times that a bank defaults. The coefficient capturing the role of a bank position in the network before the shock is also significant. Interestingly, it reveals that banks that are highly interconnected are less likely to default following a shock scenario, but more likely to suffer larger losses. This result is consistent with our expectations: on the one hand, a higher degree of interconnectedness reflects a higher degree of diversification of interbank assets, thus reducing the frequency of bank defaults across scenarios; on the other, being directly exposed to a high number of counterparties can induce larger losses. The coefficients of the shares of interbank lending directed to the riskiest banks in the system confirm our intuition that being exposed to the most leveraged and least liquid banks increases both the likelihood of bank failure and the amount of losses experienced. These "exposure metrics" are however less important than network centrality and banks' own financial ratios in economic terms. Finally, it is interesting to note that structural network characteristics do not explain different degrees of bank vulnerability. The only exception is the extent to which the interbank network tends toward a core-periphery structure. More specifically, a system where few banks have several times the number of counterparties of the average institution seems to be more resilient to the propagation of interbank losses.

We obtain similar evidence for 2009, although the network variable that turns out to better explain bank fragility is eigenvector and not closeness centrality. For this year, longer intermediation chains can explain both a lower fragility and a lower systemicity of the average bank. Results are consistent across years with minor differences.

Bank systemicity. Table 3.A.12 shows the results for $Y(i, n, t)$ being successively the average number of defaults and average amount of losses caused by the failure of bank i in network (pair) n in $t = 2008$ over a set of 500 shock scenarios. Similarly to the results for bank fragility, a bank's own financial ratios appear to be the most important determinants of its contagious impact. The magnitude of estimated coefficients is, however, lower than in the previous tables both for the average proportion of bank defaults and the average amount of losses. Closeness centrality turns out to increase a bank systemicity: the closer a bank is to a higher number of counterparties because of its numerous direct lending exposures, the higher the proportion of banks failing and the proportion of capital lost in the banking network following the propagation of a shock. Differently from the fragility regressions, these tables show that being exposed to the riskiest counterparties does not influence a bank's systemic importance. However, being largely exposed to the most indebted banks increases both the likelihood of causing other failures and the proportion of losses following a shock.

3.6 Conclusions

This paper investigates the scope for cross-border contagion in Europe based on true exposure data at a bank-to-bank level in a joint framework of solvency and liquidity contagion. We analyze geographical patterns of shock propagation between 73 European banking groups from end-2008 until end-2012.

We exploit for the first time a unique dataset of interbank money market transactions, with various maturities, estimated from TARGET2 payment data (see Arciero et al. (2013)) to obtain a realistic representation of how European banks are connected through their long- and short-term claims. We rely on the money market database to construct realistic probability maps of interbank exposures. This maps, together with the amount of individual banks' aggregate loans to other banks, are used to simulate a large number of long- and short-term exposure matrices through a novel methodology proposed by Halaj and Kok (2013).

Simulation of multiple networks from real data probability maps with significant heterogeneity among them allows us to analyze not only the vulnerability of one particular network realization retrieved from the real data, but of plenty of potential realistic networks. We find that both solvency and liquidity contagion are tail risks: losses averaged over stress-scenarios, initial bank defaults or simulated networks are rather limited; however, averaging conceals rare extreme events. We document that losses at the tail of the distributions can reach one third of the system capital in 2008, and that the resilience of the system improves significantly over time.

We find that, under extreme equity market stress and following the exogenous default of one bank, cross-border contagion can materialize in the European banking system. The average and maximum losses caused by a foreign bank's default, however, varies remarkably over time. In particular, in 2009 and 2010 the European banking system seems to have significantly increased its capacity to withstand the same kind of adverse financial conditions that it had to face after the default of Lehman Brothers. In 2011-2012, banks reduce their interbank positions, and most notably so cross-country, possibly as a consequence of continued sovereign-bank financial tensions in Europe. This leads to lower contagion losses overall, concealing however a high heterogeneity across-countries.

Finally, we document a strong impact on the cross-border propagation of losses of heterogeneity and concentration in the structure of interbank exposures. Moreover, the number of defaults resulting from extreme market stress coupled with one bank's default can be more than three times larger depending on the underlying structure of interbank linkages. This is consistent with recent models of contagion in financial networks relying on simulated networks of exposures (see, Georg (2013) and Arinaminpathy et al. (2012)), and points to the need to account for the evolving nature of the web of interbank linkages when running contagion analysis. Furthermore, we exploit this heterogeneity in order to investigate the determinants of bank fragility or systemicity that drive contagion outcomes with both banks' balance sheet and exposure characteristics.

Further research agenda will include two main points: first, we will extend our econometric exercise to include analysis of the determinants of system-wide and country-level contagion by exploiting within-year across-networks heterogeneity. Second point concerns the money market dataset that we rely upon to build the probability maps. It matches potential loan payments between direct TARGET2 participants (i.e. settler banks). However, it would be interesting to study how the network and cross-border patterns may change if we exclude intermediation activity of the banks by taking into account information on originators and beneficiaries of TARGET2 transactions (i.e. indirect TARGET2 participants). This database has been recently made available.

Appendix

3.A Appendix

3.A.1 The model

3.A.1.1 Common market shock

We model a shock with both a common component and an idiosyncratic component. First, a market shock hits all listed banks' capital. As mentioned by Upper (2011), contagion is more likely with such a shock. Second, a bank is exogenously assumed to fail.

The market shock is modeled using a one-factor model for equity returns. The principal factor and loading coefficients for all listed banks[18] in our sample (42 institutions) are computed using daily equity returns over a period spanning from January 1999 to December 2008. The first factor is fitted to a Student t distribution, from which 100,000 simulations are drawn. The 500 left-tail realizations of the first principal component are kept, corresponding to approximatively 5% tail shocks. The impact on each bank's capital is recovered through the factor loadings.

We keep the same market shock for each year in order to make sure about the change in fragility of the system to contagion during these five years.

Simultaneously, one bank is forced to default. One advantage of such a shock is that it enables analyzing the systemic importance of each institution, even though it abstracts from actual bank probabilities of default. Losses through solvency and liquidity channels are then computed.

[18]Non-listed banks are assumed to face no market shock, as their equity value is assumed not to be correlated with market prices.

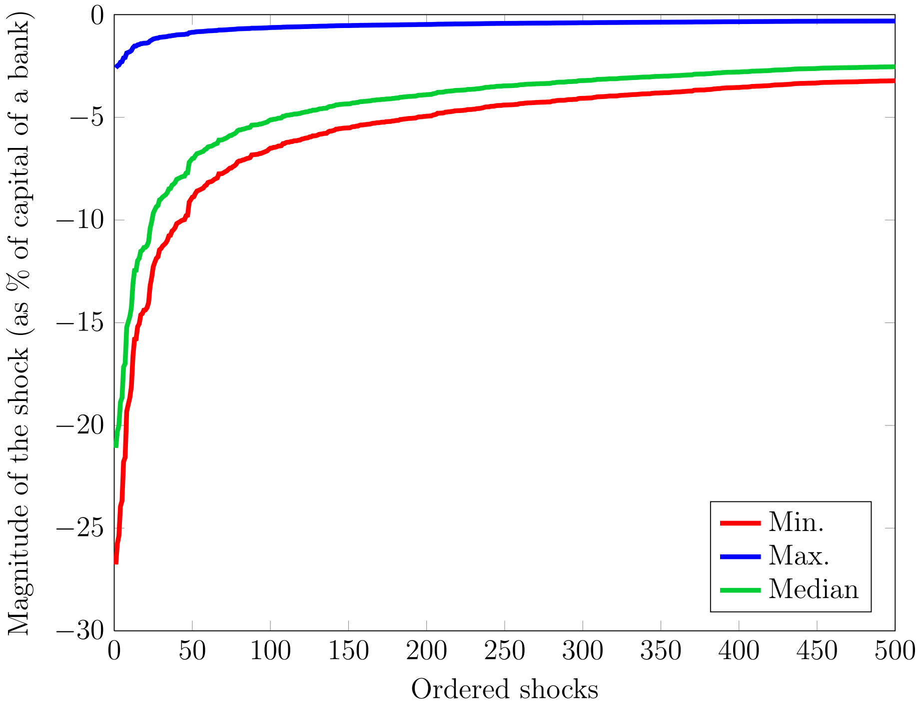


Figure 3.A.1: Distribution of the shocks to individual banks over 500 shock scenarios, measured as percentage of banks' capital

Table 3.A.1: Distribution of the idiosyncratic and market shocks to the whole system measured as percentage of total system capital

	Min	Mean	Median	Max
Idiosyncratic shock	0,04%	1,37%	0,70%	6,64%
Market shock	1,94%	3,38%	2,66%	16,17%

3.A.1.2 Solvency contagion

We closely follow the model by Fourel et al. (2013). At time $t = 1$, banks are hit by a shock ϵ according to the methodology previously described. If the initial losses are higher than the capital of a bank, the latter goes into bankruptcy. We can therefore define the set of all banks defaulting due to a market shock, named "fundamental defaults", as

$$\begin{aligned} \mathbf{FD(C)} &= \left\{ i \in \mathbf{N} : C_0(i) + \underbrace{\epsilon(i)}_{\text{initial shock}} \leq 0 \right\} \\ &= \{ i \in \mathbf{N} : C_1(i) = 0 \}, \end{aligned} \tag{3.6}$$

where $C_1(i) = (C_0(i) + \epsilon(i))^+$ is the capital of bank i just after the initial shock.

From this situation, we can define a *solvency default cascade* (in Amini *et al.*'s terminology) as a sequence of capital levels $(C_2^k(i),\, i \in \mathbf{N})_{k\geq 0}$ (where k represents the algorithmic step) occurring at time $t = 2$ and corresponding to the defaults due to insolvency:

$$\begin{cases} C_2^0(i) = C_1(i) \\ C_2^k(i) = \max(C_2^0(i) - \sum_{\{j,\, C_2^{k-1}(j)=0\}} (1 - R^S) \times E_0(i,j); 0), \text{ for } k \geq 1, \end{cases} \tag{3.7}$$

where R_S is an exogenous recovery rate for solvency contagion.

The sequence is converging (in at most n steps) since $(C_2^k)_k$ is a component-wise decreasing sequence of positive real numbers. Note that subscripts are used for periods of time and superscripts for rounds of cascades. By "period", we mean the sequential spread of losses through different channels. This should not be interpreted *stricto sensu*: we rather consider a sequence of events that can concomitantly occur in a short period of time, e.g. within one week.

Comparison of the banks initially in default (that is $\mathbf{FD(C)}$) and the banks in default at the end of $t = 2$ corresponds to the set of institutions that defaulted only due to solvency default contagion. We label this set S_2.

3.A.1.3 Liquidity hoarding

In the liquidly hoarding section of our contagion simulations we employ a different functional form than in Fourel et al. (2013). We closely follow their model in the remaining sections.

Decision on how much to hoard

To know how much liquidity a bank hoards in total, and how much it hoards from each counterparty, we make some assumptions. First of all, the total amount of liquidity withdrawn depends on the size of the shock to the bank's capital: the bigger the losses due to the market shock, the more the bank hoards liquidity. The proportion of liquidity to be hoarded by bank i is $\lambda(i) \in [0; 1]$. It is assumed to depend on the capital loss $Loss(i)$: at time t, we denote $\lambda_t(i) = a\, Loss(i)\, \mathbf{1}_{[A;B]} + b\, Loss(i)\, \mathbf{1}_{[B;100]}$, where $\mathbf{1}$ is an indicator function[19].

[19] We test a range of parameters value in order to check the robustness of our results.

We assume that bank i curtails its positions in the short-term interbank money market by stopping rolling over debt for a total amount $\lambda_t(i)E_t^{ST}(i)$ where $E_t^{ST}(i) = \sum_{j \in S_{t-1}} E_{t-1}^{ST}(i,j)$ and S_{t-1} is the set of non-defaulted banks at the end of period $t-1$.

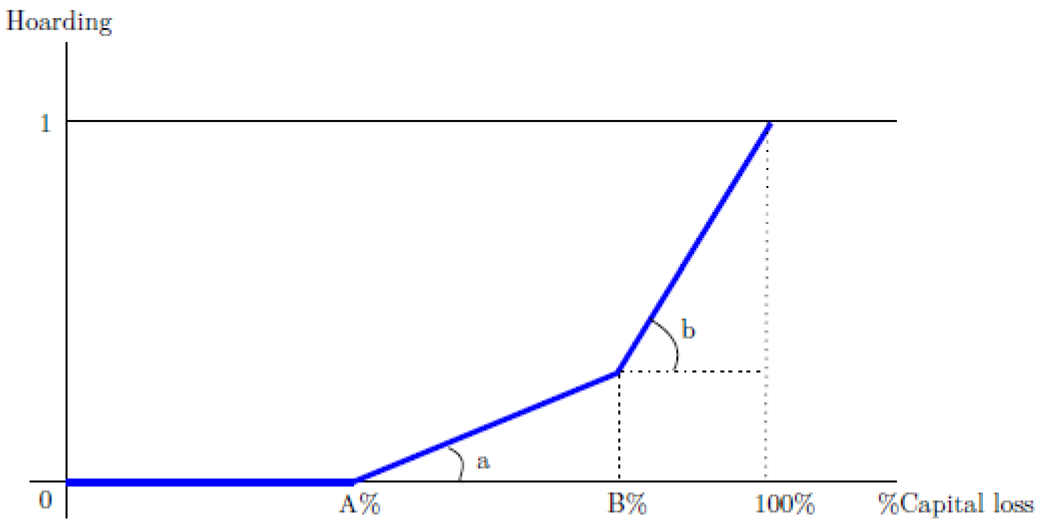


Figure 3.A.2: Liquidity hoarding behaviour.

How much to hoard from each counterparty

Second, the amount of liquidity the bank hoards from each counterparty depends on the generalized market perception of its credit risk, for which the leverage ratio can be used as a proxy. The higher the leverage, the riskier a bank is perceived, the more its counterparties will hoard from it. Defining $\mu_t(j)$ as $\mu_t(j) = 1 - C_t(j)/TA_t(j)$, we can decompose the total amount of liquidity hoarded by bank i from its counterparties as follows:

$$\lambda_t(i)E_t^{ST,k-1}(i) = \lambda_t(i)E_t^{ST,k-1}(i) \underbrace{\sum_{j, C_t^{k-1}(j) \geq 0} \frac{\mu_t(j)E_t^{ST,k-1}(i,j)}{\Sigma_h \mu_t(k)E_t^{ST,k-1}(i,h)}}_{=1}. \tag{3.8}$$

Liquidity condition

When a bank hoards liquidity, it improves its short-term funding position, whereas liquidity withdrawals by its counterparties deteriorate it. The following liquidity condition must hold:

$$\underbrace{Ca_t(i)}_{\text{cash}} + \underbrace{\lambda_t(i)E_t^{ST,k-1}(i)}_{\text{hoarding inflows}} - \underbrace{\sum_{j, C_t^{k-1}(j) \geq 0} \lambda_t(j)E_t^{ST,k-1}(j) \frac{\mu_t(i)E_t^{ST,k-1}(j,i)}{\Sigma_l \mu_t(l)E_t^{ST,k-1}(j,l)}}_{\text{hoarding outflows}} > 0. \tag{3.9}$$

That is, bank i needs to have enough liquid assets, either interbank or non-interbank, to pay its short-term debt.

In line with the solvency contagion algorithm, we state that a bank is in default when its capital has been fully wiped out (solvency condition) or when it can not satisfy its short-term commitments (liquidity condition).

Update of the algorithm to account for the losses due to solvency and liquidity contagion

$$\begin{cases} C_t^0(i) = C_{t-1}(i) \\ \text{ for } k \geq 1, \\ \textbf{Solvency condition:} \\ C_t^{\prime k}(i) = C_t^0(i) - \sum_{\{j,\, C_t^{k-1}(j)=0\}} (1-R^L) E_t^{ST}(i,j) \\ \textbf{Liquidity condition:} \\ C_t^{\prime\prime k}(i) = \begin{cases} 0 & \text{if } Ca_t(i) + \lambda_t(i) E_t^{ST,k-1}(i) - \\ & \sum_{h, C_t^{k-1}(h) \geq 0} \lambda_t(h) E_t^{ST,k-1}(h) \frac{\mu_t(i) E_t^{ST,k-1}(h,i)}{\Sigma_l \mu_t(l) E_t^{ST,k-1}(h,l)} < 0 \\ C_t^{\prime j}(i) & \text{otherwise} \end{cases} \\ \textbf{Updating equation:} \\ C_t^k(i) = max(C_t^{\prime k}(i); C_t^{\prime\prime k}(i); 0) \end{cases} \tag{3.10}$$

At the end of period t, the algorithm provides the status of each bank (alive or in default), its capital level and short-term exposures. Some banks may have defaulted during period t, thus some non-defaulted banks have recorded losses on their capital level. If the capital is then lower than their economic one, another round of liquidity hoarding treated in period $t+1$ will take place.

3.A.1.4 Model calibration

The following exogenous values are used to calibrate the model.

Table 3.A.2: Parameters used to calibrate the model

	Values of exogenous parameters
Recovery rate (R^S)	0,4
First hoarding threshold (A)	0
Amount hoarding (a)	0,1
Second hoarding threshold (B)	0,3
Amount hoarding (b)	0,5
Proportion of free cash	0,4

3.A.2 The sample

Table 3.A.3: The sample

Country	Bank Name	Country	Bank Name
AT	Erste Group Bank	GR	Alpha Bank**
AT	Raiffeisen Bank International	GR	ATE Bank*
AT	Oesterreichische Volksbanken	GR	Eurobank Ergasias*
BE	Dexia	GR	National Bank of Greece**
BE	KBC Groep	GR	Piraeus Bank*
CH	Credit Suisse Group	GR	TT Hellenic Postbank*
CH	UBS	HU	OTP Bank Nyrt
CY	Bank of Cyprus Public**	IE	Allied Irish Banks
CY	Cyprus Popular Bank Public**	IE	Bank of Ireland
DE	Bayerische Landesbank	IT	Banca Monte dei Paschi di Siena
DE	Commerzbank	IT	Banca Popolare dell'Emilia Romagna
DE	DekaBank	IT	Banco Popolare Società Cooperativa
DE	Deutsche Bank	IT	Intesa SanPaolo
DE	HSH Nordbank	IT	Unicredit
DE	Hypo Real Estate Holding	IT	Unione di Banche Italiane
DE	Landesbank Baden-Württemberg	MT	Bank of Valletta
DE	Landesbank Berlin Holding	NL	ABN AMRO Group
DE	Landesbank Hessen-Thueringen	NL	ING Bank
DE	Norddeutsche Landesbank	NL	Rabobank Group
DE	Westdeutsche Genossenschafts-Zentralbank	NL	SNS Bank
DK	Danske Bank	NO	DnB ASA
DK	Jyske Bank	PL	Powszechna Kasa Oszczednosci
DK	Nykredit Realkredit	PT	Banco BPI
DK	Sydbank	PT	Banco Comercial Português
ES	Banco Bilbao Vizcaya Argentaria	PT	Caixa Geral de Depositos
ES	Banco de Sabadell	PT	Espirito Santo Financial Group
ES	Banco Popular Espanol	SE	Nordea Bank
ES	Banco Santander	SE	Skandinavinska Enskilda Banken
ES	Bankinter	SE	Svenska Handelsbanken
ES	Caja de Ahorros y Monte de Piedad de Madrid**	SE	Swedbank
ES	Caja de Ahorros y Pensiones de Barcelona	SI	Nova Ljubljanska Banka
FI	Op-Pohjola Group	UK	Barclays
FR	BNP Paribas	UK	Lloyds Banking Group
FR	BPCE	UK	HSBC Holdings
FR	Crédit Agricole	UK	Royal Bank of Scotland
FR	Crédit Mutuel	UK	Standard Chartered
FR	Société Générale		

This table provides the sample of 73 banks used for the default simulations and the econometric analysis, as well as their domestic country. It is a subset of the list of banks that underwent the 2011 stress tests carried out by the European Banking Authority (EBA (2011b)). The * and ** indicate banks which are not included in the 2011 and 2012 sample, respectively, due either to failures or to unavailable data. The country abbreviations are as follows: AT = Austria, BE = Belgium, CH = Switzerland, CY = Cyprus, DE = Germany, DK = Denmark, ES = Spain, FI = Finland, FR = France, GR = Greece, HU = Hungary, IE = Ireland, IT = Italy, MT = Malta, NL = Netherlands, NO = Norway, PL = Poland, PT = Portugal, SE = Sweden, SI = Slovenia, UK = United Kingdom.

3.A.3 Descriptive statistics

Table 3.A.4: Descriptive statistics of sample banks' balance sheet ratios

	Year				
	2008	**2009**	**2010**	**2011**	**2012**
Cash and cash Equivalents / Total Assets					
Average	9.96%	9.54%	8.68%	9.64%	9.68%
Minimum	1.44%	1.45%	1.03%	1.09%	0.99%
Median	8.70%	8.49%	7.71%	8.38%	8.34%
Maximum	32.78%	29.35%	30.64%	29.88%	27.53%
Standard deviation	5.94%	5.19%	5.20%	5.48%	5.10%
Common Equity / Total Assets					
Average	4.18%	4.73%	4.73%	4.20%*	4.42%*
Minimum	0.62%	1.05%	0.08%	-5.72%	-4.54%
Median	3.90%	4.40%	4.55%	3.76%	4.33%
Maximum	11.13%	13.06%	13.32%	13.85%	14.92%
Standard deviation	2.25%	2.35%	2.42%	2.76%	2.99%
Net Loans to Banks / Total Assets					
Average	8.31%	7.93%	7.19%	7.24%	6.81%
Minimum	0.88%	0.88%	0.68%	0.64%	0.54%
Median	7.09%	6.61%	5.60%	5.49%	4.70%
Maximum	31.73%	29.14%	30.17%	29.61%	26.28%
Standard deviation	6.01%	5.55%	5.50%	5.65%	5.73%

* Excluding from the sample banks with negative common equity, we can observe an increase in the average leverage ratio from 4.20% to 4.43% in 2011 and from 4.42% to 5% in 2012. Source: SNL Financials and own calculations.

Table 3.A.5: Descriptive statistics of the 100 networks of long-term interbank exposures. Networks have been simulated using the methodology developed by Halaj and Kok (2013). The probability map has been obtained from data on actual euro money market loans with maturities from one to six months.

	Year				
	2008	2009	2010	2011	2012
Number of links					
Minimum	298.00	316.00	295.00	291.00	205.00
Median	398.50	405.50	378.50	365.50	272.00
Maximum	622.00	624.00	609.00	580.00	438.00
Standard deviation	37.40	38.92	35.32	32.38	25.97
Density					
Minimum	0.06	0.06	0.06	0.06	0.04
Median	0.08	0.08	0.07	0.07	0.05
Maximum	0.12	0.12	0.12	0.11	0.08
Standard deviation	0.01	0.01	0.01	0.01	0.00
Average shortest path					
Minimum	2.29	2.30	2.29	2.43	2.64
Median	2.64	2.80	2.80	2.77	3.14
Maximum	3.07	3.60	3.42	3.19	4.09
Standard deviation	0.15	0.15	0.17	0.14	0.22
Max / Median degree					
Minimum	2.20	2.17	2.40	2.55	3.00
Median	3.35	3.00	3.68	3.89	4.60
Maximum	5.88	4.67	7.00	6.29	7.80
Standard deviation	0.62	0.52	0.81	0.74	0.86

Table 3.A.6: Descriptive statistics of the 100 networks of short-term interbank exposures. Networks have been simulated using the methodology developed by Halaj and Kok (2013). The probability map has been obtained from data on actual euro money market loans with maturities up to one month.

	2008	2009	2010	2011	2012
Number of links					
Average	468,43	289,43	437,30	439,47	319,97
Minimum	423,00	205,00	403,00	403,00	284,00
Median	467,50	272,00	435,00	439,50	321,00
Maximum	500,00	480,00	474,00	476,00	349,00
Standard deviation	15,29	64,71	14,36	17,82	11,68
Density					
Average	0,09	0,06	0,08	0,08	0,06
Minimum	0,08	0,04	0,08	0,08	0,05
Median	0,09	0,05	0,08	0,08	0,06
Maximum	0,10	0,09	0,09	0,09	0,07
Standard deviation	0,00	0,01	0,00	0,00	0,00
Average shortest path					
Average	2,44	3,11	2,58	2,63	2,97
Minimum	2,22	2,45	2,40	2,29	2,67
Median	2,42	3,12	2,58	2,62	2,94
Maximum	3,09	3,88	2,91	2,96	3,49
Standard deviation	0,11	0,29	0,09	0,13	0,15
Max. / Median degree					
Average	2,78	4,38	2,93	3,30	3,66
Minimum	2,14	2,00	2,00	2,50	2,88
Median	2,76	4,33	2,91	3,27	3,63
Maximum	3,80	7,17	3,91	4,50	4,86
Standard deviation	0,28	1,01	0,39	0,39	0,42

Table 3.A.7: Descriptive statistics of domestic and cross-country exposures in the 100 long-term interbank networks.
The probability map has been obtained from data on actual euro money market loans with maturities from one to six months. Table A. shows statistics of total exposures of banks to their domestic counterparties over the total capital of the system. Table B. shows statistics of exposures of banks to their foreign counterparties (by country) divided by the total capital of the system.

	Year				
	2008	2009	2010	2011	2012
A. Domestic interbank exposures (country level, % of country's capital)					
Mean	15%	19%	12%	12%	19%
Min	0%	0%	0%	0%	0%
Median	1%	6%	6%	5%	3%
Max	184%	189%	112%	76%	148%
Std dev	40%	41%	24%	19%	36%
B. Cross-border interbank exposures (country level, % of country's capital)					
Mean	6%	5%	5%	7%	4%
Min	0%	0%	0%	0%	0%
Median	1%	2%	1%	2%	0%
Max	110%	116%	116%	204%	194%
Std dev	13%	11%	11%	20%	14%

3.A.4 Simulation results

Table 3.A.8: Summary statistics of simulation results averaged over 500 shock scenarios and the defaults of an initial bank.
Distribution of default outcomes over 100 pairs of networks. Default outcomes are averaged over the shock scenarios and over the defaults of an initial bank. Default outcomes are reported in terms of number of bank failures triggered by the default of an initial bank and of losses as a proportion of total system capital (i.e. of depleted capital). All the losses due to the common market shock and to solvency contagion are accounted for in '... before hoarding', whereas total losses are accounted for in '... after hoarding'. Thus the difference between the two is attributed to liquidity contagion

	2008	2009	2010	2011	2012
A. Number of defaults before hoarding					
Min	1,27	1,19	1,18	1,22	1,08
5th percentile	1,33	1,23	1,20	1,24	1,12
Mean	1,49	1,34	1,28	1,33	1,19
95th percentile	1,73	1,54	1,41	1,44	1,30
Max	1,97	1,68	1,51	1,58	1,45
Std dev	0,13	0,10	0,06	0,07	0,06
B. Percentage of depleted capital before hoarding					
Min	4,61%	4,41%	4,38%	4,46%	4,40%
5th percentile	4,67%	4,45%	4,39%	4,47%	4,43%
Mean	4,95%	4,61%	4,51%	4,58%	4,55%
95th percentile	5,45%	4,82%	4,69%	4,72%	4,77%
Max	6,38%	5,05%	5,01%	5,14%	4,95%
Std dev	0,26%	0,12%	0,10%	0,09%	0,11%
C. Number of defaults after hoarding					
Min	1,29	1,22	1,18	1,25	1,09
5th percentile	1,35	1,25	1,23	1,26	1,12
Mean	1,74	1,44	1,61	1,47	1,25
95th percentile	3,13	2,07	2,88	2,34	1,41
Max	4,55	2,49	5,21	3,25	3,11
Std dev	0,58	0,25	0,74	0,37	0,26
D. Percentage of depleted capital after hoarding					
Min	4,65%	4,45%	4,40%	4,46%	4,40%
5th percentile	4,76%	4,48%	4,41%	4,50%	4,43%
Mean	5,37%	4,71%	4,87%	4,70%	4,65%
95th percentile	7,43%	5,22%	6,74%	5,27%	4,94%
Max	13,41%	5,92%	8,65%	6,86%	10,22%
Std dev	1,29%	0,27%	0,81%	0,35%	0,61%

Table 3.A.9: Summary statistics of simulation results: maximum losses over 500 shock scenarios and the defaults of an initial bank.
Distribution of maximum default outcomes over 100 pairs of networks. Maximum default outcomes are measured in terms of maximum number of bank failures triggered by the default of an initial bank and of losses as a proportion of total system capital (i.e. of depleted capital). All the losses due to the common market shock and to solvency contagion are accounted for in '... before hoarding', whereas total losses are accounted for in '... after hoarding'. Thus the difference between the two is attributed to liquidity contagion

	2008	2009	2010	2011	2012
A. Number of defaults before hoarding					
Min	4,00	3,00	3,00	3,00	2,00
5th percentile	4,00	3,09	3,00	3,00	2,30
Mean	6,89	5,44	4,41	4,97	3,92
95th percentile	10,11	9,00	7,00	7,70	6,50
Max	13,00	11,00	9,00	9,14	9,00
Std dev	2,02	1,67	1,21	1,27	1,33
B. Percentage of depleted capital before hoarding					
Min	10,57%	8,29%	8,34%	8,61%	7,29%
5th percentile	11,84%	8,87%	9,09%	8,93%	8,61%
Mean	17,01%	12,28%	11,69%	12,13%	11,34%
95th percentile	26,41%	17,03%	15,77%	16,19%	15,86%
Max	33,43%	21,67%	18,13%	20,73%	22,34%
Std dev	4,63%	2,60%	2,06%	2,34%	2,52%
C. Number of defaults after hoarding					
Min	4,00	3,00	3,00	3,00	2,00
5th percentile	5,00	3,81	3,01	3,06	2,31
Mean	7,62	5,90	5,31	5,31	4,11
95th percentile	11,71	9,01	8,51	8,00	7,00
Max	14,00	11,00	11,02	9,14	9,00
Std dev	2,24	1,82	1,72	1,33	1,39
D. Percentage of depleted capital after hoarding					
Min	11,25%	8,35%	8,34%	8,65%	7,29%
5th percentile	12,59%	9,38%	9,30%	9,10%	8,90%
Mean	18,13%	12,81%	12,40%	12,39%	11,72%
95th percentile	29,11%	17,76%	16,98%	17,25%	16,70%
Max	33,43%	24,18%	20,50%	20,73%	22,34%
Std dev	5,04%	2,72%	2,43%	2,44%	2,67%

Table 3.A.10: Summary statistics of simulation results: domestic and cross-country losses averaged over 500 schock scenarios and the defaults of an initial bank.
Table A. presents by-country distributions of average losses (over 100 network pairs) imposed by a bank on its domestic counterparties over the total capital of the system. Table B. presents by-country distributions of average losses (over 100 network pairs) imposed by a bank on its foreign counterparties over the total capital of the system.

	Year				
	2008	**2009**	**2010**	**2011**	**2012**
A. Losses imposed on domestic banking system					
Mean	1,60%	1,56%	1,49%	1,31%	1,86%
Min	0,00%	0,00%	0,00%	0,00%	0,00%
Median	1,00%	1,20%	1,34%	0,90%	0,68%
Max	7,59%	6,00%	7,03%	4,91%	12,33%
Std dev	2,08%	1,70%	1,75%	1,53%	3,06%
B. Losses imposed on a foreign banking system					
Mean	1,29%	0,87%	1,03%	0,86%	0,56%
Min	0,00%	0,00%	0,00%	0,00%	0,00%
Median	0,86%	0,52%	0,70%	0,37%	0,19%
Max	14,36%	10,59%	7,20%	15,47%	11,81%
Std dev	1,80%	1,20%	1,19%	1,50%	1,05%

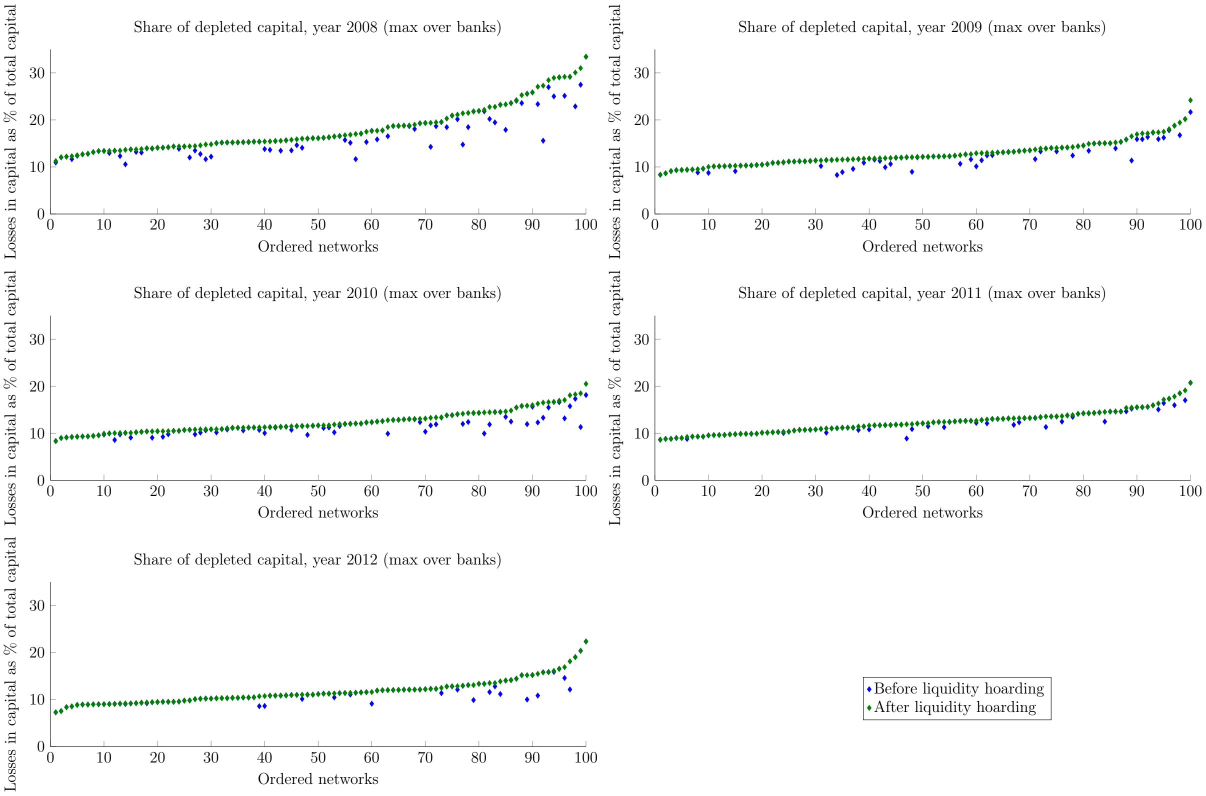


Figure 3.A.3: Share of interbank losses -before and after liquidity hoarding- ordered by the size of total losses (as % of total system capital)

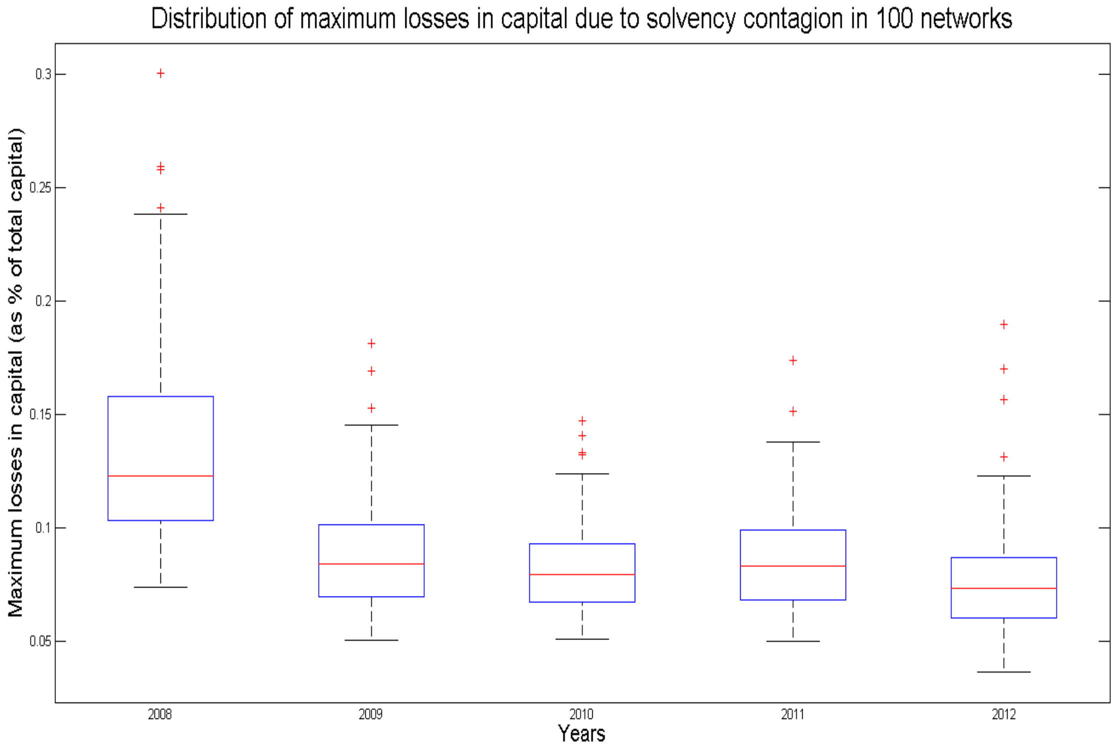


Figure 3.A.4: Distribution of losses due to solvency contagion (as % of total system capital)

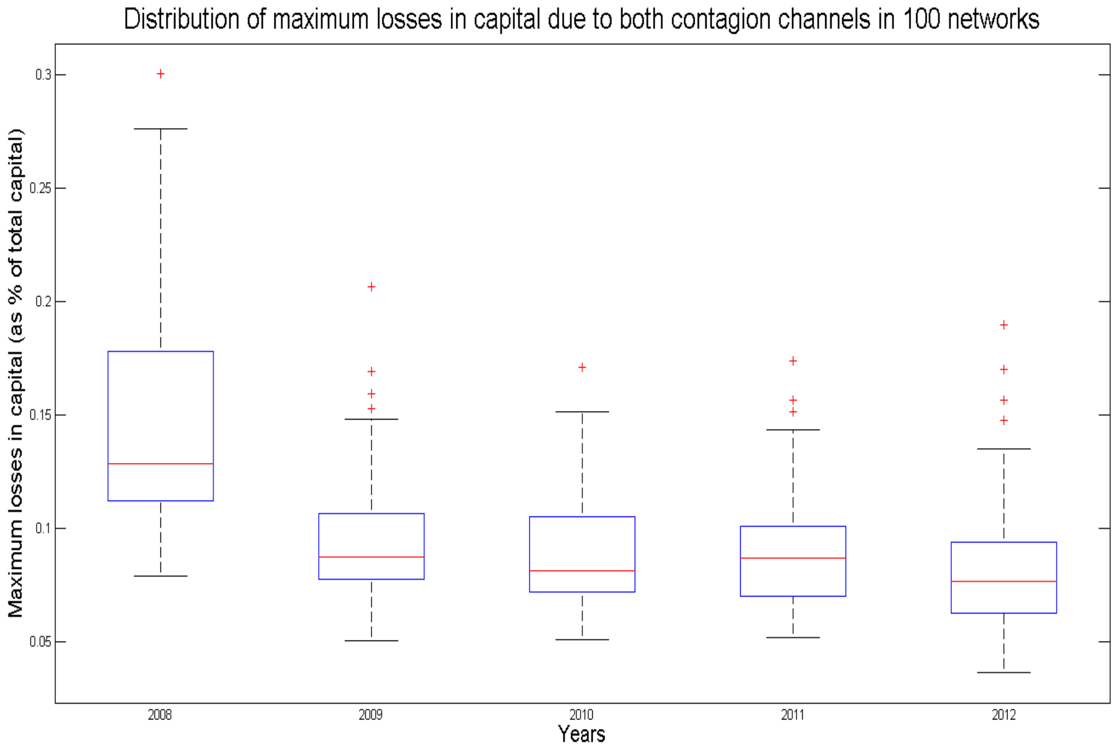


Figure 3.A.5: Distribution of losses due to both solvency and liquidity contagion (as % of total system capital)

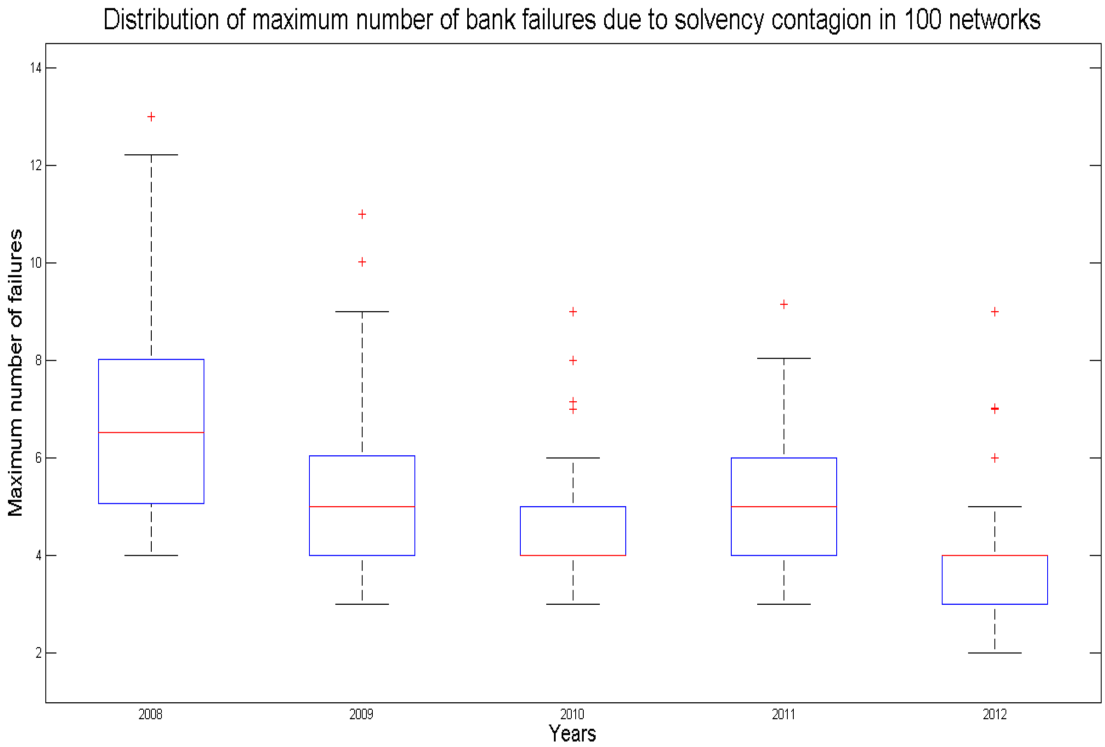


Figure 3.A.6: Distribution of maximum number of failures due to solvency contagion

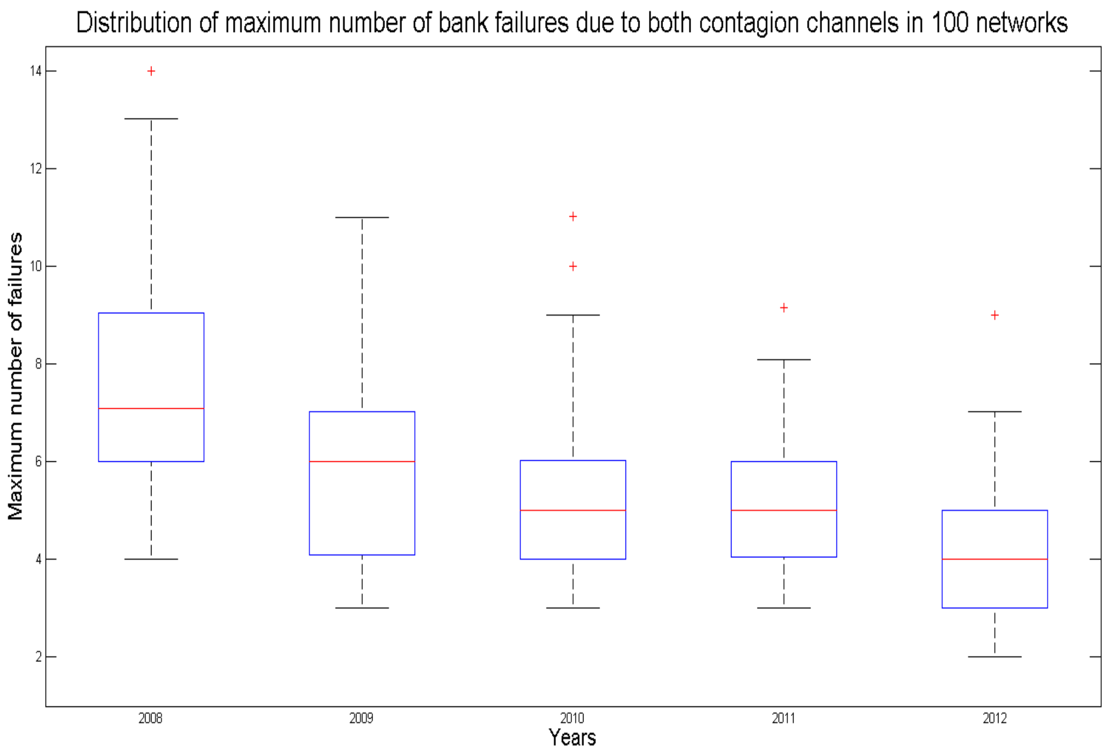


Figure 3.A.7: Distribution of maximum number of failures due to both solvency and liquidity contagion

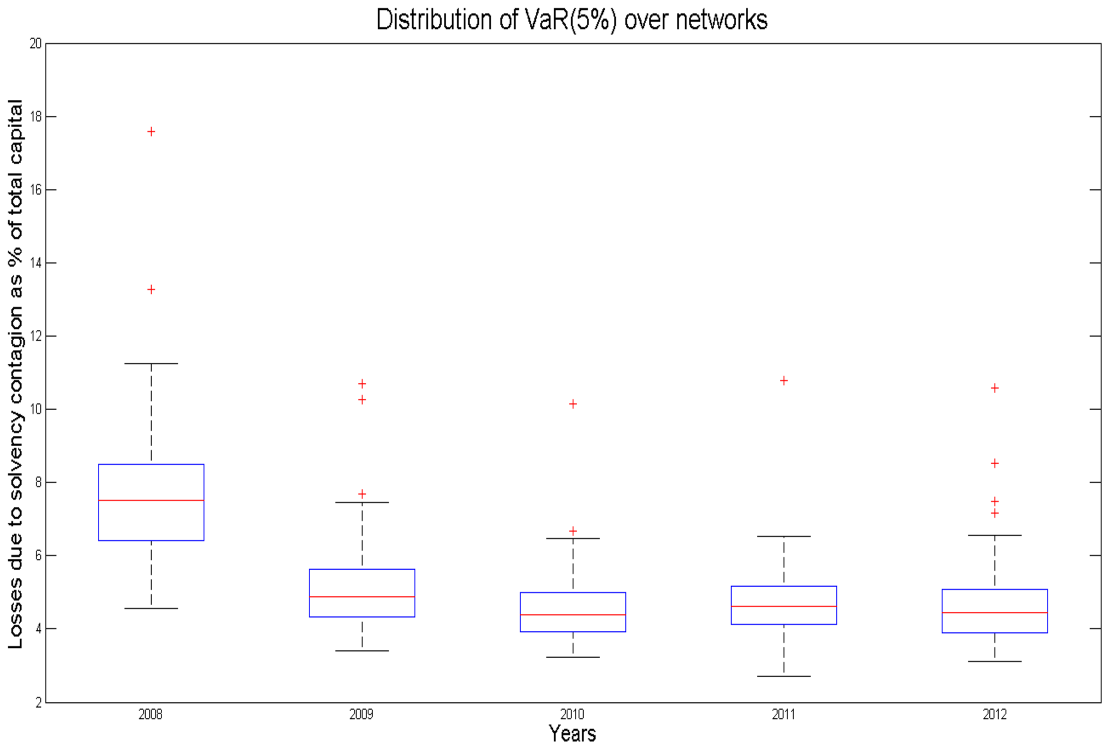


Figure 3.A.8: Distribution of the 5% worst losses due to solvency contagion over 500 shock scenarios and 100 network pairs (as % of total system capital)

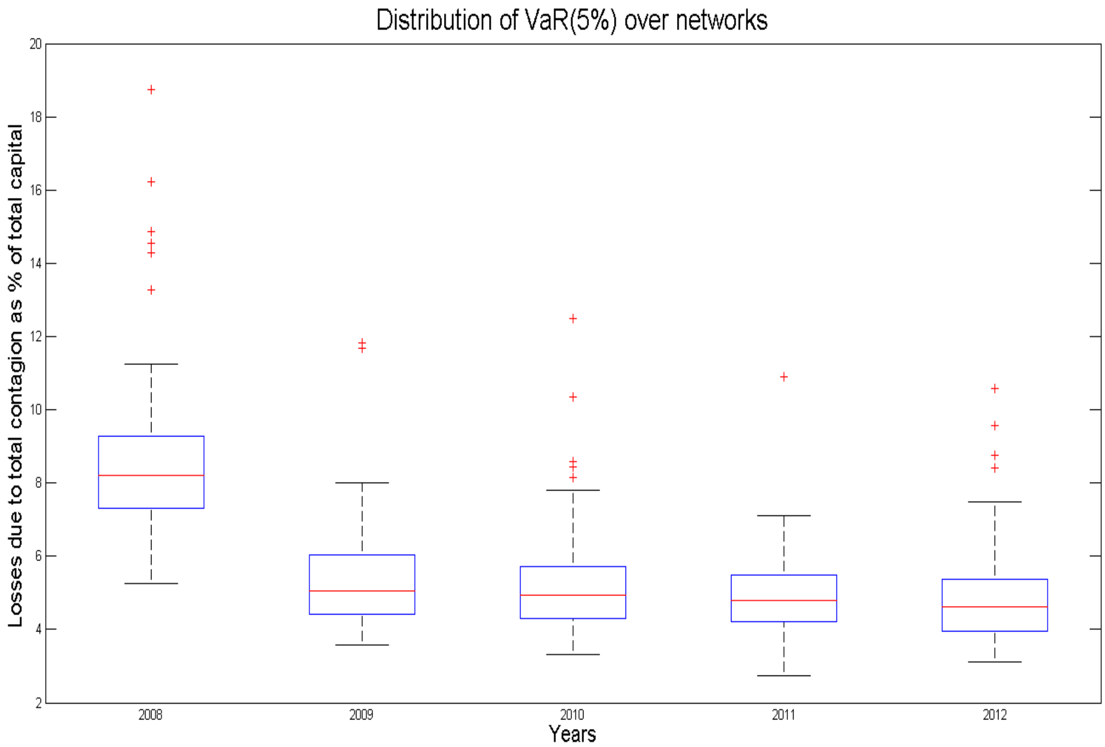


Figure 3.A.9: Distribution of the 5% worst losses due to both solvency and liqidity contagion over 500 shock scenarios and 100 network pairs (as % of total system capital)

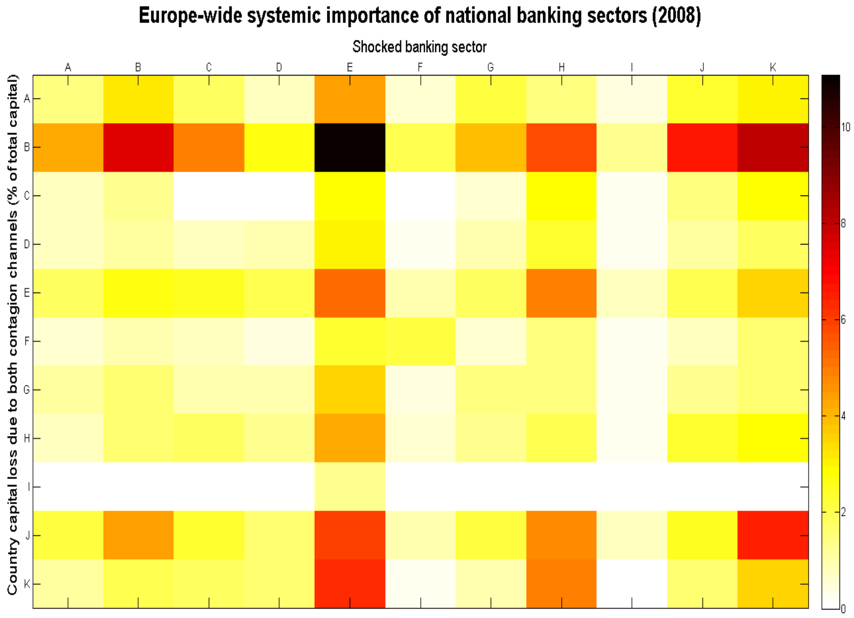


Figure 3.A.10: Total cross-border contagion in 2008
The cells $(A; B)$ of the map represent with colors the strength of the total capital loss experienced by country A's banking sector (as a fraction of its aggregate initial capital) given a common market shock and the default of a bank in the foreign banking system B. Total country capital losses are computed on average over 500 realizations of the market shock and 100 different pairs of long- and short-term exposure networks. They have been normalized to account for the different number of banks (and hence of simulations) considered for the various national banking sectors. Heatmaps have been anonymized for data confidentiality reasons; countries for which less than 3 sample banks are availble have been removed from the charts. Countries are ordered randomly, but the order is the same across years.

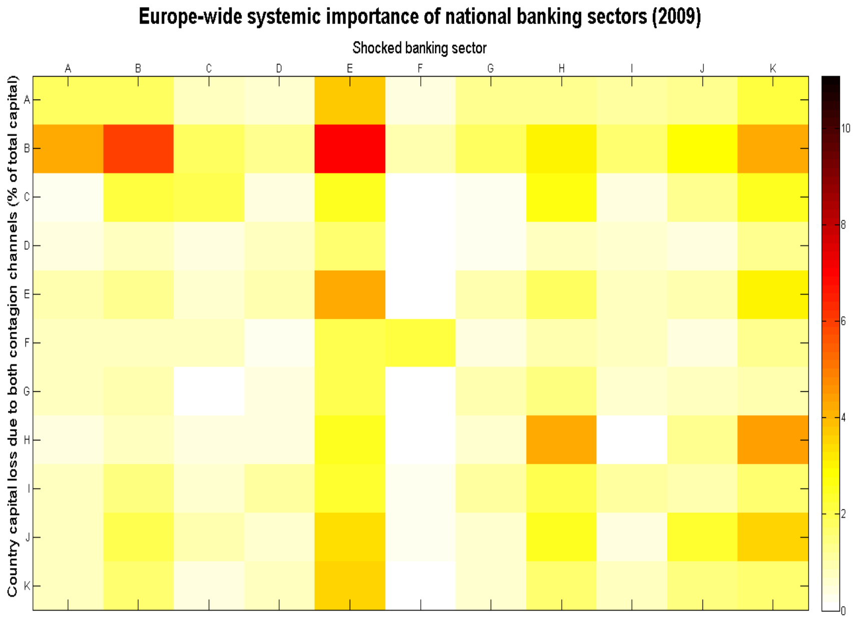


Figure 3.A.11: Total cross-border contagion in 2009
See caption in Figure 10.

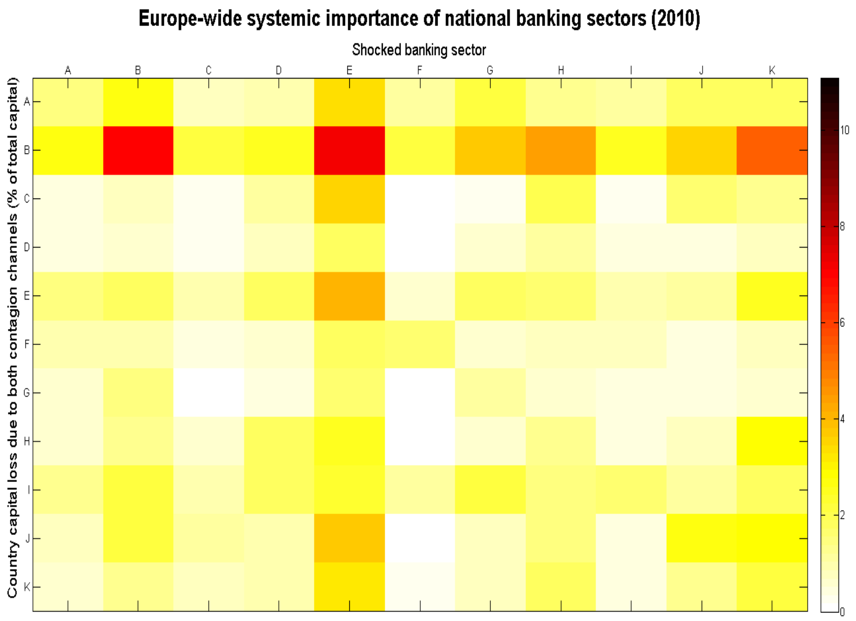


Figure 3.A.12: Total cross-border contagion in 2010
See caption in Figure 10.

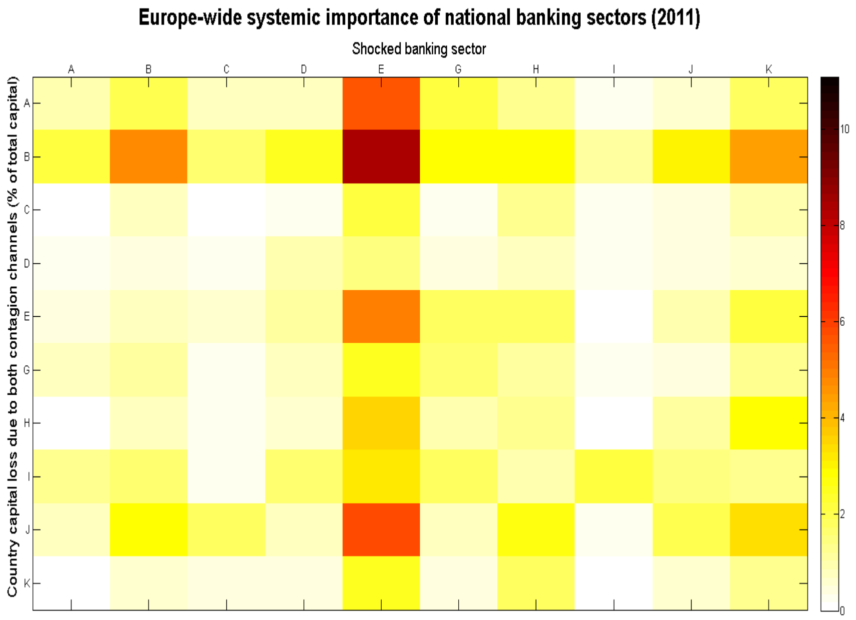


Figure 3.A.13: Total cross-border contagion in 2011
See caption in Figure 10. Note that one additional country has been removed from the 2011 heat map because of data unavailability for sample banks from this country in 2011.

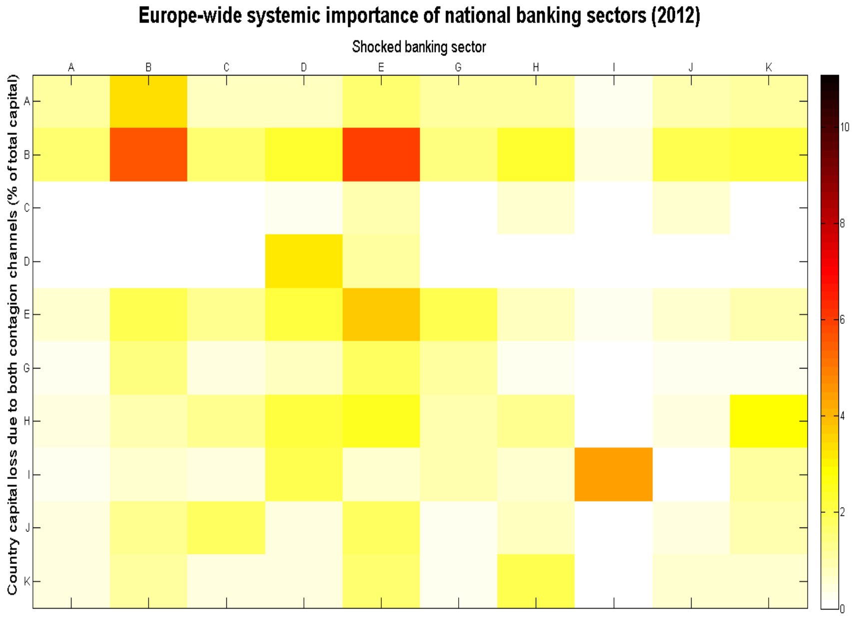


Figure 3.A.14: Total cross-border contagion in 2012

See caption in Figure 10. Note that one additional country has been removed from the 2012 heat map because of data unavailability for sample banks from this country in 2012.

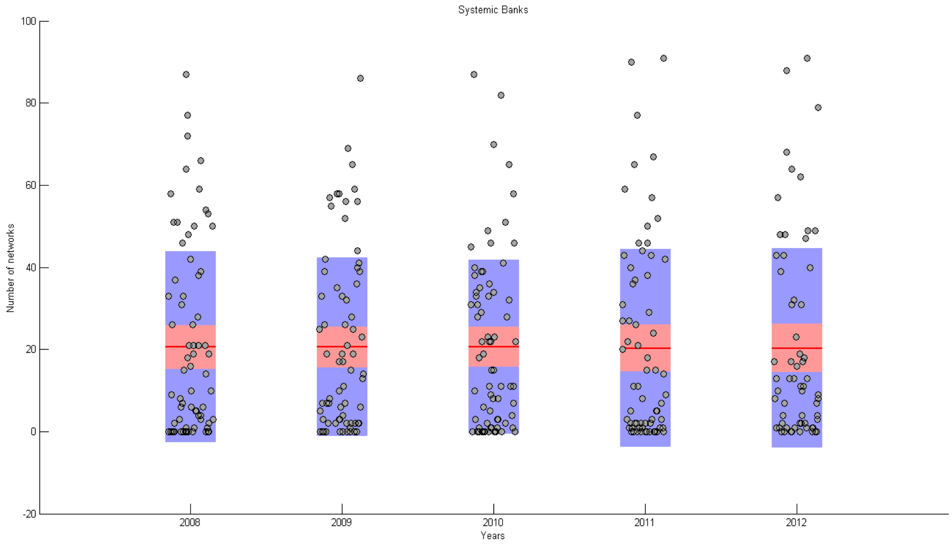


Figure 3.A.15: Systemic banks for each of the 5 years of analysis.
For each year, we have number of networks in which each bank is systemic. Most of the banks are either never systemic or rarely systemic, whereas some are systemic in almost all 100 simulated networks. We define a bank to be systemic, when losses (through both channels of contagion) imposed on the system by its default exceed 85th percentile of loss distribution.

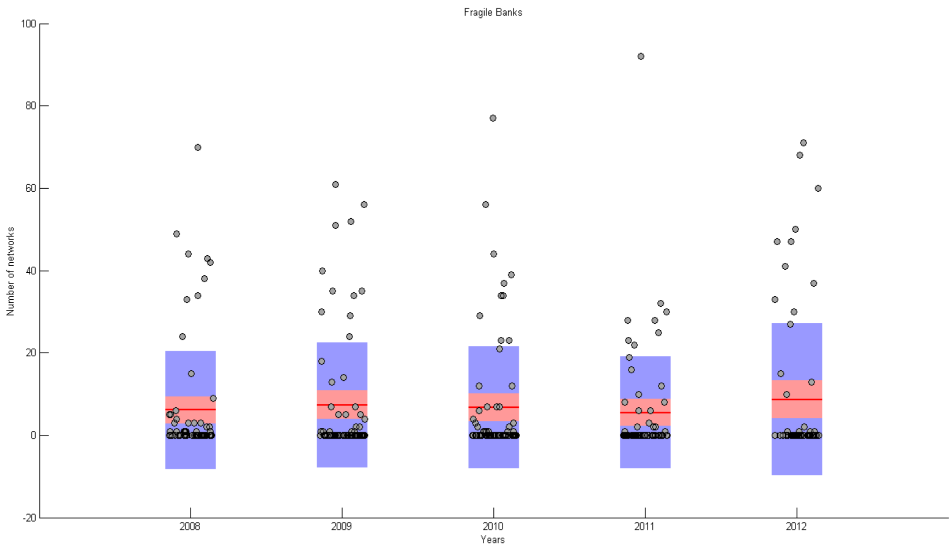


Figure 3.A.16: Fragile banks for each of the 5 years of analysis.
For each year, we have number of networks in which each bank is fragile. Most of the banks are either never fragile or rarely fragile, whereas some are fragile in more than half of 100 simulated networks. We define a bank to be fragile, when it defaults due to an initial default more frequently that 85% of other banks.

3.A.5 Econometrics

	(1) NBD	(2) NBD	(3) NBD	(4) Capital loss	(5) Capital loss	(6) Capital loss
main						
Capital ratio	-88.87***	-88.88***	-88.80***	-18.17***	-18.15***	-18.16***
	(-10.35)	(-10.36)	(-10.33)	(-20.92)	(-20.93)	(-20.95)
ST funding / Assets	20.06***	20.08***	20.13***	5.110***	5.107***	5.104***
	(9.30)	(9.45)	(9.62)	(4.79)	(4.78)	(4.79)
Closeness	-16.10**	-16.28**	-16.96**	3.593*	3.918*	3.625*
	(-2.01)	(-2.02)	(-2.10)	(1.72)	(1.85)	(1.68)
EXP. low ST funding / Assets	1.710***	1.703***	1.665***	0.852***	0.845***	0.838***
	(4.49)	(4.50)	(4.38)	(5.30)	(5.31)	(5.28)
EXP. low Capital	0.977***	0.973***	1.020***	0.489***	0.486***	0.495***
	(5.12)	(5.08)	(5.31)	(6.52)	(6.41)	(6.55)
EXP. high N. Counterparties	-0.558***	-0.556***	-0.543***	-0.156***	-0.154***	-0.153***
	(-3.64)	(-3.65)	(-3.56)	(-3.70)	(-3.65)	(-3.64)
LT Clustering		-0.182	0.581		0.516	0.781
		(-0.05)	(0.16)		(0.50)	(0.75)
LT Avg. Path length		0.368	-0.0265		0.271	0.134
		(0.52)	(-0.04)		(1.38)	(0.68)
LT Max / Mean degree		0.0603	0.0467		0.128	0.120
		(0.19)	(0.15)		(1.46)	(1.36)
ST Clustering			-2.107			-0.806
			(-0.75)			(-0.96)
ST Avg. Path length			-0.105			-0.0429
			(-0.33)			(-0.49)
ST Max / Mean degree			-0.775***			-0.266***
			(-3.19)			(-4.26)
Observations	6500	6500	6500	6500	6500	6500
BIC	.	.	.	.	.	.

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A.11: Explaining bank fragility.
The dependent variable in columns (1), (2) and (3) is the frequency of defaults of bank i, for each network n, following the default of another bank j, $j \neq i$. The dependent variable in columns (4), (5) and (6) is the share of losses suffered by bank i, for each network n, following the default of another bank j, $j \neq i$.

	(1) NBD	(2) NBD	(3) NBD	(4) Capital loss	(5) Capital loss	(6) Capital loss
main						
Capital ratio	-18.49***	-18.48***	-18.48***	-6.649***	-6.631***	-6.635***
	(-15.37)	(-15.36)	(-15.43)	(-20.03)	(-20.10)	(-20.16)
ST funding / Assets	1.574*	1.566*	1.538*	0.644**	0.639**	0.636**
	(1.92)	(1.90)	(1.88)	(2.46)	(2.45)	(2.44)
Closeness	27.79***	28.26***	28.58***	16.41***	17.01***	16.89***
	(6.71)	(6.74)	(6.62)	(11.37)	(11.68)	(11.32)
EXP. low ST funding / Assets	0.0117	0.00489	-0.0126	0.0510	0.0423	0.0383
	(0.08)	(0.03)	(-0.08)	(0.93)	(0.79)	(0.72)
EXP. low Capital	0.0818	0.0805	0.0974	-0.0928	-0.0970	-0.0939
	(0.35)	(0.34)	(0.42)	(-1.15)	(-1.22)	(-1.19)
EXP. high Beta	0.281***	0.281***	0.277***	0.156***	0.157***	0.157***
	(3.64)	(3.65)	(3.60)	(5.37)	(5.42)	(5.41)
LT Clustering		0.571	1.657		0.750	0.942*
		(0.35)	(0.97)		(1.38)	(1.68)
LT Avg. Path length		0.192	-0.0953		0.288***	0.214**
		(0.62)	(-0.31)		(2.65)	(1.96)
LT Max / Mean degree		0.146	0.127		0.199***	0.194***
		(1.54)	(1.35)		(5.91)	(5.75)
ST Clustering			-4.165***			-0.644
			(-2.59)			(-1.19)
ST Avg. Path length			-0.309			-0.0177
			(-1.51)			(-0.30)
ST Max / Mean degree			-0.634***			-0.143***
			(-5.34)			(-3.73)
Observations	6500	6500	6500	6500	6500	6500
BIC	.	.	.	.	.	.

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A.12: Explaining bank systemicity.
The dependent variable in columns (1), (2) and (3) is the frequency of failures imposed by the default of bank i, for each network n. The dependent variable in columns (4), (5) and (6) is the share of losses imposed by the default of bank i, for each network n.

Chapter 4

Payment Delays and Contagion[1]

4.1 Introduction

The smooth functioning of financial infrastructures is crucial for financial stability in a wider sense. Payment systems constitute a core element and play a central role in transmission of liquidity shocks and contagion under market distress that may lead to systemic events. Payment systems also serve as a tool to early identify and then monitor systemic liquidity stress through the behavioral patterns of its participants.[2]

Changes in regular patterns of transactions' volumes and values have proven highly informative in the recent crisis period. For instance, during the Lehman Brothers failure, payment markets were among the first to react and show signs of stress, which lasted for several weeks. Banks chose then to delay their payments or reassess their degree of involvement in the market due to concerns of counterparty default risk (Benos et al., 2012).

In this paper, we focus on payment delays –the time passing between the introduction of a payment to the system and its settlement– as they have highly relevant implications for systemic liquidity risks and also allow for early identification of potential changes in behavior of market participants. Delays tend to be reduced as queueing and liquidity-saving mechanisms are put in place to improve overall efficiency in the system design. However, as the potential remaining delays may quickly reflect strategic responses to general or particular shocks of different nature, their determinants and motivations deserve attention.

[1]This chapter is base on the paper co-written with B. Craig and M. Saldias. It has been presented at the Workshop on simulations in payment systems (Helsinki, 2014)

[2]See Manning et al. (2009) for a comprehensive summary of theory and practice of large-value payment systems (LVPS), including delays. Rochet and Tirole (1996) provide additional insights in net settlement systems and payment systems design.

Our first contribution is a characterization of delays in interbank payments via TARGET2 payment system that is consistent with findings in relevant theoretical and empirical work, including time clustering Armantier et al. (2008); Bartolini et al. (2010); Proepper et al. (2008); Massarenti et al. (2013), liquidity management trade-offs (Angelini, 1998; Bech and Garratt, 2003; Bech, 2008), operational risks Merrouche and Schanz (2010), *inter alia*. We then contribute with a first approximation to the determinants whereby a delay in incoming transactions may cause a delay in other transactions downstream under different liquidity and market conditions using probit models with endogenous regressors. Our econometric approach allows us to isolate a contagion phenomenon in normal times and the presence of common factors driving the delays under distressed market conditions.

Our estimation results show that banks do not systematically take strategic bilateral decisions towards other participants in a payment-by-payment basis as each payment is usually too small to induce a strategic game. Conversely, banks take choices on the liquidity to start operating in the system at the beginning of the day and a mechanical process runs on its own throughout the day after the initial decisions. Our estimates are robust and benefit from behavioral patterns of participant banks that we identify in the network structure of TARGET2 as instruments. In particular, we consider temporary losses of liquidity as a result of a large spike in payments needs without an accompanying increase in liquidity, transmission of delay information throughout the network nodes (Blume et al., 2010) and interplay between free riding and reputation risks in bilateral punishment equilibria (Diehl, 2013).

Based on this finding, we then assess the relevance of initial liquidity setup on the strategies of banks throughout the day. Initial liquidity of banks constitutes of the beginning-of-the-day-balance and credit line at the central bank supported by the collateral. Throughout the day, banks make and receive hundreds of payments, and though they may be fairly clear about what payments will come and go out, and the total match between initial liquidity set and in- and out-payments, they face uncertainty about the stream of payments. We find that there are two types of banks in terms of their initial liquidity and their propensity to delay on its payments: banks that set enough initial liquidity to run daily payments (low-α banks) and those which systematically put less than needed initial liquidity (high-α). In particular, high-α banks always rely on payments that come into the system to clear their payments and they account for the majority of the delays observed. In contrast, low-α banks are banks with large initial liquidity and rarely incur in payment delays. Interestingly, they account for the majority of the distribution. Moreover, banks' characterization by a low or high α status is persistent over time and across the two subsamples that characterize different market conditions. Finally, the division of the sample in two groups allows us to identify four regions of flows, where delays happen more often among high-α banks and when flows go from a high-α to a low-α bank. This result can provide an early warning in terms of market freezes, as delays among low-α banks are rare even under low market liquidity environments.

The remainder of the paper is organized as follows. Section 4.2 provides a concise review of the literature on delays in payment systems, both from a theoretical and an empirical point of view. The literature suggests that banks are involved in a game with each other, where the strategies are chosen to prevent free riding on liquidity at each payment, and the strategic instruments include bilateral limits on the implicit credit for delay of a particular counterparty and the delay in placing a payment into the system for a counterparty. We show that bilateral limits are rarely chosen strategically, but the delay in placing a payment into the system for a counterparty is difficult to assess empirically. We describe the empirical application in order to obtain and analyze the delays origination and transmission in Section 4.3. Results are provided in Section 4.3.3 where individual payment strategic interactions are shown to be a problematic view of the payments system. This leads us to explore a different approach to delays in intra-day liquidity management which focuses on the initial decisions to set a liquidity reservoir at the beginning of the day. We explore a new way to normalize liquidity decisions to account for the very different payment patterns that face each bank in 4.4.1. We show that our normalization is bimodal and persistent within a bank in 4.4.2. We then examine the payment and network patterns that contribute to having a bank to choose low liquidity relative to its payment patterns and find that total value of payments going out or coming in are not important but that network position is in 4.4.3 and look at the network implications of heterogeneity in α in 4.4.4. Conclusions and discussion of future research are summarized in Section 4.5.

4.2 Literature review

A number of contributions address payment delays from a theoretical perspective and with a game-theoretic approach. They generally link the delays to liquidity as a change of behavior of market participants to shocks or to the payment system structure. For instance, Arjani (2006) conducts a simulation analysis applied to the Canadian LVTS in order to tackle the cost trade-off between settlement delays and intraday liquidity needs in order to improve the efficiency of the system. The author is cautious about the sensitivity of the analysis' results to the assumptions about the behavior of the system participants, which highlights the need for the model to include dynamics and strategic behavior. Along these lines, Schulz (2011) tackles the liquidity-delay trade-off in a simulation exercise calibrated with real world parameters. The author also highlights the sensitivity of the results to behavioral assumptions, pointing out to the need to analyze and characterize them in the data, such as via TARGET2 transactions, in order to obtain a realistic simulations results.

From a game-theory perspective, Bech and Garratt (2003) and Bech (2008) characterize the interaction between intraday liquidity management and payment delays as a coordination game and provide rationale to the payment and delays timing. Buckle and Campbell (2003) show in a theoretical model that delays in a real-time gross settlement (RTGS) systems are likely to occur if banks care about bilateral payment imbalances.

In the empirical literature, Massarenti et al. (2013) provide a first and very thorough characterization of the intraday patterns of payments in TARGET2 between 2008 and 2011. The authors identify a number of highly relevant features, including stable and regular payment timing, time clustering for different sub-systems within TARGET2, as well as close relationships between interbank transactions made through the payment system and trading activity in financial markets. The authors also tackle delay payments along these lines and find that delays respond to timing clustering, which indicates on one hand strategic liquidity management behavior but also creates foreseeable contexts where payment delays might be more prone to create systemic liquidity distress.

Bartolini et al. (2010) match brokered trades and Fedwire payment orders and provide a thorough analysis of payment delays. The authors also find that payment delays can be to some extent predictable due to their time clustering and therefore trigger high-frequency liquidity management decisions to counteract resulting liquidity shortages. They also identify different strategies of market participants, such as the preference of delays of large transactions relative to small trades or, to a lesser extent, delaying settlement when own liquid balances are low. Benos et al. (2012) addresses payment delays in the British RTGS or CHAPS in the aftermath of Lehman Brothers bankruptcy as an exposure to counterparty default risk in a context of abundant market liquidity.[3] Finally, Heijmans and Heuver (2011) analyze the Dutch part of TARGET2 and find that delays tend to signal changes of behavior of vis-a-vis its counterparties.

[3]The authors also provide an alternative definition of delays to the one studied in this paper

4.3 Testing payment-by-payment strategic games

4.3.1 Data and preliminary analysis

Our source dataset comprises all interbank payments at transaction-level settled via TARGET2, the real-time gross settlement (RTGS) system owned and operated by the Eurosystem since November 2007.[4] We chose two days to apply our delay categorization and econometric model. In particular, we studied the delay patterns on 16 July 2010 as our *calm day*, and on 10 March 2009 as our *stress day*. The choice of these two days is based on overall transaction volume in the interbank and bank equity markets and the volatility in the latter relative to the historical trend, i.e. our calm day shows average behavior whereas both volume and transaction volatility are much higher on our stress day.

Based on this rich dataset, we first distinguish between delayed and non-delayed payments. In particular, a payment in our dataset is flagged as delayed if its execution time, i.e. the difference between the point of time that a payment is introduced to the system and the time that it is actually settled, exceeds 5 minutes during the last hour.[5] Most of the payments are introduced to the system immediately when payments messages are sent by participants; however, participants have some flexibility to decide on the introduction and clearing time by setting earliest debit time. It provides a possibility to send a payment message (e.g., at 7am) in order to indicate at what time the payment will be introduced to the system (e.g., at 10am). Moreover, payment messages can be sent to the system before the starting of the settlement operations. Therefore, the introduction time is defined as the maximum between the time the payment is sent to the system and earliest debit time if the business date the payment is settled corresponds to the business date the payment is introduced to the system; or 7am otherwise.

Delayed payments on our calm day represent 17.06% of the total, while on a stress day, this percentage is slightly smaller (15.87%), although the number is significantly larger (over 50%). Figures 4.A.1 and 4.A.2 show the distributions of transaction values of delayed and non-delayed payments. Delayed payments are on average larger than non-delayed ones;

[4]TARGET2 processes payments by three categories of participants: 1) Central banks payments; 2) Ancillary systems; and 3) Commercial institutions. In our analysis, we are interested only in transactions between commercial institutions which make the majority of all the transactions in the system and are also responsible for the most delays. There are 20 classes of transactions, but interbank and customer payments make together 70% of the total number. They are also the ones that are the most delayed. For the current version, we keep all the types of payments between commercial institutions.

[5]This definition excludes delays caused by technical processing time difficulties and we are not interested in the duration of the delay but on its relevance as a determinant of further delays.

however there is graphically no significant difference between the two distributions, meaning that banks do not have any strategy of delaying or not a payment based on the transaction value.

Finally, figures 4.A.3 and 4.A.4 show the kernel distributions of the sum of incoming delayed payments (in log) separately for those payments that in turn produced new delayed payments. For both calm and crisis days, we observe that total values of incoming delayed payments are much higher for the payments that caused delays themselves (red line), in other words, larger delayed incoming payments are in principle associated to a higher probability of a subsequent payment to be delayed. This relationship is especially pronounced on the calm day, which implies that delays are closely related with delay contagion. On the crisis day, there may be also other reasons behind delays as the figures suggest that banks delay more on a crisis day even without having suffered an incoming payment with a delay.

4.3.2 Econometric model of delay drivers

The important behavior we are estimating with the delay data is the extent to which a delay in one transaction causes a delay in another transaction downstream. In other words, when bank **A** receives a payment or series of payments that are delayed, to what extent does this cause it to delay its payments to other banks? The importance of this question is that if the delayed payments cause the bank to delay its own payments, then the network, under certain measurable circumstances, can become absolutely frozen, or to mix metaphors, to tip, causing the entire connected network to be in delay.

Measuring the effect of a delayed payment on the probability of a delay propagation is essential to understanding whether the network properties of the system intensify the delays, and under what circumstances could the payments system tip and have delays throughout the system. Our measurement, then, could be written as a probit model with endogenous regressors:

$$y^* = X\beta + Z\gamma + \varepsilon$$

$$y = \begin{cases} 1 & \text{if } y^* > 0 \\ 0 & \text{otherwise} \end{cases}$$

Here y^* is an unobserved latent variable, $\mathbf{X}$ is an observed vector of characteristics (including only the intercept in this application), and $\mathbf{Z}$ is some measure of delays coming into the node. $\boldsymbol{\varepsilon}$ has a known distribution, such as a $N(0,1)$ distribution. The parameters

$\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are to be estimated, and the coefficient of $\mathbf{Z}$, $\boldsymbol{\gamma}$, especially can be used to describe the behavior of the system, i.e. positive statistical significance would indicate that incoming delayed payments are likely to cause a delay in payments of a given node.

Measuring the causality of delays on further delays in our data is complicated by several issues. First, one or a set of common factors could cause delays to be more probable within the entire system. In this case, delays do not propagate themselves, but can look like they do. In our notation, a common shock affects both $\boldsymbol{\varepsilon}$ and $\mathbf{Z}$, in that this shock hits the entire system and thus affects the individual shock $\boldsymbol{\varepsilon}$ and the probability that the delays occur beforehand, $\mathbf{Z}$, in the sense that after the first responder to the common shock, all subsequent responses must follow that first response, leading to a sense that they are responding to the early responses to the common shock rather than to the common shock itself. The delay variable is endogenous, and so the variables $\boldsymbol{\varepsilon}$ and $\mathbf{Z}$ are correlated and a false causality is measured.

Second, a bank that observes a consistent pattern of delays in a single partner can elect to withhold its liquidity from this bilateral partner until this partner clears its own payments. These two nodes can be in a punishment game equilibrium. Because we are interested in how the delays propagate to the rest of the system, we are interested in the effects of $\mathbf{Z}$ on $\mathbf{y}$ which abstract from this. In this scenario, the variables $\boldsymbol{\varepsilon}$ and $\mathbf{Z}$ are correlated because in cases where node $\mathbf{A}$ delivers $\mathbf{Z}$ of delayed clearing to node $\mathbf{B}$, $\mathbf{A}$ decides as a punishment to delay clearing to node $\mathbf{B}$, and so on, and $\boldsymbol{\varepsilon}$ goes up. We handle this latent endogeneity through the use of instrumental variables, using those delayed payments in $\mathbf{Z}$ that do not have a counterpart of a delayed payment from the paying node as instruments, which we denote instrument set Z_1.

The third set of errors is somewhat more subtle. These are the errors mentioned in Blume et al. (2010), where a pair of nodes is more likely to delay together. Either because of proximity, or because of similar business models, or exposure of risk from the same funding sources, this pair of nodes share a common unobserved local factor that drives both of them to delay. We solve this problem in an analogous way to their solution, we use the nodes that are not immediately connected to node $\mathbf{A}$ as instruments for the delays to node $\mathbf{A}$. In particular, we look those nodes that are connected to $\mathbf{A}$ in delays only through an intermediary in a second layer back as instruments for the delays to $\mathbf{A}$ and that do not go through the self reflecting nodes, described above. This set of instruments are labeled Z_2. Figures 4.A.5 to 4.A.8 provide an intuitive representation on the estimation strategy and the choice of the instruments.

4.3.3 Results: Delays' propagation

Results of the models described above are reported in Table 4.A.1 for a market calm day and in Table 4.A.2 for the stress day. In both cases, the benchmark model is presented in columns [1] and corresponds to the case where no instruments are used and we measure the effect of total (log) value of all incoming payments delayed more than 5 minutes during the last hour on the propagation of delays downstream. Columns [2] show the results of the model where incoming delayed payments are instrumented by Z_1, i.e. delayed payments that do not have a counterpart of a delayed payment from the paying node. Finally, columns [3] show the results of the model where the instrument Z_2, where payments are at least one link removed from the node that produces the delay in order to remove the local reflecting, as described in Section 4.3.2.

First, we analyze the calm day. Table 4.A.1 shows a positive and statistically significant dependence between the delay of a payment and the value of delayed incoming payments to this bank, in other words, large delayed payments to a given bank are associated with a higher probability of subsequent payment delays to other banks. Results of model [2] show a similar picture, after dealing with the potential endogeneity in measuring the causality of the delays using an instrument for mutual delays. The dependence is still positive and significant, therefore the delays between the two nodes are not explained by a common factor, and delay contagion takes place. Finally, in order to assess whether a delay is explained by delay contagion, that is if a delayed payment of bank i is explained by the delayed payment of bank j to bank i, which itself had a delayed payment by bank k. The results in column [3] also show a positive positive and significant effect of large incoming delays. Based on this evidence, we conclude that on the normal day, a payment is delayed with higher probability if other banks delayed a payment to a bank, and they themselves had delayed incoming payments, that is some sort of contagion of delays mainly due to the mechanics of the system.

The estimation results on the crisis day are shown Table 4.A.2 and provide different conclusions from what would be expected from theoretical work, where an increase in contagion should be a result of information propagation, punishment mechanisms, end so forth. In the benchmark model [1], a payment is delayed with higher probability the higher is the size of delayed incoming payments: the coefficient is positive and significant. However, when we tackle the potential endogeneity problem with our data and use the instruments (columns [2] and [3]), the coefficients become negative and significant. This result means that delays on the crisis day are largely explained by mutual delaying and second-round effects, which probably means that all the banks are affected by a common factor which makes them delay payments rather than a contagion mechanism. This result means that a closer analysis of the nature of the common unobserved factors is required along the lines of Hsiao et al. (2012).

This set of results mean that banks do not systematically take strategic bilateral decisions towards other participants in a payment-by-payment basis as each payment is usually too small to induce a strategic game. They rather indicate that banks make their choices on the liquidity to start operating in the system at the beginning of the day and a mechanical process runs on its own throughout the day after the initial decisions, which embeds some persistent prior decisions on liquidity needs and outflows. Finally, as our data and previous empirical work (Diehl, 2013) reveal that bilateral limits are hardly used if at all on a daily basis, which reinforces the empirical evidence against the notion of strategic games from the theoretical literature.

4.4 Initial liquidity and delays

4.4.1 Normalization

In the further discussion below, we test a different hypothesis, namely that delays in the payments system occur due to banks' certain liquidity management behavior. We examine two different months for liquidity management of the banks. The first month, September 2008, was characterized by a scarcity of liquidity brought on by the uncertainty generated by the crisis. Overnight markets were in the process of breaking down and short term liquidity rates were uncertain. We contrast this with the behavior of the banks during a recent month, May 2014 where markets were awash with short term liquidity, available at extremely low rates.

Each bank, when it sets its liquidity, does so in the knowledge of its own particular daily payments patterns. These highly idiosyncratic time series patterns are crucial in influencing the probability that a delay will occur. For example, a bank that knows that its payments are very likely to alternate between payments that arrive and payments that go out with approximately the same amounts can set a liquidity considerably lower than a bank with payments that go out over the beginning of the day and then come in at the end and it still will have a smaller probability of settling at least one of its payments with a delay. Modeling this process parametrically so that the essential part of the process that sets the delays is very difficult. We opt for the more robust non-parametric procedure that block-bootstraps the bank's payments, both incoming and outgoing, during the business part of the day, between 8 am and 4 pm, to come up with a distribution on payments patterns for the bank.

The size of the block is set to be the maximum of 10 payments and the value calculated from Politis et al. (2009). The minimum payment number allowed for a day is 30 payments. Otherwise α is not calculated. Although this represents an optimal size for variance rather than the minimum, we experimented in our data with different values and found little variation around this value. The bootstrap is then combined with the bank's initial liquidity to calculate a probability that the bank will delay, given the pattern of payments it confronts. This probability, denoted α in this paper, is analogous to the classical Type I error, α, where a high value implies a large error and thus large delay propensity. The bootstrap was sampled 10,000 times, and this value was also examined in a sample of payment-days. We found that increasing the number of bootstrap replications did not change α more than 1%, which was certainly accurate enough for our purposes.

4.4.2 Empirical patterns: High- and low-α Bank

Our main finding from the normalization procedure is that some banks persistently miscalculate the amount of initial liquidity to provide to the system, therefore being high-α banks, whereas the majority feed the system with liquidity, being low-α banks. Figures 4.A.9 and 4.A.10 show the distributions of average daily α values (over the respective months) for each bank for two periods, September 2008 and May 2014. We see a clear split: a group of banks with α greater and lower than 0.5, especially so for times of scarce liquidity (September 2008). Moreover, figures of transition probabilities, 4.A.11 and 4.A.12 demonstrate that banks have very regular behavior by staying in the same category from one day to another. This finding points out to a persistent liquidity management policy over time, therefore confirming our hypothesis that banks do not incur in strategic games but rather make their morning decisions about the intraday liquidity allocation.

Before analyzing the behavioral patterns of high- and low- α banks, it is worth recalling that the banks in our whole sample are rather big and active, because in order to compute α values, we keep only banks that make on average more 100 daily transactions during the month. Figures 4.A.13, 4.A.14, 4.A.15 and 4.A.16 confirm that since for both periods the two types of banks have similar distributions of number and total value of in- and out-transactions, with the only difference that distributions of high-α banks have a bit fatter right tails. Notwithstanding that, throughout the day, the two groups seem to exhibit different patterns (see Figures 4.A.17 and 4.A.18): high-α banks tend to receive bigger volumes in the morning and send it in the afternoon, while low-α banks do the opposite.

High-α banks also delay more (Figures 4.A.19 and 4.A.20), and the difference in delayed values is particularly remarkable in September 2008 when liquidity was scarce. During that period, high-α banks transact twice as many payments as low-α banks, whereas they delay ten times bigger volume of payments. It is worth particularly noting that in times of scarce liquidity, high-α banks delay especially to other high-α banks. This finding suggests contagious nature of those delays where potential dynamics may look as follows: a bank with short liquidity relies on the incoming liquidity to clear its payments; meanwhile it delays its payments to other banks downstream. If its counterparts are also high-α banks, they will delay their payments as well since they also count on the incoming liquidity.

4.4.3 What determines a High-α Bank?

We collected a large number of possible determinants of α. Because of data confidentiality issues, we were not able to match the banks with balance sheet determinants. However, the payments data themselves gave us a large number of possible explanatory variables with which to explain the bank's liquidity behavior. We divide the day of the bank into four periods. Two periods, "night" (the hours from 4 pm to 7 am in the morning) and "7-9" (early morning hours) represent the evening settlement hours and the early morning settlement hours where the bank realizes its liquidity for the day, where the evening hours are realized payments in for the next day. Two periods, "morning" (9 am to 12 noon) and "afternoon" (12 noon until 4 pm, just before the large net settlements from other payments systems) represent those times of payments where the daily work day payments are handled, after much of the liquidity reservoir for the payments are set. We tried other ways to denote the daily periods, with little or no changes in our results. These four periods of the day gave times where the different behaviors of the payments give rise to different networks. A bank that is more central in the morning will not be as central in the evening.

The payments network is given by four variables, each measuring a different aspect of the network. While we used other variables to assess the behavior of the payments network, these four seemed to characterize our regressions as well as the other sets of variables. We use the Bonacich[6] centrality measure to focus on the information available to the bank from

[6]Bank with the highest Bonacich centrality is the most connected bank in a network; this centrality measure takes into account all connections while the contributions of distant nodes are penalized.

its payments coming in. Bonacich centrality includes a parameter, β, that must be set which determines how the bank has payments coming from other central nodes. The parameter can be set between the largest eigenvalue of the adjacency matrix which defines the network and the negative of this number. If β is larger, then a higher central node is more likely to be connected (in the sense of payments coming in) with other central nodes. If the parameter is lower, then a more central bank is likely to be connected to more peripheral banks. We report coefficients on the Bonacich centrality for extremely high values of β, following the advice of Bonacich (1987) The Bonacich centrality represents the information coming to the bank. Banks that are more central are able to assess the fact that more or fewer payments of value are coming to it from other central banks, thus providing it with information that is not available to more peripheral banks.

A second parameter, “in degree”, simply measures the number of links coming into the bank. It is related to Bonacich in that it represents the total number of paying banks that a bank has access to, and so it tells something about the health of the network available as information to the bank. It also represents the complexity of the network of payments coming into the bank. Banks with low in-degree depend on their payments coming in from only a few banks that can be easily monitored, but they also have access to information only from a few nodes, and therefore can see only a part of the network, rather than the health of the whole.

The third parameter, ”weighted in clustering”, represents the riskiness of the position of the payments coming into the bank, following Watts and Strogatz (1998). More formally, it measures the probability that two banks who make payments into a node will make a payment to each other. This measures the riskiness in that while a bank may be able to accurately assess the likelihood that a direct counterparty can make its payment on time, the fact that two counterparties are linked creates a correlation between the two, making one delay more likely to generate a delay on the part of the other, delaying payments from both parties. In this sense, a higher clustering coefficient implies a higher probability of a major delay in incoming payments.

Finally, we choose an obvious measure of the position of the node in the network, the absolute size of the payments coming into the bank, which we calculate as the logarithm of the total incoming payments coming into the bank during a time period. We run two types of probit equations with α as the dependent variable. In one case, we choose α to be a continuous variable, and in the other case, we choose a cutoff value for high and low α to be 0.5, so that high α is set to 1 and low to 0 in the probit estimates. The cutoff value was varied and did not really matter, but reflects the bi-modality of the α values. These are denoted 0-1 in Table 4.A.3 where we report our results.

For convenience of interpretation, we divide our results into two times of the day. First, those times which might influence how much liquidity is set. This would be the character of the payment inflows of the evening before and the early morning of the day that the bank observes before its liquidity is topped off at the beginning of the day. Second, the character of payments during the day that might affect the noise of the payments, which would lead, in turn, to a more likely delay. The first we call the "morning liquidity" determinants of α. The second, we call the "day complexity" determinants, because they are aspects of the complexity of the patterns of payments that can lead to delays in payments.

Turning to results in Table 4.A.3, we see several patterns. First, the determinants of high α is much more strongly associated with the low liquidity September 2008 month than with the high liquidity May 2014. Coefficients on the each of the variables in the 0-1 regression are all significant for the morning variables which determine the initial liquidity set. High α banks are privy to more information that develops during the evening of the day before through their central network position, although this is mitigated a little bit during the early morning hours (although banks that are central to both evening before and early morning networks are quite likely to be high α banks.) The same could also be said about information obtained from a variety of connections, as evidenced from the in-degree coefficients of the evening, although this, also is mitigated slightly in the morning. Banks that shoulder more risk, as evidenced by the high in-weighted clustering are also more likely to be high α, which is not surprising in that being a high α bank is a risky behavior.

Finally, total payments in have little to do with any α behavior. This is very interesting for several reasons. First, the standard chestnut that banks that process a lot of payments have a riskier liquidity profile because they rely on large numbers just is not borne out in the data. Second, a bank's network position is much more likely to affect its risk attitude to delays. Big payments providers are as likely to be high liquidity providers as not, once network position is taken into account.

When we examine the high liquidity month, network position has generally the same effect, but much weaker. The coefficients are smaller and of less significance throughout the network variables, or the coefficients have no statistical significance. This is what we might expect from a time period where the costs of mistakes in liquidity can be easily solved by recourse to liquidity cheaply available from a variety of sources. However, the once huge difference between the periods lies in the different importance of size. In highly liquid times, the high α banks are likely to be only those who process more payments in the early morning. This may have to do with the fact that high α banks adjust their liquidity at the latest moment when liquidity is cheap.

A look at the lower portion of Table 4.A.3 shows less strong influence of information than in the morning, but a continuing association of high α banks with risk. The morning cluster coefficient associated with riskier network position is also associated with high α. There is also some evidence that more complex morning market positions are associated with high α, although this effect disappears if the complexity continues into the afternoon markets. In the cheap liquidity markets, there are few patterns that can be seen in the estimates. Almost all are insignificant. This suggests that in a regime of cheap liquidity, the only strong influence on whether a bank is a high α bank is the total value of the payments received during the early morning hours.

4.4.4 Network Implications of High- and Low α Banks

Finally, the two well-defined groups allows us to define a four regions of flows and analyzed their systemic properties. Indeed, flows across these four regions show that delays are more likely to occur between high-α banks and for flow from a high-α bank to a low-α bank. This result could provide an early warning of contagion as delays from high-α to low-α banks and subsequently among low-α banks are signs of market freezes. While this section provides only a hint of the possibilities of a network analysis, it is a focus of our continuing research. The simulation studies of Bech and Soramaki (2005) and others indicate that gridlock can be a common occurrence, particularly in systems which face expensive liquidity shortages. However, these simulation studies take time and focus only on a single array of payments structures. A certain level of heterogeneity is assumed in the behavior of the banks which influence the results. Our focus on the high α banks suggest that the payments system could be even more delicate and subject to gridlock in times of expensive liquidity than previously thought.

Payments gridlock occurs because of delays that are not netted out as pointed out in Bech and Soramaki (2005) and others, including Angelini (2000). Liquidity is needed for the netting out of payments between more than two parties in the Target 2 system because the settlement algorithm will only net out bilateral obligations that do not have enough liquidity to settle. While the system as a whole might have enough liquidity to settle, local areas of the payments network can become sinks where liquidity is unable locally to settle out the obligations. Gridlock is more likely to occur within these low liquidity groups where liquidity does not enter from the outside more liquid areas of the network. Simulation studies in Denmark and Sweden suggest that the probability of gridlock is linearly related to the amount of liquidity available to the network as pointed out in Pettersson (2005). This is more likely to occur in sub networks where there is a lack of liquidity if the subnetwork has little liquidity to begin with, and it does not trade with those groups that have liquidity. The question is whether there is a sub-network in the sense that the lack of liquidity churns within a local area of the network with little entry of liquidity from the outside more liquid banks.

Our evidence from the low liquidity month of September suggests that this may indeed be the case. Figure 4.A.21 has several very intriguing features. The figure shows the payments that occur between low and high α banks and between banks that are both high or both low α. If the local areas are well connected to each other, then we should see lots of transactions between them. Figure 4.A.21 suggest that not only are the largest numbers of transactions within banks that share α characteristics, but also the lowest number of transactions are from the liquid low α banks to the lower liquidity banks. Further, it is the high α banks that are sparking the delays and our evidence is that the subgroup of high αs tend to pass most of their delays to themselves, making gridlock more likely, although they also pass delays to the other group. In other words, delays propagate most within the high α group leading to concern that gridlock will spark here. Interestingly, the low α group does not pass delays to itself. We can take from this several observations. If gridlock occurs in a network where the total liquidity is "adequate", it will occur within a local low liquidity area of the network that is isolated from the rest of the network. This suggests a stress indicator which measures the degree of connectedness of the local low liquidity high α banks with the low α banks. If this connection is robust, then liquidity flows easily into the high α banks lubricating their transactions. If, as in September 2008, the number of payments from the low α to high α banks are reduced, then the probability of stress increases. A stress indicator could be designed that focused on the liquidity flows from the low α to the high α groups. Without access to the low α liquidity, the probability of gridlock increases within the local high α area of the payments.

In times of cheap liquidity, this is less likely to occur. Figure 4.A.22 has the corresponding numbers for May of 2014. In this scenario, the flow of payments from low to high α is more plentiful than even the flows within the low liquidity banks themselves. Although the system experiences delays, the delays are not focused on the local areas and are less likely to cause gridlock. They are more likely to be one-off occurrences that do not affect the rest of the system and are quickly resolved. Further, a single bank failure is less likely to drag the rest of the system down as the payments to the downstream counterparties from other more liquid banks prevent a gridlock. The degree of connectedness of the low to high α provides a direct indicator of the matter of great concern in a time of crisis: that banks with sufficient liquidity withdraw their liquidity from banks that they deem to have insufficient liquidity. This is clearly a topic of great interest and one of focus in our continuing research.

4.5 Concluding Remarks

This paper made a characterization of delays in interbank payments via TARGET2 payment system and conducted a first approximation to the determinants whereby a delay in incoming transactions may cause a delay in other transactions downstream under normal liquidity and market conditions and also in distressed times. Taking into account potential endogeneity problems with the data, we estimated probit models with endogenous regressors and found that in normal times the probability of a bank to delay its payments is positively affected by the series and amount of incoming payments that are delayed. This result points out to a contagion phenomenon taking place with important systemic liquidity implications in the network.

This result is robust to the use of alternative instruments that take into account behavioral patterns of nodes/banks. In particular, we look at local liquidity sinks, i.e. a local area of the network that has a temporary loss of liquidity as a result of a large spike in payments needs without an accompanying increase in liquidity. We also consider transmission of delay information throughout the network nodes and free riding bilateral punishment equilibria.

We also find that this contagion phenomenon does not materialize under distressed market conditions and delay contagion is likely to be caused by the presence of common factors, mutual delaying and second-round effects. This result is also robust to the different behavioral patterns of the network nodes described above. This conclusion leads future research to conduct a closer analysis of the nature of the common unobserved factors.

A characterization of the banks according to their initial liquidity allocation provides another interesting set of results. First, we identify two types of banks in terms of their initial liquidity and their propensity to delay on its payments: low-α banks start each day with large initial liquidity and rarely incur in payment delays whereas high-α banks are exactly the opposite and account for the majority of delays in both high and low liquidity environments. This bank split is consistent over time and also allows allows identifying four regions of flows, where delays happen more often among high-α banks and when flows go from a high-α to a low-α bank. The latter constitutes in turn an early warning for market freezes.

Appendix

4.A Appendix

Table 4.A.1: Probit model with continuous endogenous regressors: **Calm day estimates**

Dependent variable	Model		
Delay propagation	[1]	[2]	[3]
Intercept	-2.343	-1.469	-1.851
	(-229.90)	(-149.22)	(-177.11)
Incoming delays	0.0969	0.0511	0.0619
	(-166.14)	(-95.36)	(-98.10)
Observations	206177	206177	206177

Notes: Incoming delays are transformed in log. All coefficients are statistically significant at 5%, t statistics are presented in parentheses. See Section 4.3.2 for details of the model specification.

Table 4.A.2: Probit model with continuous endogenous regressors: **Stress day estimates**

Dependent variable	Model		
Delay propagation	[1]	[2]	[3]
Intercept	-1.576	-0.394	1.428
	(-213.52)	(-56.31)	(164.49)
Incoming delays	0.0383	-0.0205	-0.1270
	(86.53)	(-54.35)	(-330.68)
Observations	317754	317754	317754

Notes: Incoming delays are transformed in log. All coefficients are statistically significant at 5%, t statistics are presented in parentheses. See Section 4.3.2 for details of the model specification.

	September 2008	———Low———	—-Liquidity—	————	May 2014	High	Liquidity	
	Morn Liquidity	Morning Liquidity	Day Complexity	Day Complexity	Morning Liquidity	Morning Liquidity	Day Complexity	Day Complexity
		0-1		0-1		0-1		0-1
night_Bon_Centrality	430.5	130.5***			-1.359	-16.51*		
	(1.48)	(3.14)			(-0.40)	(-1.73)		
7-9_Bon_Centrality	0.611	-1.016**			1.270	-0.0992		
	(0.51)	(-2.40)			(1.31)	(-1.35)		
night_in_clust	-1.265	0.891**			-1.450**	-0.0661		
	(-1.50)	(2.09)			(-2.00)	(-0.11)		
7-9_in_clust	3.004**	3.682***			-1.057*	1.162**		
	(2.49)	(4.47)			(-1.68)	(2.01)		
night_in_degree	-0.0150	0.0289***			-0.0144	0.00935		
	(-0.85)	(2.74)			(-0.80)	(0.82)		
7-9_in_degree	0.00135	-0.00831***			-0.00813**	-0.00181		
	(0.24)	(-2.81)			(-2.25)	(-0.74)		
night_in_tot_paym_log	-0.00124	-0.0206			-0.158*	0.000914		
	(-0.02)	(-0.65)			(-1.66)	(0.03)		
7-9_in_tot_paym_log	-0.0678	0.0895			0.492***	0.199**		
	(-0.33)	(1.02)			(3.81)	(2.11)		
aft_Bon_Centrality			0.241	0.0765			0.245	0.113
			(0.89)	(0.52)			(1.05)	(1.50)
morn_Bon_Centrality			-0.222	0.110			0.293	-0.0395
			(-0.58)	(0.61)			(0.85)	(-0.53)
aft_in_clust			-4.822	0.278			-0.577	-1.372
			(-1.30)	(0.12)			(-0.22)	(-0.58)
morn_in_clust			6.923*	5.312**			0.592	2.953
			(1.81)	(2.23)			(0.22)	(1.24)
aft_in_degree			-0.00368	-0.0486**			-0.0222	-0.0376*
			(-0.12)	(-2.41)			(-1.08)	(-1.87)
morn_in_degree			0.00443	0.0529**			0.0160	0.0399*
			(0.12)	(2.46)			(0.75)	(1.87)
aft_in_tot_pay			0.449	0.190			-0.461	0.394
			(0.58)	(0.53)			(-1.17)	(1.20)
morn_in_tot_pay			-0.588	-0.112			0.680*	-0.199
			(-0.76)	(-0.31)			(1.86)	(-0.60)
Constant	2.379	-4.362**	3.896	-5.849***	-3.717	-5.967***	-1.999	-6.392***
	(0.67)	(-2.17)	(1.11)	(-2.90)	(-1.52)	(-2.97)	(-0.67)	(-3.02)
Observations	210	210	210	210	210	210	210	210

Table 4.A.3: Regressions of banks' α value on network characteristics of the banks. T statistics are in parentheses. *, **, *** denote significance at 10%, 5% and 1% respectively.

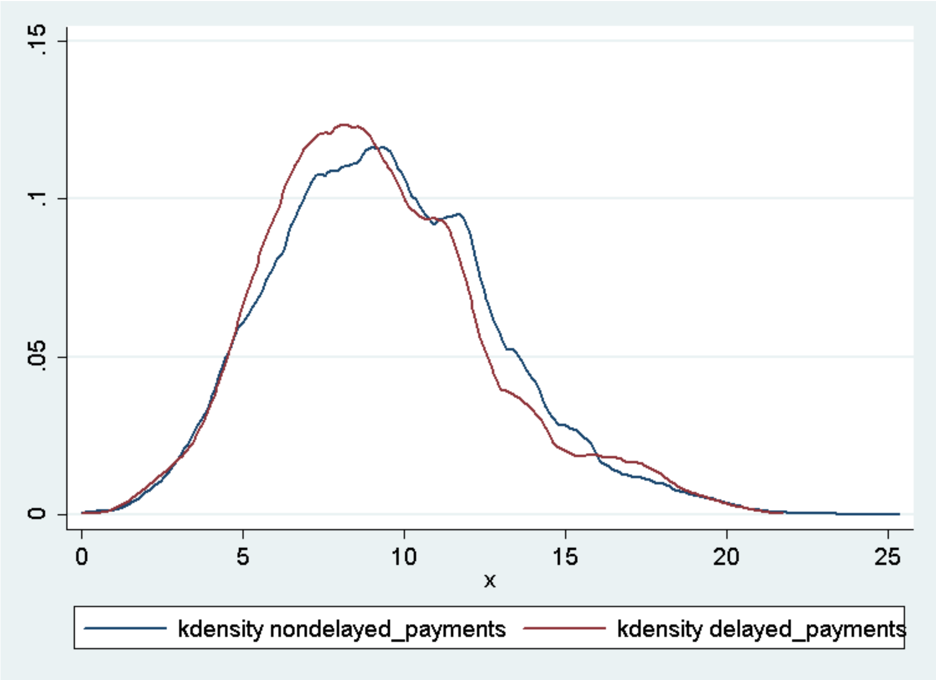


Figure 4.A.1: Calm day: Distributions of values of delayed and non-delayed payments

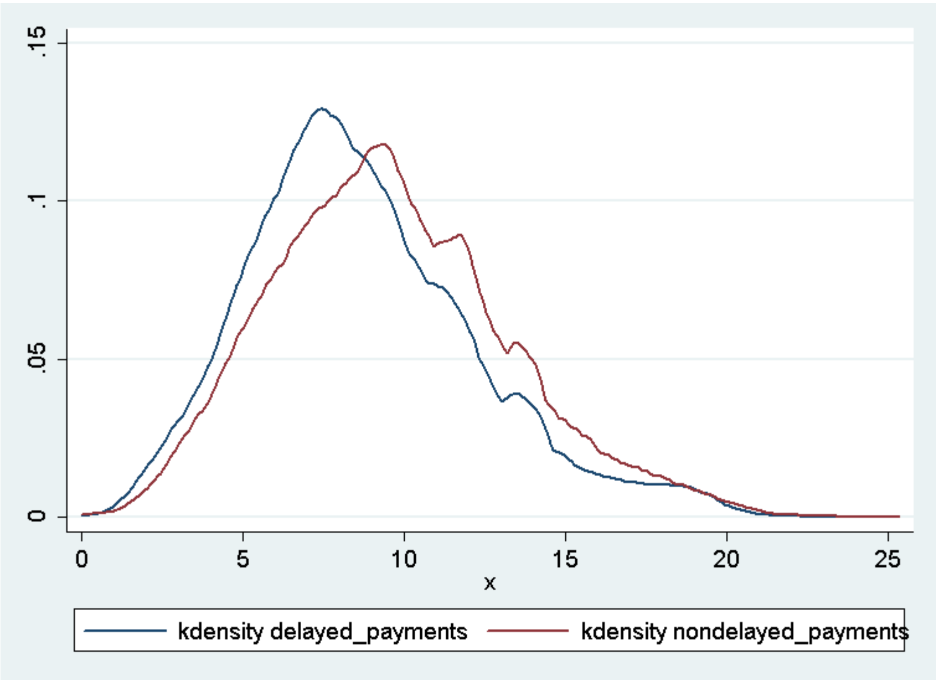


Figure 4.A.2: Stress day: Distributions of values of delayed and non-delayed payments

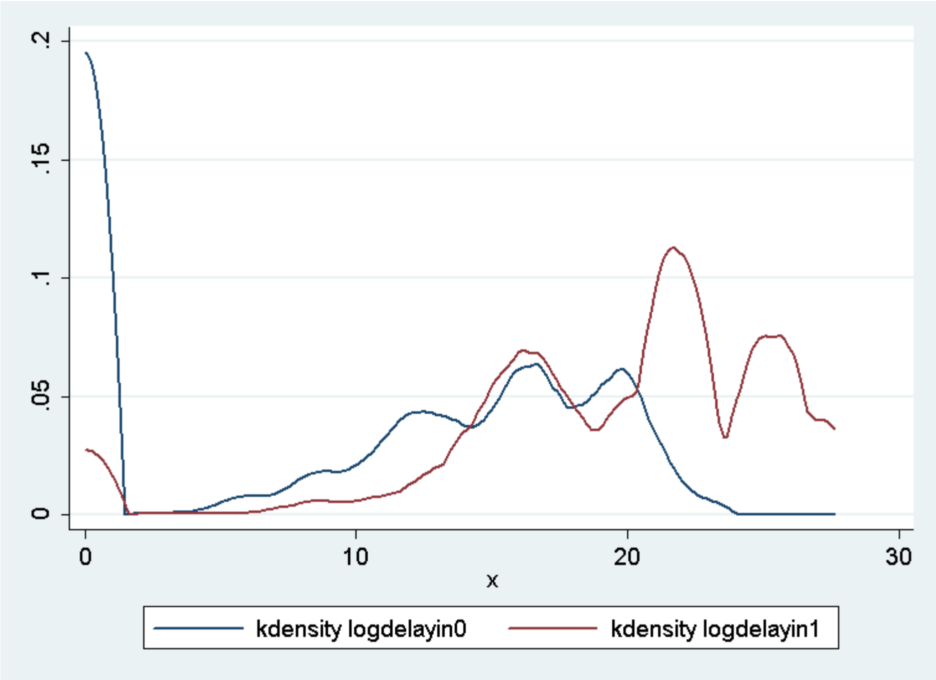


Figure 4.A.3: Calm day: Distributions of values of delayed payments that cause and do not cause subsequent delays

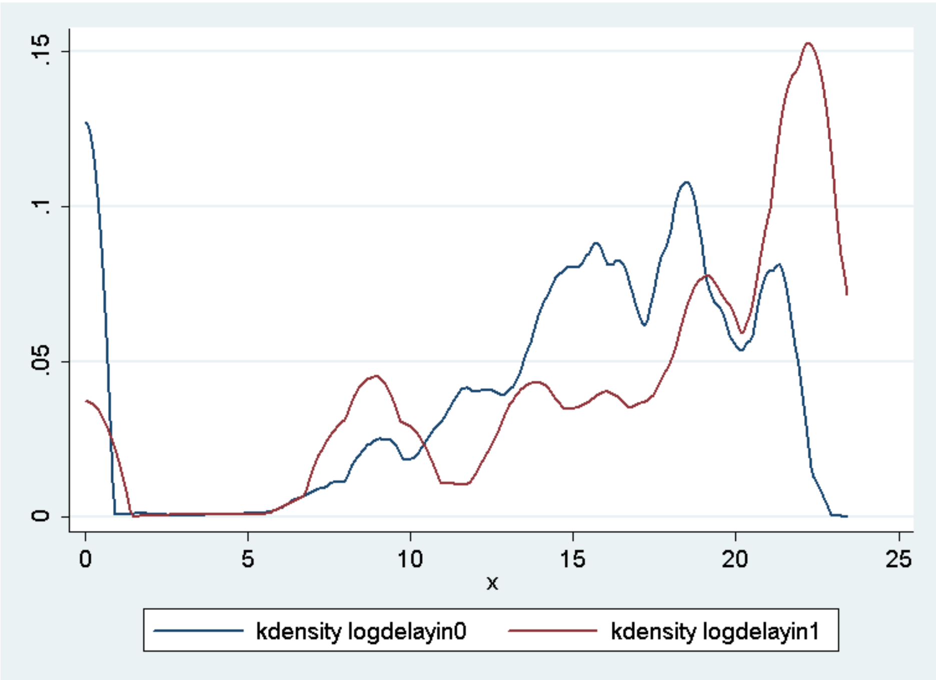


Figure 4.A.4: Stress day: Distributions of values of delayed payments that cause and do not cause subsequent delays

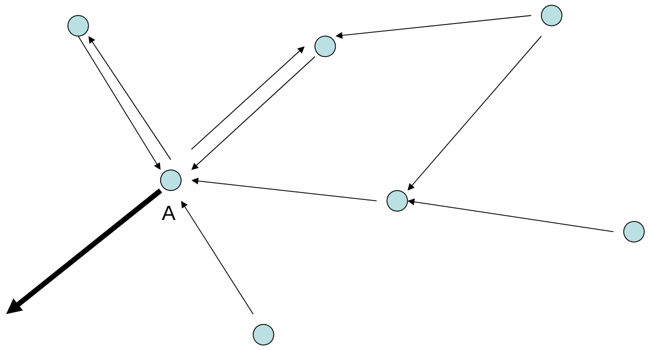


Figure 4.A.5: We are interested in measuring the probability of a delay from node **A**, given that node **A** is making a payment. All delays are marked with arrows.

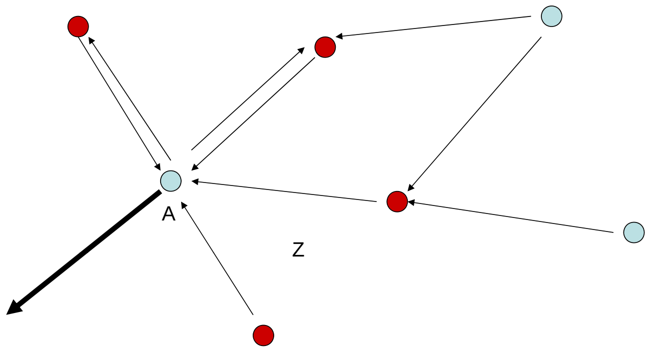


Figure 4.A.6: The amount of delays coming in, marked by the sum of the arrows from the red nodes to node **A** are the delays that may be propagated by **A**'s behavior. If all is exogenous, then the instruments would be the same set of arrows.

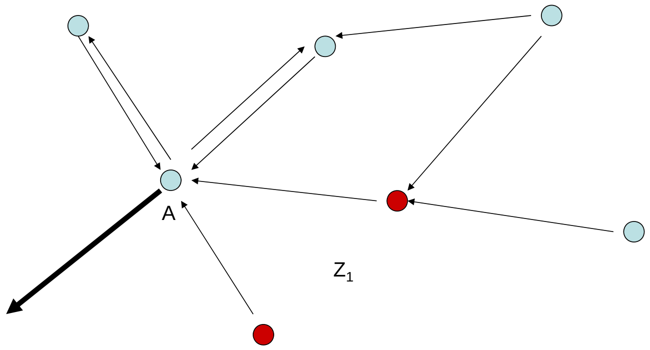


Figure 4.A.7: The set of instruments Z_1 are represented by the sum of the arrows going in from the red nodes that do not have a direct reflecting arrow coming back from node **A**.

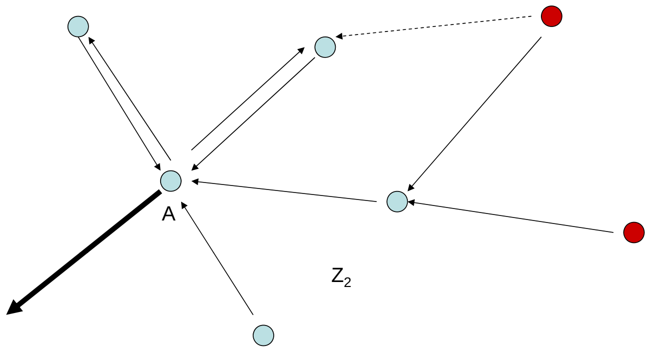


Figure 4.A.8: Analogous to Blume et al. (2010), we use instruments Z_2, which are at least one link removed from **A**. In order to remove the local reflecting, the instruments do not include those vectors that go through a self reflecting node, so the dotted vector is excluded.

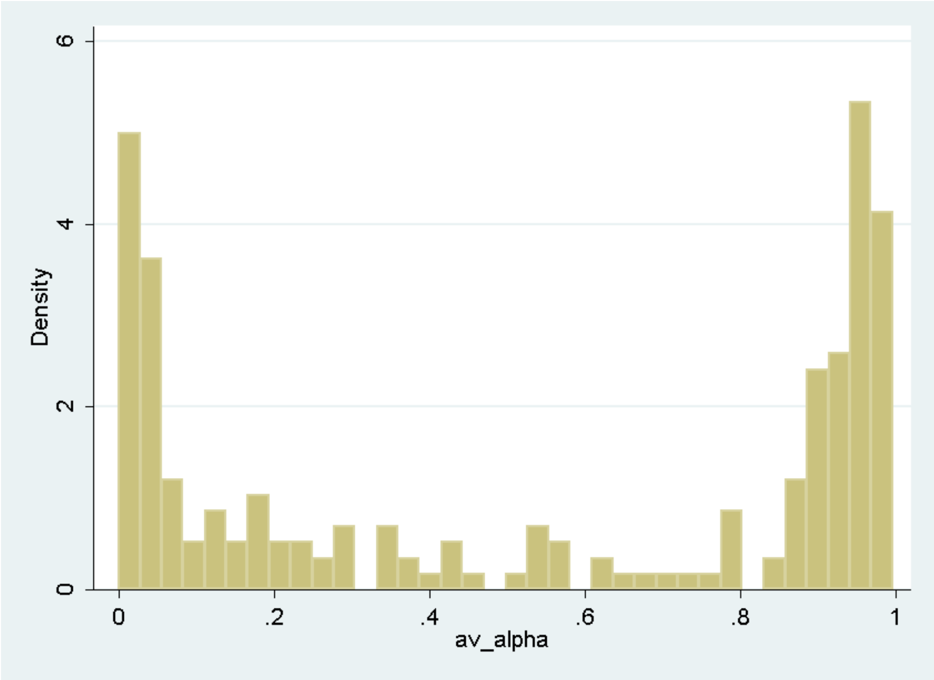


Figure 4.A.9: Distribution of alpha values for banks: alpha is an average daily value over September 2008

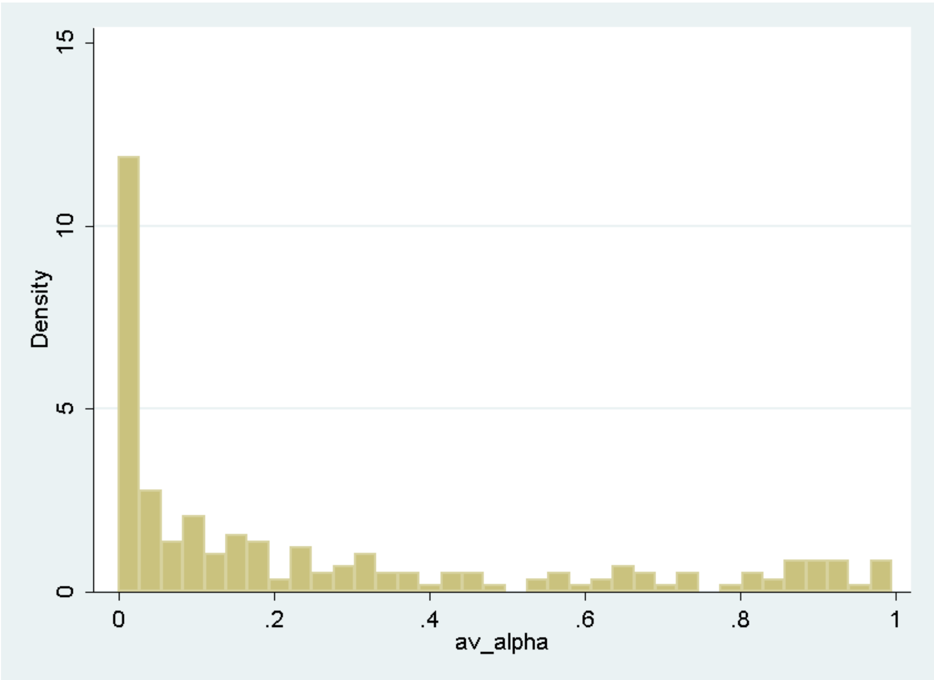


Figure 4.A.10: Distribution of alpha values for banks: alpha is an average daily value over May 2014

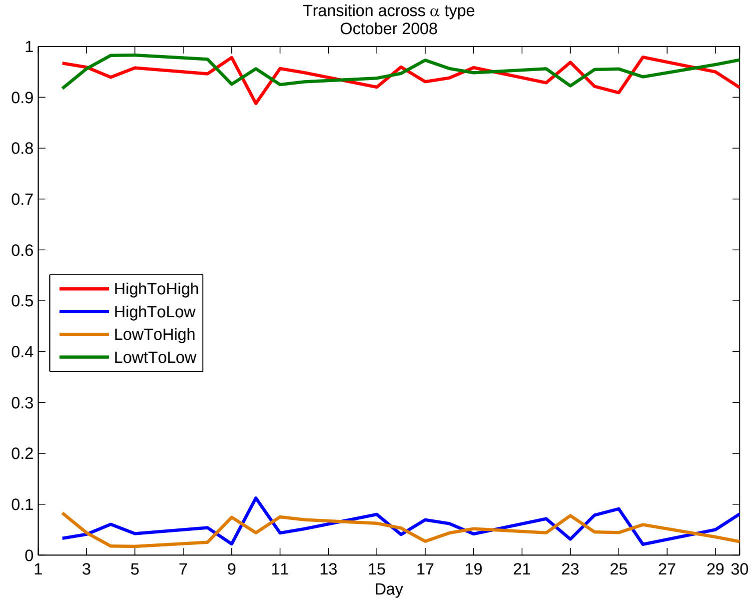


Figure 4.A.11: Transition probabilities across *alpha* status

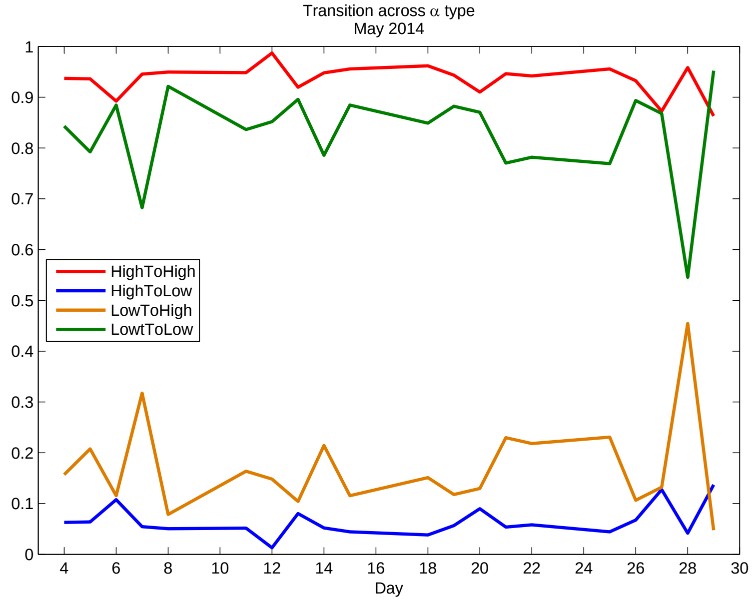


Figure 4.A.12: Transition probabilities across *alpha* status

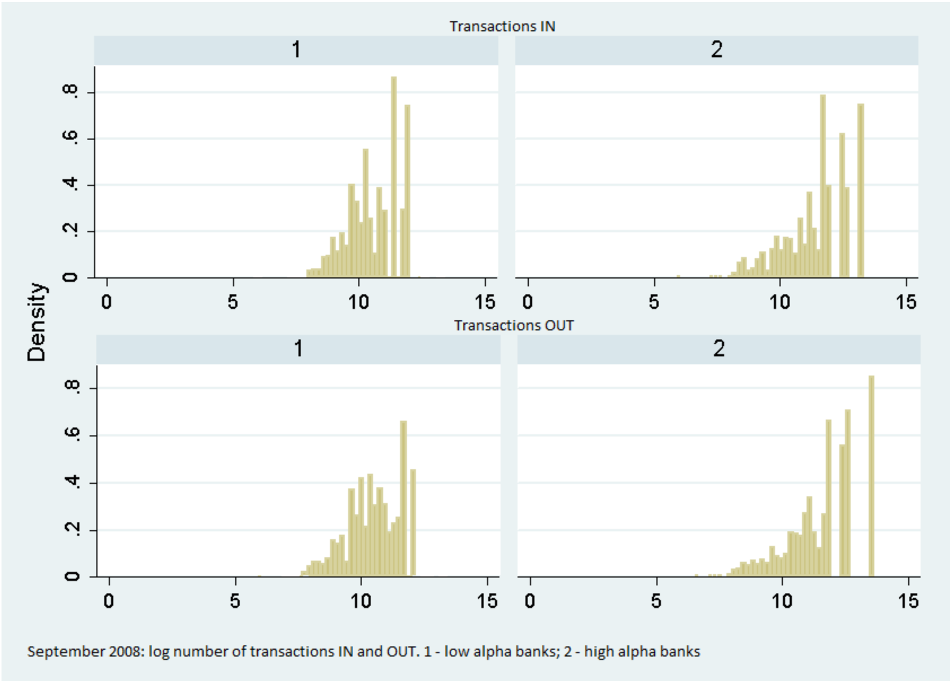


Figure 4.A.13: Log number of IN and OUT transactions by two types of banks in September 2008

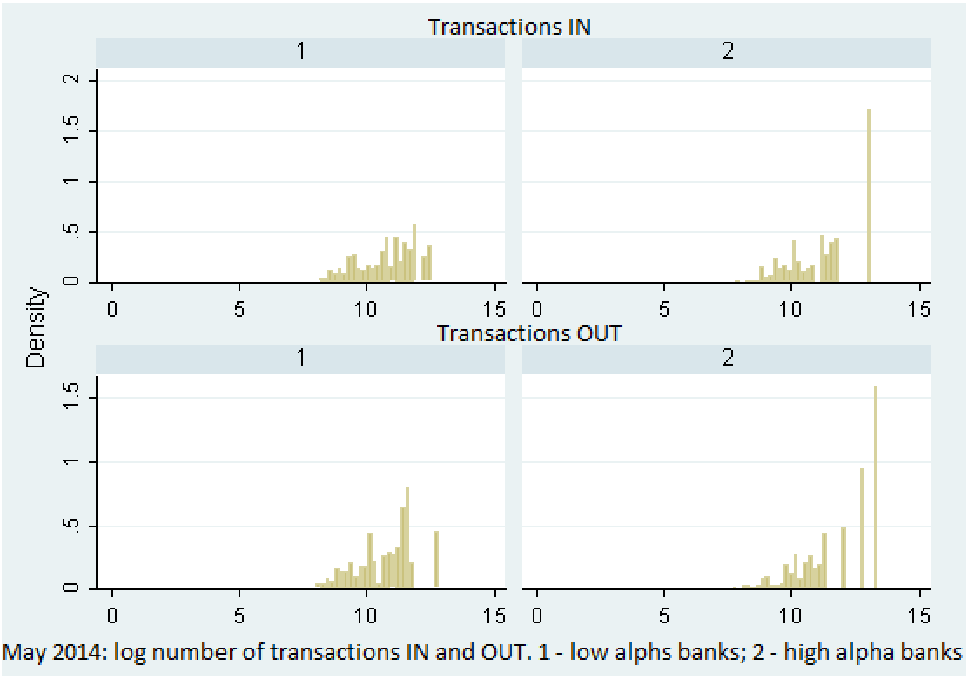


Figure 4.A.14: Log number of IN and OUT transactions by two types of banks in May 2014

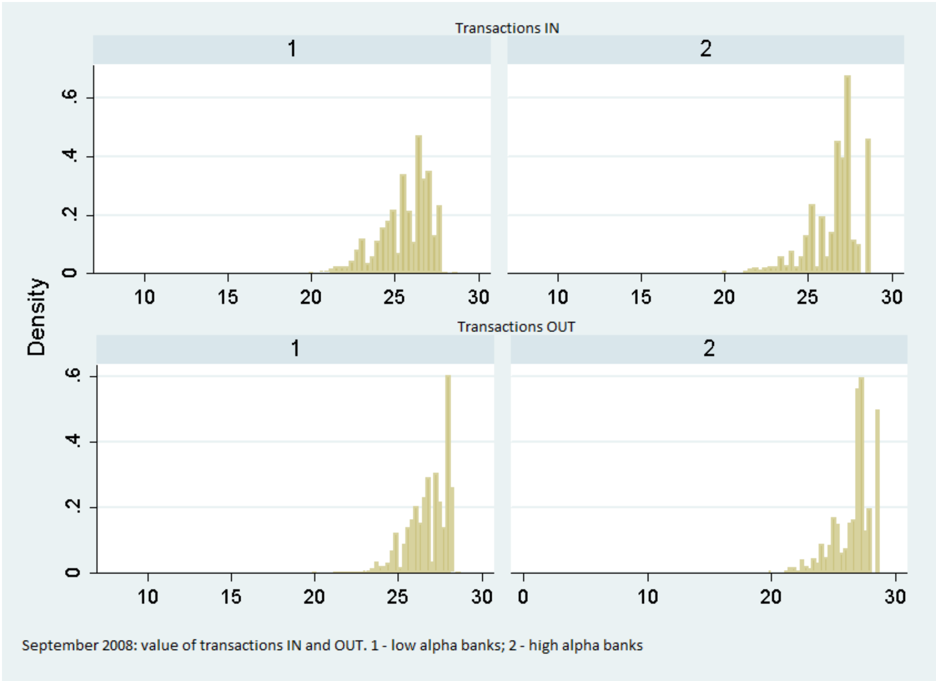


Figure 4.A.15: Log value of IN and OUT transactions by two types of banks in September 2008

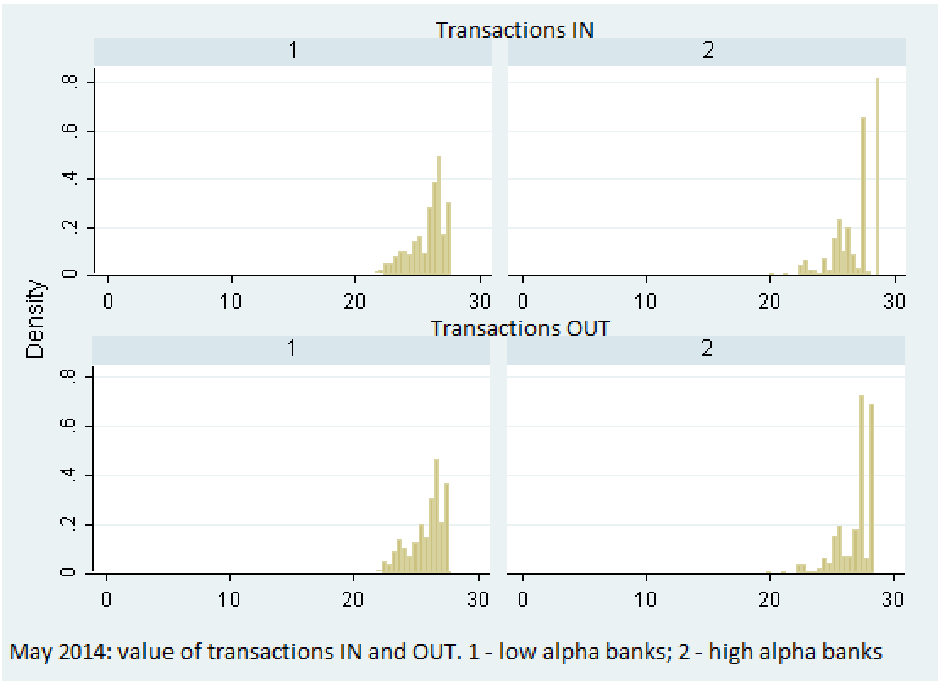


Figure 4.A.16: Log value of IN and OUT transactions by two types of banks in May 2014

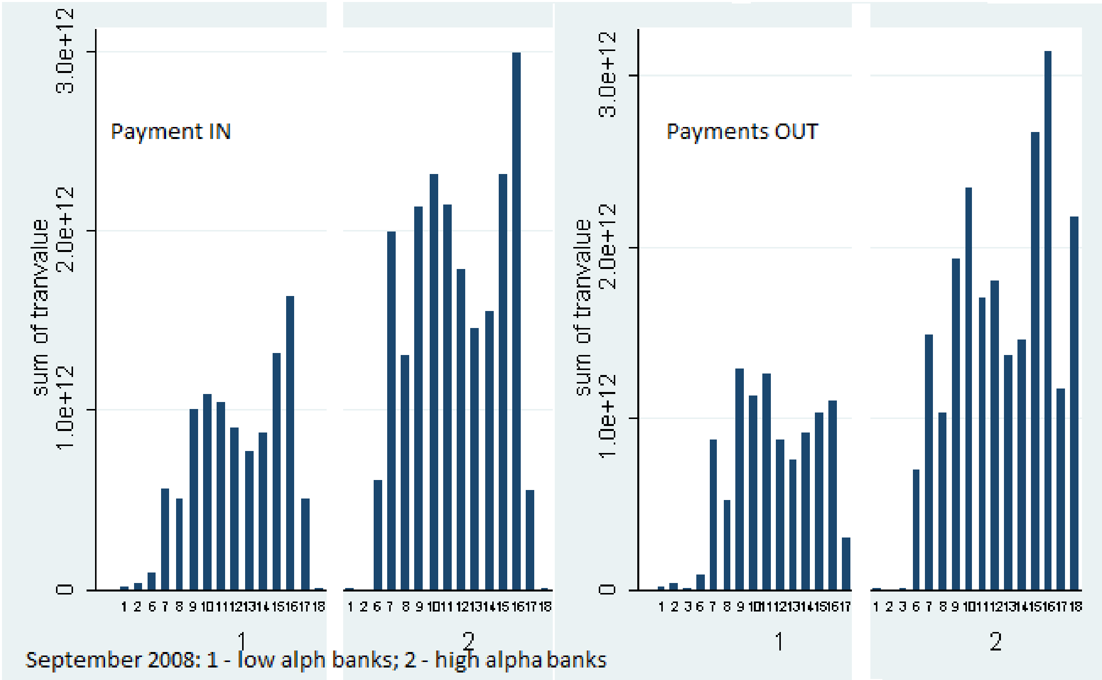


Figure 4.A.17: Value of IN and OUT payments by two types of banks throughout the day in September 2008

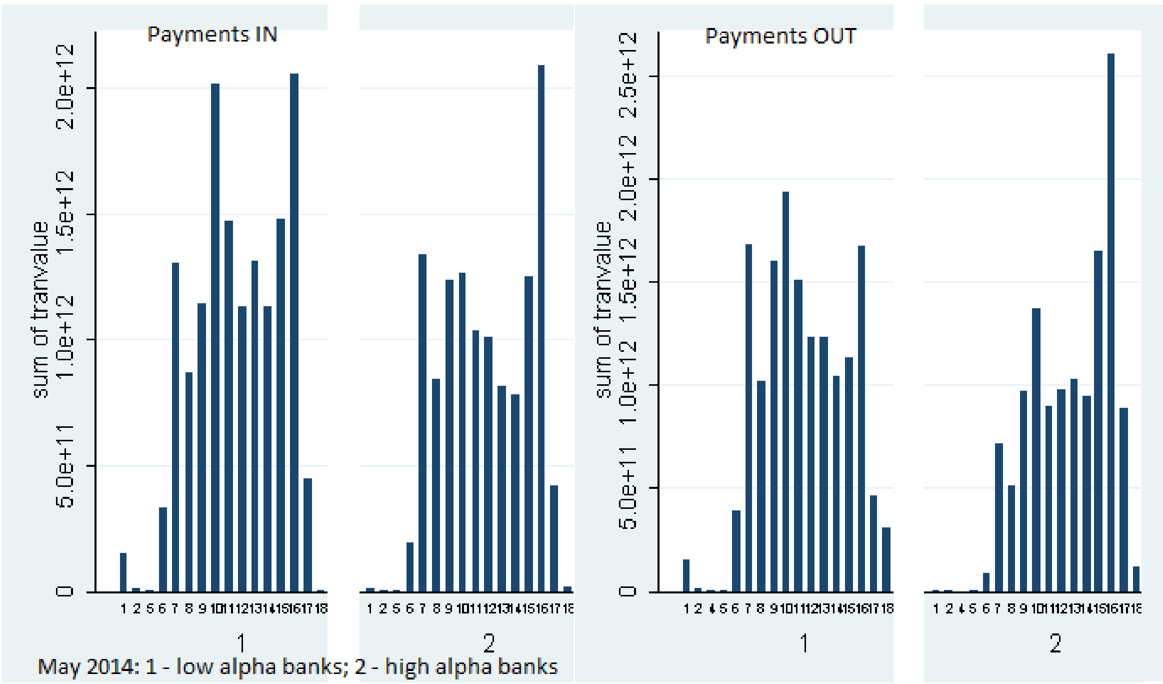


Figure 4.A.18: Value of IN and OUT payments by two types of banks throughout the day in May 2014

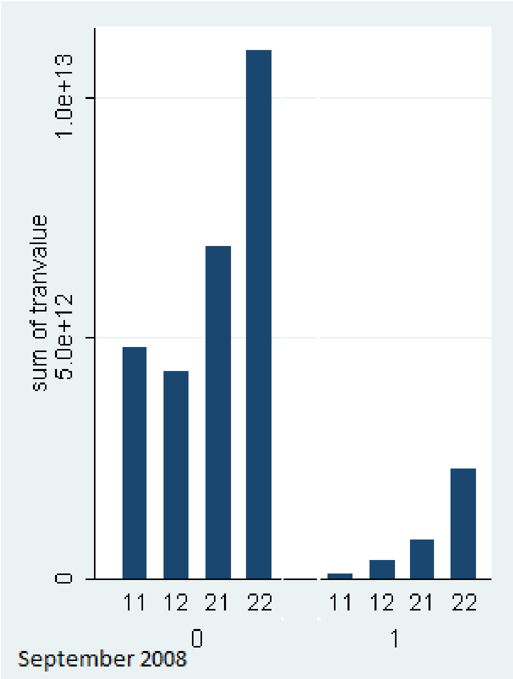


Figure 4.A.19: Total value of transacted (0) and delayed (1) payments in September 2008 by transaction category: 11 - from low to low alpha banks; 12 - from low to high; 21 - from high to low; 22 - from high to high

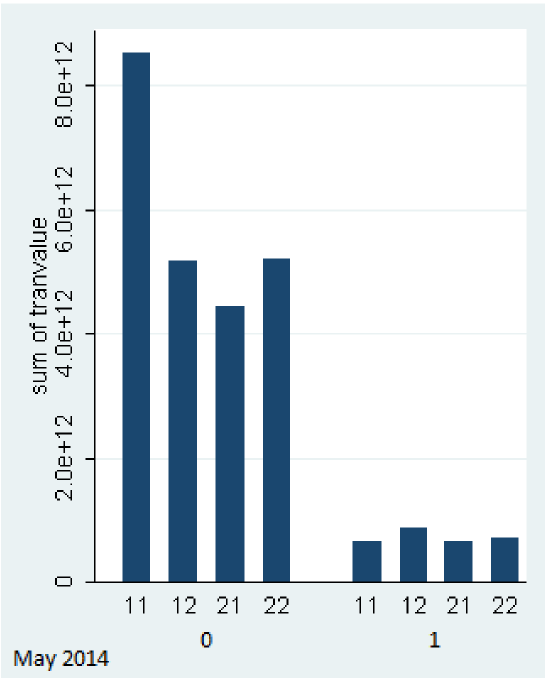


Figure 4.A.20: Total value of transacted (0) and delayed (1) payments in May 2014 by transaction category: 11 - from low to low alpha banks; 12 - from low to high; 21 - from high to low; 22 - from high to high

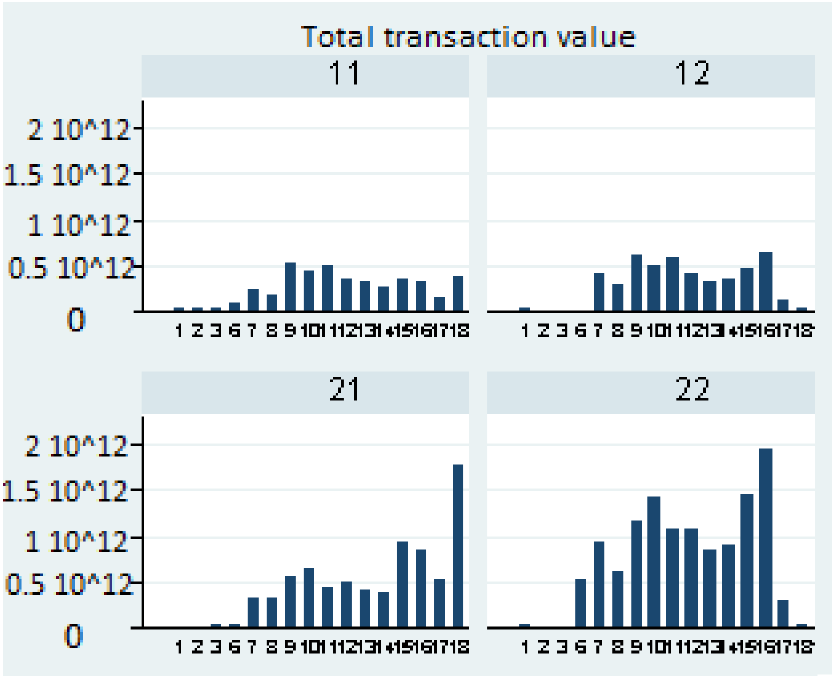


Figure 4.A.21: Total transaction value of payments by category throughout the day in May 2014 (hourly averages): 11 - from low to low alpha banks; 12 - from low to high; 21 - from high to high; 22 - from high to high

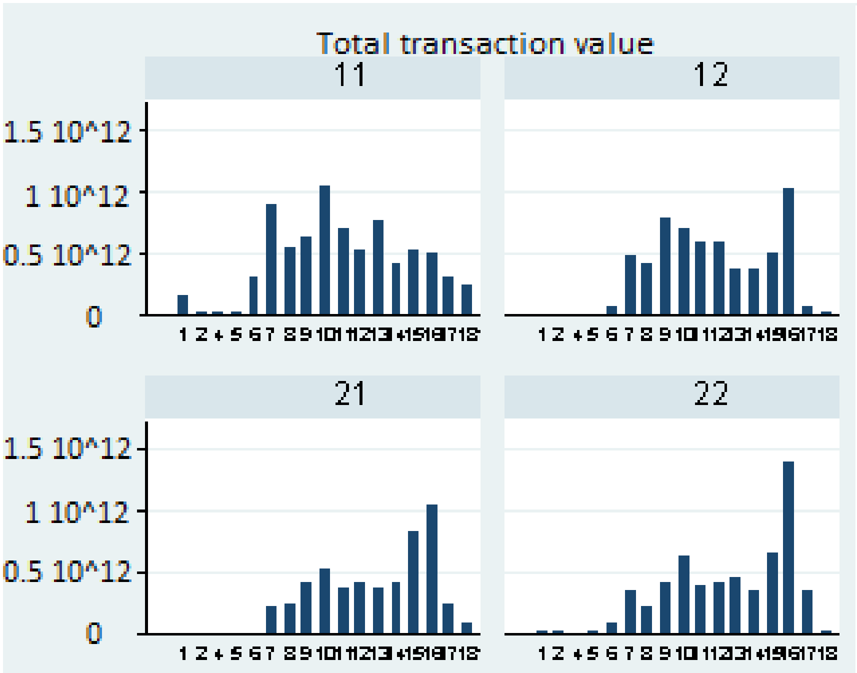


Figure 4.A.22: Total transaction value of payments by category throughout the day in September 2008 (hourly averages): 11 - from low to low alpha banks; 12 - from low to high; 21 - from high to high; 22 - from high to high

Conclusion

La crise financière de 2007-2009 a révélé la fragilité du système financier mondial, en mettant en avant le rôle du maillage financier dans l'amplification et la propagation des chocs. Elle a surtout rappelé la capacité, quelque peu négligée, d'un rationnement de la liquidité bancaire à déstabiliser l'ensemble du système financier. Dans cette thèse, nous nous intéressons à la structure en réseau du système financier mondial, à la problématique d'un asséchement de ces marchés financiers et aux effets de contagion qui s'en suivent comme source d'instabilité du système.

Après une revue de la littérature appuyant la nécessité de la prise en compte de la dimension réseau du système financier, les chapitres 2 et 3 analysent l'ampleur des effets de contagion dans, respectivement, les réseaux bancaires français et européens, et ce, selon deux canaux de transmission, en l'occurrence les défauts de solvabilité et la thésaurisation de la liquidité.

Le chapitre 2 contribue plus particulièrement à la littérature sur les *stress-tests* en proposant notamment un modèle qui étend le cadre standard de propagation des chocs, généralement limité à la seule considération de la solvabilité, en incorporant la propension constatée des agents à conserver leur liquidité, provoquant des contraintes de refinancements chez leurs contreparties. Le modèle génère également des chocs de marchés issus de données détaillées relatives à la situation du marché financier français au 31 décembre 2011. Il documente ainsi, et pour la première fois dans la littérature, les principales caractéristiques du réseau financier français: une forte densité du réseau représenté par 11 holdings bancaires dont les 5 plus importantes concentrent plus de 80% du total des actifs bancaires, représentant un réseau quasi-complet. Le résultat central de ce chapitre est de démontrer que le canal de la liquidité est à lui seul capable de provoquer des faillites bancaires sans qu'il n'y ait pour autant de contagion de solvabilité. Un résultat qui reproduit parfaitement le scénario de la dernière crise financière. Ce chapitre soutient donc la nécessité d'inclure le canal de la liquidité en plus du canal habituel de la solvabilité. Par ailleurs, le système, tel qu'il a été simulé, paraît particulièrement résilient face aux chocs de marché. Ce résultat est néanmoins à relativiser dans la mesure où, à la date du 31 décembre 2011, le système financier français avait déjà été bien recapitalisé mais aussi du fait que le système bancaire français est largement ouvert à l'international et plus particulièrement à l'Europe, impliquant un degré d'exposition domestique relativement faible.

Une extension possible de ce chapitre concernerait l'élargissement du réseau bancaire étudié à l'ensemble du système financier européen. En effet, compte-tenu du degré actuel élevé de l'intégration financière en Europe, les exercices de *stress-tests* ne peuvent plus être menés en se limitant au seul niveau national. Il est, en outre, crucial de tenir compte des expositions transfrontalières des institutions financières et d'étudier le phénomène de la propagation des chocs en y incluant la dimension temporelle pour analyser sa dynamique.

Le troisième chapitre s'inscrit ainsi dans la continuité du chapitre précédent en étendant l'analyse à l'ensemble du réseau bancaire européen sur la période 2008-2012. Certaines études se sont déjà intéressées à la question des expositions transfrontalières mais se sont vite confrontées à la problématique de la disponibilité des données. En effet, comme indiqué dans le section 1.5 sur les *stress-tests*, l'ensemble des articles sur la contagion financière internationale utilisent les statistiques interbancaires de la BRI qui ne comportent que les engagements agrégés d'un système financier national vis-à-vis d'un autre, faisant ainsi abstraction des hétérogénéités au sein d'un même système. Une telle approche réduit de fait la pertinence de l'analyse des effets de contagion comme elle contraint, pour la simulation des chocs, la prise en compte de l'hypothèse peu probable d'un défaut de l'ensemble du système financier.

Notre approche se base sur les données issues de la base TARGET2 du système européen de paiement et nous utilisons l'algorithme développé par Halaj and Kok (2013) pour la détermination des expositions interbancaires au niveau individuel. Nous établissons ainsi une carte de probabilité, qui se présente sous la forme d'une matrice de degré d'intensité des expositions interbancaires, que nous exploitons pour simuler divers réseaux réalistes à la Halaj and Kok (2013). Contrairement aux réseaux modélisés dans la littérature, notre modèle reproduit bien les caractéristiques conventionnelles des réseaux réels, à savoir des lois de puissance de distributions des degrés des noeuds, une basse densité du réseau et un faible degré de séparation entre deux sommets.

Nous réalisons plusieurs exercices de stress-tests sur 73 groupes bancaires européens rassemblés dans 100 réseaux simulés différents sur la base de leurs situations financières à la fin de chaque année, de 2008 à 2012. Cette approche nous permet de dresser une distribution des différents réseaux potentiels plutôt que de se fier à une représentation du réseau à une date particulière.

Les résultats de nos simulations soulignent le caractère crucial de la structure du réseau dont dépend fortement le niveau des pertes. Ces dernières dépendent, de plus, du poids des banques choquées initialement. Ainsi, certaines banques se sont avérées être plus systémiques que d'autres. Par ailleurs, le degré de résilience des réseaux est apprécié aussi bien par le niveau des pertes que par leur distribution. En se basant sur ces deux critères, nous montrons que la résilience du système financier européen s'améliore significativement avec, certes, des niveaux élevés de capitaux et de trésorerie mais également avec un degré d'exposition des banques réduit, les expositions transfrontalières étant par ailleurs plus critiques que les expositions nationales.

Une extension de cette analyse serait d'exploiter la multitude des réseaux simulés pour mener une étude économétrique afin d'identifier les déterminants à l'origine de la vulnérabilité des réseaux face aux effets de la contagion. Une autre approche intéressante, bien qu'elle s'écarte de celle des *stress-tests*, est d'évaluer les effets de contagion dans un cadre dynamique pour une meilleure appréhension de la stabilité des systèmes. Cela permettra en l'occurrence de savoir comment évolue le comportement des agents à la suite d'un défaut d'une banque du réseau.

Le dernier chapitre s'intéresse à ce titre à l'analyse de la propension des banques à augmenter les délais de paiement en comparant, notamment, leurs comportements en période d'accalmie financière à une période sous tension. Nous mobilisons pour cela des données issues, là-encore, de TARGET2 portant sur le mois de septembre 2008 et de mai 2014. Nous montrons que, contrairement à ce que suggèrent les articles basés sur la théorie des jeux, la décision de retarder un paiement n'est pas afférente à chaque transaction. Les retards de paiement résultent en effet du processus de gestion de la liquidité adoptée par les banques. Nous distinguons ainsi deux principaux types de comportements et donc aussi de banques : un premier groupe qui, à chaque début de journée, engage un niveau initial de liquidité suffisant pour répondre à ces engagements journaliers, et un deuxième groupe de banques qui gère sa liquidité en quasi flux-tendus. Ce dernier étant à l'origine de la majorité des retards de paiements enregistrés aussi bien en période d'accalmie qu'en période de crise. Bien qu'étant inapproprié, ce comportement consistant à retarder les paiements n'est pas nécessairement dangereux quand le marché est suffisamment liquide. En revanche, il est susceptible de provoquer un grippage de l'ensemble du système de paiement en cas de manque de liquidité. Un développement futur de ce chapitre serait de construire un indicateur qui permettrait d'approximer le moment ou les retards de paiement acquièrent une dimension systémique. En outre, ce travail ouvre également le champ à plusieurs extensions possibles telles que l'identification de déterminants des comportements des banques en se basant éventuellement sur les données de bilan, les rendements des actions ou encore d'autres caractéristiques de leur activité afin de mieux identifier les banques profitant de ce mode de gestion de la liquidité et d'analyser leur aptitude à créer des distorsions au niveau de la compétitivité sur le marché interbancaire. La nature systémique du risque induit par ce type de comportement pose la question de l'attitude du régulateur à adopter afin d'éviter un tel scénario: faudrait-il pénaliser les retards des paiements au risque de pénaliser les transactions dans leur ensemble? Ou vaudrait-il mieux imposer un certain niveau plancher de la liquidité initiale? Dans ce dernier cas, nous envisageons comme prochaine extension de notre travail la détermination du niveau optimal de cette liquidité initiale, tenant notamment compte du nombre et des volumes des transactions.

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