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How to Measure Interconnectedness between Banks, Insurers and Financial Conglomerates?

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Keywords: Interconnectedness; Insurers; Conglomerate; Systemic Risk.
JEL: G22, G28.

Comment mesurer l'interconnectivité entre banques, assurances et conglomérats financiers ?

Résumé

L'interconnectivité des institutions financières est considérée comme une composante fondamentale du risque systémique. Néanmoins, aucun consensus sur la manière de la mesurer n'a émergé. En analysant une base de données unique d'expositions entre 21 institutions financières français, nous comparons trois stratégies de mesure : la ressemblance des distributions des expositions, l'identification d'une structure cœur-périphérie et les modèles de contagion. La ressemblance des distributions des expositions est un outil adapté à la détection de comportements atypiques. La structure "cœur-périphérie" qui est habituellement utilisée pour analyser les réseaux bancaires, s'applique aussi lorsque le réseau comporte des assureurs. Cependant, cette structure n'est pas adaptée quand les liens sont normalisés par les fonds propres, dans une optique de gestion des risques. Ce résultat met en perspective les analyses précédentes où les expositions n'étaient pas normalisées. Les méthodes fondées sur les stress-tests de contagion sont les mieux adaptées à l'identification des institutions systémiquement fragiles. Ces techniques constituent donc un outil indispensable à la supervision. Enfin, en s'appuyant sur l'évaluation de ces techniques de mesure, nous analysons le rôle pivot des conglomérats financiers présents à la fois dans les secteurs bancaire et assurantiel.

Mots clés: interconnexions, assureurs, conglomérats, risque systémique.
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L'interconnectivité des institutions financières est considérée comme une composante fondamentale du risque systémique. Néanmoins, aucun consensus sur la manière de la mesurer n'a emergé. En analysant une base de données unique d'expositions entre 21 institutions financières français, nous comparons trois stratégies de mesure : la ressemblance des distributions des expositions, l'identification d'une structure cœur-périphérie et les modèles de contagion. La ressemblance des distributions des expositions est un outil adapté à la détection de comportements atypiques. La structure "cœur-périphérie" qui est habituellement utilisée pour analyser les réseaux bancaires, s'applique aussi lorsque le réseau comporte des assureurs. Cependant, cette structure n'est pas adaptée quand les liens sont normalisés par les fonds propres, dans une optique de gestion des risques. Ce résultat met en perspective les analyses précédentes où les expositions n'étaient pas normalisées. Les méthodes fondées sur les stress-tests de contagion sont les mieux adaptées à l'identification des institutions systémiquement fragiles. Ces techniques consituent donc un outil indispensable à la supervision. Enfin, en s'appuyant sur l'évaluation de ces techniques de mesure, nous analysons le rôle pivot des conglomérats financiers présents à la fois dans les secteurs bancaire et assurantiel.

Mots-clefs: interconnexions, assureurs, conglomérats, risque systémique.
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1 Introduction

The danger stemming from interconnections between financial institutions has been highlighted during the last financial crisis with the defaults of AIG, Lehman-Brothers or Bear Stearns... Interconnectedness between financial institutions has nowadays become a major concern for supervisors and regulatory authorities. With the support of the G-20, Financial Stability Board FSB (2009) propose a general framework to identify Systematically Important Financial Institutions (SIFIs). The three key criteria are size (the volume of financial services provided by the individual component of the financial system), substitutability (the extent to which other components of the system can provide the same services in the event of a failure) and interconnectedness (i.e. linkages with other components of the system). These three criteria cannot be assessed separately for each institution. They require a system-wide analysis.

This general framework to identify SIFIs has been specified separately for banks and for insurance companies. For Global Systematically Important Banks (G-SIBs), the Basel Committee [see BCBS (2013a)] uses a score based on the average of 5 indicators: cross-jurisdictional activity (20%), size (20%), interconnectedness (20%), substitutability (20%) and complexity (20%). Considering interconnectedness is motivated by the fact that "financial distress of one institution can materially increase the likelihood of distress at other institutions given the network of contractual obligations in which these firms operate". For Global Systematically Important Insurers (G-SIIs), the International Association of Insurance Supervisors [see IAIS (2013)] uses 5 indicators that are size (5%), global activity (5%), interconnectedness (40%), non-traditional and non-insurance activity (45%), substitutability (5%). For G-SIBs, the regulation of interconnectedness is currently under debate. Basel Committe [see BCBS (2013b)] proposes to have a more severe limit for interbank exposures between G-SIBs. Moreover Qualifying a financial institution as SIFI may lead to requirements in terms of "Higher Loss Absorption" (HLA), i. e. to an increase in minimum capital.

The identification of SIFIs puts a premium on interconnectedness and has significant practical implications. The challenge is to propose indicators of interconnectedness, or summary statistics of the degree of interconnection, which are linked to contagion risk.

The objective of our paper is to understand and to assess the impact of interconnections between financial institutions. The many interpretations of interconnectedness have led to different measurement methods. We analyze their similarities and discrepancies in order to identify what each method really measures. The presence of financial conglomerates[1] in France provides us an interesting case of where the banking sector

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[1] For clarity, we adopt the continental European vocabulary, contrasting with the Anglo-Saxon practice. From an Anglo-Saxon point of view, a conglomerate, sometimes called "universal bank", is a bank combining pure banking activity (collecting deposit and granting loans) and securities activities (investment). In this paper, we do not distinguish commercial banking activity from securities activities. We distinguish banking activity that encompasses commercial banking activity and securities activities from insurance activities. Therefore, a conglomerate is a group with banking and insurance activities. European Directive 2002/87/EC defines the supervisory features concerning financial conglomerates.

and the insurance sector are interconnected.

Our paper has three main contributions. First, we document interconnections between different financial institutions (banks, insurance companies and financial conglomerates) using a unique database on bilateral exposures across 21 French financial institutions, and review several strategies to measure interconnectedness. In addition,we propose simple statistical methods to disentangle two features of interconnectedness that are the substitutability (*i.e.* the similarity of lending relationship) and the integration (*i.e.* the degree of involvement in the network), respectively. Second, we show that the core-periphery structure is still valid when considering insurers in top of banks. However, this specific structure only applies for volume analysis and thus appears as inadequate from a risk perspective. Last, we focus on financial conglomerates providing quantitative assessment of their potential impact on the contagion risk between the insurance sector and the banking sector.

The paper is organized as follows. Section 2 reviews the literature on interconnections between financial institutions and on the analysis of financial conglomerates. Section 3 describes the database. In Section 4, we introduce and apply two closeness measures of exposures distributions that we call network-substitutability and network-integration measures. Section 5 provides a critical application of the core-periphery structure identification. In Section 6, contagion risk is assessed by a network stress-test. Section 7 suggests few policy implications discussing the adequacy of methods to policy concerns. Section 8 focuses on financial conglomerates that most methods point out at a clear specific group. Section 9 concludes.

2 Literature Review

In this section, we review first theoretical literature on the potential motive for interconnections between banks and insurers. This literature provides us conceptual framework to interpret our empirical findings. Second, we report main results from empirical analysis of interconnections. Most paper considering bilateral exposure database consider only banks, whereas our database includes also financial conglomerates and insurers.

2.1 Theoretical insights on interconnections

Basic economics suggest different interconnection profiles for banks and insurance companies. On the one hand, the core activity of banking is maturity transformation and screening. The maturity transformation mechanism leads banks to borrow partly from other financial institutions and to invest in (typically) non-financial institutions. On the other hand, insurance companies –either life or non-life– are expected to lend to other financial institutions since their liabilities are composed of commitments to the policyholders. They invest the proceeds of the policyholder's premium, notably in financial institutions.

Several motives have been put forward by the literature to explain interconnections between financial institutions leading to different forms of exposures, either on- or off-balance sheet. Let us review few of them.

i) Liquidity. In a short-term perspective, interconnections mirror the resolution of the liquidity needs. One solution to this asynchronism of in-flows and out-flows is that every institution keeps its own cash buffer. This individual solution leads to a very large overall cash buffer: at any time each institution holds cash whereas only few cash buffers are used. Another solution is cooperation which holds in normal times (as opposed to "crisis time"): when liquidity shocks do not impact simultaneously all the institutions, a liquidity pool is a sound tool [Holmstrom and Tirole (1998), Rochet (2004), Tirole (2010)]. Liquidity pools enable institutions to form a mutual insurance system for liquidity risk. Each institution slightly contributes to a common cash reserve that is used to cover the needs for liquidity. When liquidity shocks are small and homogenously distributed, the contributions in cash are smaller than the individual cash buffers. This mechanism has been developed in corporate finance. It has been applied to financial networks by Allen and Gale (2000), who analyze optimal network structure according to the characteristics of liquidity shocks. More recently, Acemoglu et al. (2013) extend this approach to the renegotiation of loans.

ii) Horizontal integration. Industrial organization theory points to horizontal integration since banks and insurance companies share the same customers (households and firms). Horizontal integration can be illustrated by the case of a household looking for a home. The household contracts a credit loan from a bank to buy its house. In order to be hedged against unemployment or death risk, the household seeks (or is legally forced to seek) an insurance policy. Of course, the insurance contract can be closed independently from the credit loan. However, the bank and the insurance company have incentive to collaborate with sharing information and resources to have a more efficient screening and pricing process. This horizontal integration leads to revenue enhancement and cost savings [Berger and Ofek (1995), van Lelyveld and Schilder (2003)]. It is not unusual that the credit officer proposes jointly to the credit an insurance contract issued by a partner insurance company. The credit officer get a commission on all the insurance contracts he sells. Depending on the degree of (horizontal) integration, this motive can lead to mergers [Gollier and Ivaldi (2009)], to financial conglomerates or to interconnections between financial institutions from different market segments. When considering interconnections, this type of commercial relationships has no impact on the balance sheet since commissions received by the bank on the insurance policies it sells are rather flows than stocks. However, the commission scheme results in moral hazard issues. Explicit balance sheet interconnections, such as cross share holding, is one way to avoid free-riding.

iii) Vertical integration. Industrial organization also points out to vertical integration as regard risk transfers between financial institutions. Reinsurance is and securitization are another well-known risk transfer mechanism. Subramanian and Wang (2013) model the optimal strategy of an insurer to deal with its tail risks. The insurer combines self-insurance, re-insurance and securitization. The model underlines the trade-off between transferring tail risks and signaling a risky portfolio. More generally, off-balance sheet instruments (such as guarantee or credit commitment) and hedging derivatives (CDS for instance) are also a support of vertical integration. Generally speaking, risk transfer generates mostly off-balance sheet interconnections. In a particular way, the liquidity motive can be seen as a specific both-way vertical integration (whereas usual vertical integration is unidirectional).

2.2 Empirical analysis of interconnections

Data confidentiality on bilateral exposures between financial institutions makes empirical analysis sparse. Consequently, academics propose alternative approaches to assess the interconnections within the financial sector. Three major strands of literature can be identified.

First, banking supervisors propose empirical analysis of interconnection between banks using structural models to assess contagion risk between banks: Furfine (2003) for USA, Wells (2002) for the UK, Upper and Worms (2004) for Germany, Lublóy (2005) for Hungary, van van Lelyveld and Liedorp (2006) for the Netherlands, Degryse and Nguyen (2007), Toivanen (2009) for Finland, Mistrulli (2011) for Italy, Gauthier et al. (2012) for Canada, Cont et al. (2013) for Brazil, Fourel et al. (2013) for France, etc. These empirical analysis draw various stylized facts for national banking sectors. A core-periphery structure is usually identified. Banks are gathered in two distinct groups that are the core and the periphery. The core banks are fully interconnected between themselves, while peripheral banks are linked only to core banks [Craig and von Peter (2014)]. The core banks are interpreted as financial intermediaries while peripheral banks are either borrowers or lenders. Additionally, network stress-tests show little evidence of (solvency) contagion. Along these lines, Alves et al. (2013) carry out the analysis on 53 major European banks: the network tends to be more complete, contrasting somewhat with the core-periphery structure at a national level, while also contagion is limited.

Second, some authors study the impact of insurance sector on the re-insurance sector. Using aggregate data on balance-sheet of US insurers and re-insurers, Cummins and Weiss (2014) assess the potential contagious channel for different activities (core-activity, life-insurance, banking activity...). They conclude that "life insurers are vulnerable to intra-sector crises; and both life and property-casualty insurers are vulnerable to reinsurance crises". With bilateral exposures between insurers and re-insurers, Frey et al. (2013) examine the interconnectedness between French insurers and re-insurers. Contrary to the network analyses on banks that consider usually on-balance sheet items (in particular, loans), Frey et al. (2013) focus on provisions ceded between solo entities. They find preliminary results regarding the good resilience of the network but suggest additional investigations.

Third, due to the confidentiality on individual data, several research papers investigate the relationships between publicly traded equity returns. This approach gives interesting insights on the degree of interconnections between financial institutions as perceived by market participants. Of course, this network inferred from market data can differ from structural networks. One strategy is to identify simultaneous abnormal returns with contagious events underlying interconnections. Minderhoud (2003) finds "evidence of contagion for the US, Germany and the UK [and that] this result is stronger for the insurance sector than for the banking sector" by exploiting extreme stock return co-movements. Event studies for contagion between banks and insurers, such as Brewer and Jackson (2002) for US or Stringa and Monks (2007), present contrasted results. More recently, Billio et al. (2011) proposed to infer a network between financial institutions based on Granger causality test. Intuitively, there is a link from institution i to institution j when the returns of institution i have a direct impact on the returns of institution j. This approach leads the authors to analyze a time series of networks. Among other results, they show that the network structure is unstable.

Our paper clearly builds on the first field since we use similar database and structural models. However, we extend the methodology to a broader set of institutions by taking into account insurers. Our results can be put in contrast with the second and third strands.

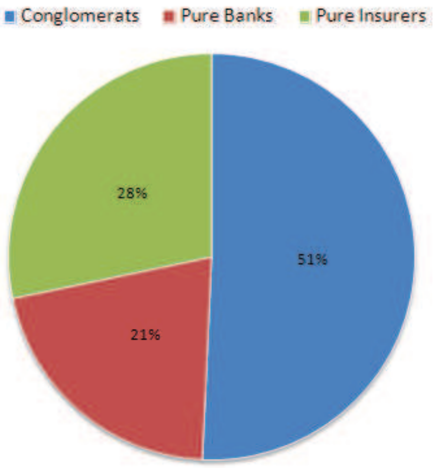
3 Data

In this section, we present the perimeter of our database: institutions, instrument, date. Through summary statistics, we characterize the distribution of links and exposures. We also provide basic analysis of the risk attached to theses exposures distinguishing a credit risk component from a funding risk component.

3.1 Perimeter

We select 21 large French financial institutions that are representative of the French financial sector. Among the 21 institutions, 6 of them (BNP, Crédit Agricole, Société Générale, BPCE, Crédit Mutuel and La Banque Postale) are financial conglomerates; 4 of them (HSBC, Crédit Logement, CRH and Oseo) are considered as pure banks and 11 of them (AG2R-La Mondiale, Aviva, Axa, Allianz, CNP, Generali, Groupama, Covea, Maif, Macif and Scor) are considered as pure insurance companies. The analysis is carried out at 12/31/2011. The selected banking/conglomerate institutions account for about 90% of the total assets of the French banking sector while the selected insurers represent about 85% of the total assets of the French insurance sector. For confidentiality restriction, financial institutions are not identified hereafter.

All institutions are considered at a fully consolidated level gathering all activities and geographical areas. Pure banks are institutions with no significant insurance activity, whereas pure insurers are institutions with no significant banking activity. Conglomerates are institutions with significant insurance activity and significant banking activity. Conglomerates represent about half of the sector in terms of total equity while pure banks and pure insurers account for a quarter each (Figure 1). The conglomer-



Source: ACPR Data.

Figure 1: Repartition of Total Equity between Conglomerates, Pure Banks and Pure Insurers. 12/31/2011

ate population presents more heterogeneity than the insurance population. Pure bank population is very heterogeneous with a key global bank and small domestic banks.

The exposure matrices are built on regulatory reports on "Large Exposures" for banks (pure banks and banking subsidiaries of conglomerates) and "TCEP" reports for insurers. On the one hand, the Large Exposures reports gather all exposures at a consolidated level larger than 300 Million Euros (or 10% of capital). Since we consider only major players in the financial sector, we are confident that the censoring has little impact. On the other hand, TCEP is exhaustive (security-by-security basis) but only exposures of French subsidiaries are reported. This censoring is more pregnant for international groups (such as Axa, Allianz, Aviva or Generali) than for domestic-centered groups. Therefore, the data we analyze underestimates exposures between financial institutions (for more details, see Appendix A).

In terms of instruments, we gather on-balance sheet exposures composed of shares securities, equity investments, loans, debt securities, etc. Off-balance sheet items are excluded as they are not available in the TCEP report for insurance. In addition off-balance sheet exposures can correspond to incompatible events (for instance, a call and a put with same strike written on the same underlying asset are not activated at the same time). Excluding off-balance sheet exposures and derivatives exposures may imply that we fail to capture approximately one third of the total exposures [see Table 1 in Alves et al. (2013)]. The exposures are on-balance sheet items gathered in two classes, according to the Value-of-the-Firm by Merton (1974). In Merton's model, two classes of stakeholders are distinguished: shareholders who are granted the net value of asset over nominal debt, and creditors who owns the debt. This partition corresponds to a risk decomposition: shareholders hold more risky assets than creditors. To mirror this decomposition, the first class is composed of all instruments corresponding to equity (shares, capital investments, etc.) while the second class is composed of all instruments corresponding to debt (debt securities, subordinated debt, borrowing, etc.). For simplicity, the first class is called "equity instruments" and the second class is called "debt instruments". When the reporting institution is an insurer, the latter class is almost only composed of debt securities, which represent a small fraction of the total debt that is mostly composed of mathematical provisions (i.e. commitments to policyholders).

Thus we build two exposure matrices, one for equity instruments and one for debt instruments, between the 21 nodes representing the financial institutions. Summing these two matrices element by element, we get a all-instrument (or total) exposure matrix.

3.2 Network plotting

Figure 2 represents the network of all-instrument exposure. Nodes represent financial institutions[2] while arrows represent exposures. The positioning of nodes is hand-made. The inner ring is composed of the six conglomerates represented by the six red nodes and six pure insurers represented by yellow nodes. The outer ring is composed of the four pure banks represented by blue nodes and fifteen pure insurers (represented by yellow nodes). Exposures are represented by arrows. An arrow from an institution A to an institution B is an asset for A and a liability for B. To help reading, all arrows are not straight but bent on the left.
No clear structure is caught at first glance. For instance, we do not observe a community of banks and a community of insurers with conglomerates as gatekeepers between these community. On the contrary, the exposures seems to be shared across all institutions. The largest arrows involve conglomerates.

3.3 Summary statistics of exposures

We characterize the distribution of all-instrument exposures between nodes according to their class (Conglomerate/Pure Bank/Pure Insurers) as well as the numbers of exposures. We complete the picture by examining instruments (equity/debt instruments). These steps lead to several stylized facts characterizing the French financial network.

The 21 financial institutions report a total of €227 bn. There are 261 non-zero bilateral exposures (over 420 possibles links) leading to a density of 62%. The distribution of exposures is very specific. First, 48% of potential exposures are zero. Second, among the 62% exposures that are non zero, there is a large mass of very small exposures. However, we observe a few large exposures. With round numbers, half of exposures are lower than €250 mn, and only a quarter of them are higher than €800mn. Figure 3 provides the empirical percentiles of (non-zero) bilateral exposures.

To describe more accurately the allocation of exposures between institutions, we report three indicators distinguishing the nature (Conglomerate/Pure Bank/Pure Insurers) of the counterpart. First, we present the local density which is the fraction

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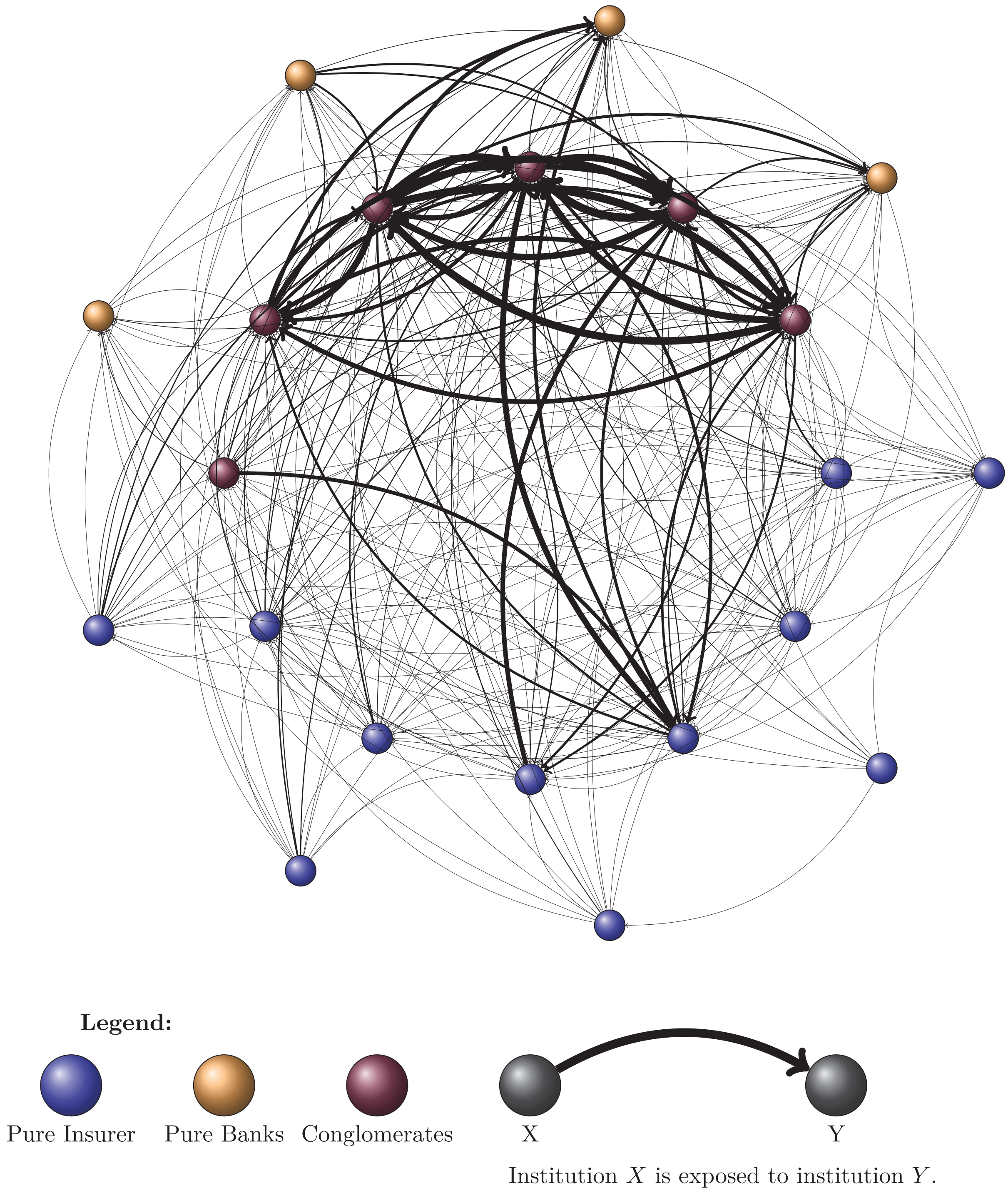
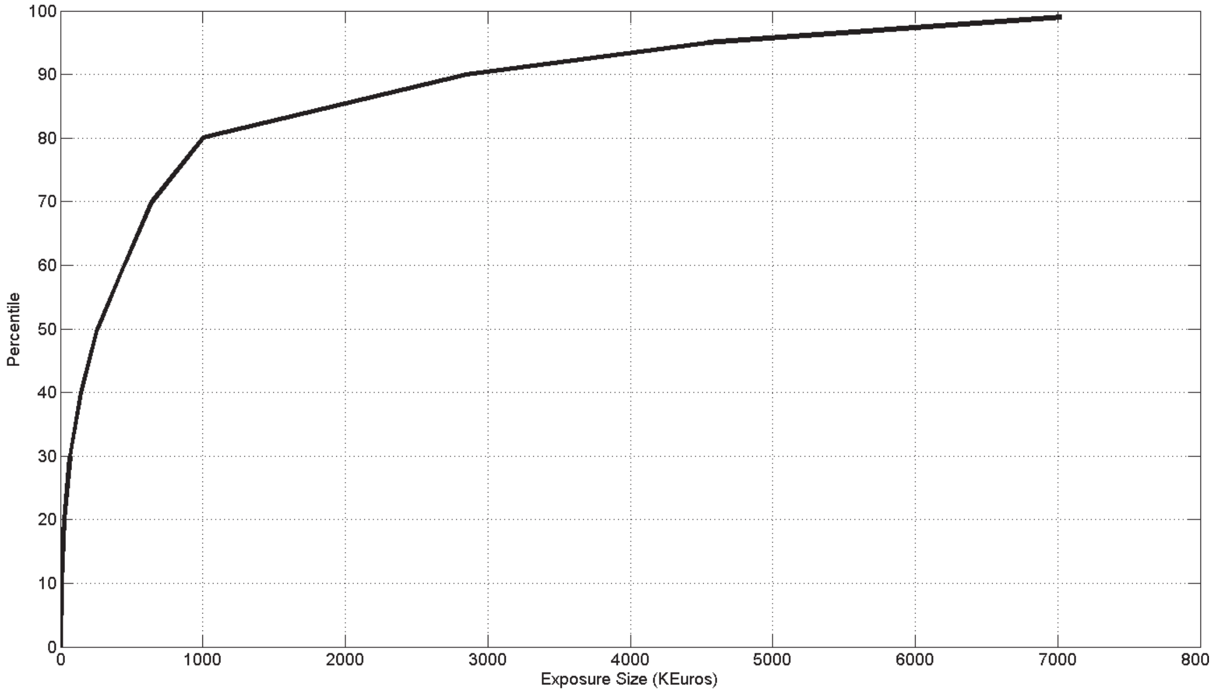
[2] For confidentiality restriction, they all have the same size



Source: ACPR Data.

Note: Node color indicates institution class (red for conglomerates, blue for pure insurers and yellow for pure banks), edge width is proportional to exposure. Arrow starts from the owner of the exposure and ends to the counterpart with a left bend profile.

Figure 2: Network of French Financial Institutions for All-Instrument Exposures. 12/31/2011



Source: ACPR Data, authors' computations.
Note: 80% of non-zero bilateral exposures are smaller than €1mn.

Figure 3: Empirical Percentiles of Non-Zero Bilateral Exposures

of non-zero bilateral exposures over all potential exposures in Table 1. The aggregate density of 62% encompasses different situations. At one extreme, conglomerates form an almost complete network with 97% of potential links. On the contrary, pure banks report almost no exposures to pure insurers. Pure insurers seem to have a funding role in the network since they are exposed to almost all conglomerates and pure banks but few pure banks or conglomerates are exposed to them. This feature can be explained by the nature of insurance activity with respect to the banking activity as well as by a diversification motive.

Second, we adopt a quantitative perspective and report the proportion of exposures between groups of institutions (over the total of €227bn) in Table 2. First, about half of the exposures are between conglomerates. Second, exposures of pure insurers to conglomerates accounts for about 20%. Then, exposures of conglomerates to pure banks and to pure insurers represent about 10% each of the total volume.

Moreover, the distributions of non-zero bilateral exposures according to the legal status of the counterparts presents a similar shape as displayed in Figure 3. Table 2 summarizes the "average" size of exposures. To measure the dispersion, we report the quartile ratio (i.e. the ratio of the third quartile over the first quartile) in Table 3. A high value indicates a high heterogeneity in the exposures sizes (regardless of the mean size reported in Table 2). Most exposures distributions are quite homogeneous

		to:		
	Exposures	Conglomerates	Pure Banks	Pure Insurers
of:	Conglomerates	97%	92%	51%
	Pure Banks	70%	33%	7%
	Pure Insurers	91%	80%	52%

Source: ACPR Data, authors' computations.

Note: The table presents the percentage of non-zero exposures of institutions in the first column towards institutions in the firs row. For example, the ratio of non-zero bilateral exposures between conglomerates over all potential exposures between conglomerates is 97%. The ratio of non-zero bilateral exposures of a conglomerate to a pure banks is 92%.

Table 1: Local Density According to Institution Class (All Instruments). 12/31/2011

		to:		
	Exposures	Conglomerates	Pure Banks	Pure Insurers
of:	Conglomerates	47.7%	9.8%	8.2%
	Pure Banks	4.7%	0.4%	0.1%
	Pure Insurers	20.8%	6.0%	2.3%

Source: ACPR Data, authors' computations.

Note: 47.7% of the total volume of exposures concern exposures between conglomerates. 20.8% of the total volume of exposures are reported by insurers against conglomerates. Sum of all cells is 100%.

Table 2: Breakdown of Exposures According to Institution Class (All Instruments). 12/31/2011

	Exposures (GEuros)	*to:*		
		Conglomerates	Pure Banks	Pure Insurers
of:	Conglomerates	5.9	2.7	60.2
	Pure Banks	5.7	19.7	2.4
	Pure Insurers	4.7	36.2	14.5

Source: ACPR Data, authors' computations.

Legend: the table reports the ratio "q_3/q_1" of non-zero bilateral exposures.

Note: the level of the top 25% exposures of conglomerates to pure banks is 2.7 times the exposures of the bottom 25%.

Table 3: Quartile Ratio of Exposures According to Institution Class (All Instruments). 12/31/2011

	Exposures	*to:*		
		Conglomerates	Pure Banks	Pure Insurers
of:	Conglomerates	98.6%	92.8%	62.1%
	Pure Banks	99.9%	100.0%	96.0%
	Pure Insurers	85.7%	98.9%	73.1%

Source: ACPR Data, authors' computations. Note: 98.6% of the exposures between conglomerates are based on debt instrument. 92.8% of the exposures to pure banks reported by conglomerates are based on debt instruments.

Table 4: Shares of debt instrument exposure over all-instrument exposures according to legal status. 12/31/2011

with quartile ratio lower than 6. However, some heterogeneous distributions are present such as the exposures of conglomerates to pure insurers.

Third, the debt instruments account for 91.8% of the exposures (that is 8.2% of exposures are composed of equity instruments). The breakdown according to institution class is provided in Table 4. In most situations, exposures are very intense in using debt instruments. The sole cases where equity instrument is not negligible are exposures from conglomerates to pure insurers and exposures between pure insures. The non negligible exposures of conglomerates to pure insurers in terms of equity instruments is mainly explained by the existence of joint-ventures between the conglomerates and the pure insurers.

All in all, these summary statistics draw four stylized facts. First, the exposures are modest: about one third of potential exposures are zeros and, for the rest, most exposures are small. However, large exposures are not absent. Second, the conglomerates appear to be the most important players in terms of number of links and in terms of volume. Third, pure insurers are mostly net fund providers to other institutions, in particular of conglomerates. This behavior is in line with basic economic arguments. Fourth, debt instrument are the most common instruments of exposures.

3.4 Individual risk indicators

The previous summary statistics provide a broad view on the distribution of exposures but they are not informative on individual situations. In particular, they give no insight on the interconnectedness dimension or more generally on the riskiness of institutions. Reporting summary statistics on individual exposures does not appear a proper way to assess risk since an exposure is a volume notion. A loan of \$1 billion from a large bank to another large bank is not the same as a loan of \$1 billion from a large bank to a small bank. Similarly, a loan of \$1 billion received by a large bank is not the same as a loan of \$1 billion received by a small bank. Volumes are the same but risks are not. Actually, an exposure represents two risks. For the lender, there is a credit risk while for the borrower, there is a funding risk. All in all, to transform a volume perspective into a risk perspective one has to control for the size of the counterparts.

To properly derive further indicators we introduce the following notations. We denote by n the number of financial institutions. E^K is the $(n,n)-$equity instruments exposure matrix. $E^K_{i,j}$ is the exposure composed of equity instruments from institution i to institution j. Similarly, E^L is the $(n,n)-$exposure matrix for debt instruments. The total exposure matrix is $E^T = E^K + E^L$. Moreover, the equity of institution i is denoted K_i. For the sake of simplicity, indicators are presented for the Total Exposures. Extensions to equity instrument exposures and to debt instrument exposures are straightforward. Since institutions are considered in a consolidated basis, the diagonals of all exposures matrices are filled with zeros.

To gauge the credit risk of exposures we normalize all exposures by the equity of the lender. The equity of the lender is the buffer absorbing potential loss. We denote CR the credit risk matrix defined as:

$$\forall (i,j) \in [1;n]^2, \quad CR_{i,j} = \frac{E^T_{i,j}}{K_i}.$$

For the funding risk, we normalize the exposure by the equity of the borrower.[3] We denote FR the funding risk matrix defined as:

$$\forall (i,j) \in [1;n]^2, \quad FR_{i,j} = \frac{E^T_{j,i}}{K_i}.$$

We find the distributions of (credit and funding) risk exposures have a shape similar to the distribution of (volume) exposures: most of exposures are very small even if there is a non-negligible spread. If the shape is similar, it is not to say that institutions with the largest exposures in volume are the ones with the riskiest exposures. We simply see that risk taking appear concentrated in few exposures.

Using summary statistics on the rows and the columns of the risk matrices to derive individual interconnectedness metrics raises a few questions. One first challenge is to deal with the zero exposures. Keeping the zero exposures will lower most statistics. It can be become artificial. For instance, if the perimeter is extended to institutions

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[3] Using liquid assets, that can be seen as the buffer to face liquidity needs, would be more convenient. However, defining liquid assets and then identifying them in the balance sheet report leads to conceptual and empirical challenges.

	Credit Risk	Funding Risk
1^{st} quartile	0.19%	0.22%
Median	1.34%	0.80%
4^{st} quartile	7.50%	2.46%

Source: ACPR Data, authors' computations.

Note: Half of exposures represent less than 1.34% of the equity of the lender.

Table 5: Summary statistics of credit and funding risk exposures. 12/31/2011

which are not connected, most indicators –such as mean, quartiles, etc.– will tend to zero. However, considering only non-zero exposures could lead to misinterpretation. For instance, one institution can deliberately prefer to get connected to few but reliable institutions rather than be connected to everyone, including some fragile institutions. A second challenge is to analyze the rows or the columns. Analyzing the rows provides indicators on the risk taken by the institution. If all coefficients $CR_{i,j}$ are larger than all coefficients of $CR_{i',j}$ (for all j), all exposures of institution i represent a larger share of its equity than the exposures of institution j. Therefore institution i is taking more credit risk than institution i'. Analyzing the columns leads to indicators on the risk generated by the institutions. A column with large value in matrix FR indicates that the corresponding institution is a significant source of funding for its counterparts.
For confidentiality sake, we analyze here the distribution of credit and funding risk exposures without distinguishing institutions. However, we also analyze the indicators at the individual level for robustness check. Table 5 reports the three quartiles of the non-zero credit risk exposures and the non-zero funding risk exposures. Half of exposures represent less than one percent of the equity of the owner and less than one percent of the equity of the borrower. The tail of credit risk is fatter than the tail of funding risk. A quarter of exposures represent more than 7.5% of the equity of the owner whereas a quarter of exposures represent only 2.46% of the equity of borrower. Therefore, funding sources seems to be more diversified than investment targets.

To conclude this section, we note that summary statistics on credit risk matrix and funding risk matrix are simple interconnectedness indicators. They illustrate a few interesting challenges when measuring interconnectedness. First, interconnectedness should, in our view, be distinct from size since size is already a criterion to identify systemic institution. Second, even when computed at the level of one institution, these indicators are system dependent. For instance, the median of credit risk of one institution depends on the counterparts considered. Consequently, there is no purely individual interconnectedness measure. The considered system should be always clearly specified. Third, interconnection corresponds to different risks. We have spotted two –the credit and funding ones–, and do not aggregate them. This feature leads to question whether interconnectedness is, or should be, a one-dimensional concept. We keep in mind that a parsimonious set of indicators is always better than a large bunch of figures to take actions.

	1)	2)	3)	4)	5)	6)
1)	0	2.7	3.0	5.0	2.1	3.2
2)	2.0	0	2.9	4.9	2.2	3.3
3)	1.9	2.9	0	3.1	5.1	2.0
4)	0.5	0.1	0.6	0	2.1	0.7
5)	1.1	1.5	1.3	1.9	0	1.9
6)	2.0	4.1	4.9	3.7	2.1	0

Table 6: Fictitious Example for Integration and Substitutability

	1)	2)	3)	4)	5)	6)
1)	X	2.7	X	5.0	2.1	3.2
3)	X	2.9	X	3.1	5.1	2.0

Table 7: Fictitious Example: Common Exposures of Institutions 1 and 3

4 Substitutability and integration

Descriptive statistics are useful to understand the exposures between institutions. However, they are open to criticism. Loosely speaking, they may be overly crude indicators of interconnectedness. Moreover, we have seen that interconnectedness is likely to have many dimensions. In this section, we discuss and propose a framework to model two features of interconnections related to risk monitoring: *integration* and *substitutability.*[4] The strategy here is not to propose additional metrics but to compare institutions in order to detect "uncommon" behavior. Basically, we provide a distance measure between each pair of institutions to characterize the likeliness of their exposures. First, two institutions can be said to have similar exposures when their exposures tends to have the same size. This closeness in terms of size of exposures is called *integration*. If two institutions reports similar amount of exposures, they are similarly integrated in the network. Second, one could say that two distributions of exposures can present similar amounts but very distinct allocations. This concern corresponds to the notion of *substitutability*. From a network perspective, two institutions are substitute if they are exposed to the similar counterpart with similar exposures.

To illustrate the difference between these two dimensions, we consider the following fictitious example of 6 institutions whose exposure matrix is given in Table 6. Let us consider institutions 1 and 3. Their common exposures –that are exposures to institutions 2, 4, 5 and 6– are reported in Table 7. The exposure series are similar since each amount in the exposures of institution 1 can be mapped to an exposure of institution 3: 2.7 with 2.9, 5.0 with 5.1, 2.1 with 2.0 and 3.2 with 3.1. Let us consider now institutions 1 and 2. Their common exposures –that are exposures to institutions 3, 4,

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[4] Here substitutability is the substitutability *within the network*. This notion differs from the substitutability item in the BCBS or IAIS guideline to identify systemic banks (G-SIBs) or insurers (G-SIIs). For BCBS and IAIS, substitutability concerns the specificity of the services provided by financial institution to the real economy.

5 and 6– are reported in Table 8. The exposures are very similar since amounts are roughly the same (3.0 to 2.9, 5.0 to 4.9 for instance) and they concern the same counterpart. Institution 1 and institution 3 are considered close in terms of substitutability and in terms of integration: they lend similar volumes to the same counterparts. In contrast, institution 1 and institution 2 are close in terms of integration but distant in terms of substitutability: they lend similar volumes but not to the same counterparts.

	1)	2)	3)	4)	5)	6)
1)	X	X	3.0	5.0	2.1	3.2
2)	X	X	2.9	4.9	2.2	3.3

Table 8: Fictitious Example: Common Exposures of Institutions 1 and 2

These two components of the interconnectedness can be derived in terms of total (or volume) exposures (E), credit risk exposures (CR) and total funding risk exposures (FR). As before, running these three parallel flows enable us to control our results for size.

4.1 Methodology

In this section, we formalize the notion of integration and substitutability building on statistical tools. Let us consider for instance institution i_0 and institution i_1 (with $i_0 < i_1$) and the volume exposures. We have to compare the two distributions:

$$I_0 = (E(i_0,1), ... \ E(i_0,i_0-1), E(i_0,i_0-1), ... \ E(i_0,i_1-1) E(i_0,i_1+1), ... \ E(i_0,n)) \in \mathbb{R}^{n-2}$$

and $I_1 = (E(i_1,1), ... \ E(i_1,i_0-1), E(i_1,i_0-1), .. \ E(i_1,i_0-1), E(i_1,i_0+1), ... \ E(i_1,n)) \in \mathbb{R}^{n-2}$.

4.1.1 Integration

We analyze the integration between institutions by measuring the similarity between their bilateral exposures to the rest of the network regardless of the allocation between counterparties. We use the statistic associated to the Mann-Whitney test:[5]

$$U(i_0,i_1) = max \left[\sum_{1 \leq i \leq (n-2), 1 \leq j \leq (n-2)} \mathbb{1}_{I_0(i)-I_1(j)>0}; \sum_{1 \leq i \leq (n-2), 1 \leq j \leq (n-2)} \mathbb{1}_{I_1(i)-I_0(j)>0} \right].$$

Here, $U(i_0,i_1)$ is the maximum between the number of exposures of institution i_0 that are larger than the exposition of institution i_1 and the number of exposures of institution i_1 that are larger than the exposition of institution i_0. For instance, if one institution has always higher exposures than the other one, they are very dislike and $U(i_0,i_1) = (n-2)^2$. This statistic measure the distance between the two distributions and does not consider the allocation to counterparts.

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[5] Mann-Whitney test is sometimes called Wilcoxon rank-sum test.

Let us emphasize that we only use $U(i_0, i_1)$ as a distance metric, and not as a test statistic. The motivation to use this specific metric is the existence of statistical foundations under additional independence assumptions. If one assumes that the elements of I_0 are iid, the elements of I_1 are iid and that I_0 is independent of I_1, the test statistic $U(i_0, i_1)$ is a free variable as soon as I_0 and I_1 are drawn from the same continuous distribution. The asymptotic behavior of $U(i_0, i_1)$ is known [see Mann and Whitney (1947)]. Applying these assumptions to financial networks can raise discussions. First, the independence between the components of I_0 (or of I_1) states that the exposures of institution i_0 to institution j is independent of the exposures of institution i_0 to institution $j' \neq j$. This feature is not compatible with basic portfolio theory where exposures to all counterparts are simultaneously chosen. However, one could argue that we consider long-term exposures that are made over several periods whereas portfolio theory corresponds to short-term positions. Second, the independence between I_0 and I_1 can be seen as neglecting demand effect. If institution j seeks for €X of funding, and institution i has already provided to institution j a loan of €Y, institution i_1 is constrained to offer only €$(X - Y)$ to institution j. The exposures to a same counterpart are constrained by the demand of this counterpart. Yet, we have no proof that the demand constraint is strictly binding: with new opportunity of funding comes new opportunity of investment.

For the rest of our analysis, we do not need to side for or against the validity of these assumptions, since we only use U as a distance. The whole Mann-Whiteney test framework is used as a general guideline, not an adamant prescription. We apply a hierarchical clustering analysis (HCA) using matrix of the U as a distance matrix. HCA is an automatic method to finds clusters. The institutions of one cluster are very closed while two institutions from two different clusters are very distant.

4.1.2 Substitutability

The substitutability between institutions correspond to similar exposures to the same counterparts. We use the statistic associated to the Wilcoxon test:[6]

$$W(i_0, i_1) = max\left[\sum_{k=1}^{n-2} k(\mathbb{1}_{Z_{(k)}>0}; \sum_{k=1}^{n-2} k\mathbb{1}_{Z_{(k)}<0})\right],$$

where $Z_j = I_0(j) - I_1(j)$ ordered according to $|Z_{(1)}| \leq |Z_{(2)}| \leq ... \leq |Z_{(n-2)}|$. The test statistics is derived from pair-wise comparison of exposure. This pair-wise feature captures the restriction to "same counterparts". Note if the exposures are exactly the same to the same counterparts, the variable Z_j are zeros and $W(i_0, i_1)$ is also zero. When discrepancies between the two distributions arise, the variable Z becomes large and the T increases. As for Mann-Whitney test, additional independence assumptions result in properties on the asymptotic behavior of $W(i_0, i_1)$ [see Wilcoxon (1945)].
As for integration, we use the matrix composed of the $W(i_0, i_1)$ to run a hierarchical clustering analysis.

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[6] Wilcoxon test is sometimes called Wilcoxon signed-rank test.

4.2 Results

Figure 4 and Figure 5 report the dendrogram associated to integration and substitutability respectively. The inverted Π-shaped lines represents the distance between two institutions or between clusters. Loosely speaking, the maximum altitude of the path between two institutions indicates the distance between themselves. A cutting level ensuring three or four boxed clusters has been arbitrary selected to help discussion.

Considering integration with volume (Figure 4.a), the six conglomerates shape a clear group while, except for two insurers (PI10 and PI11), banks are hardly distinguished from insurers. The picture is similar in terms of credit risk (Figure 4.b). Conglomerates are very homogeneous and banks and insurers seems to be exposed similarly. Note that the same two insurers (PI10 and PI11) stand apart for volume. Moreover, insurer PI1 is close to conglomerate in terms of credit risk (while close to insurers and banks for volume analysis). For funding risk (Figure 4.c), the insurers forms homogenous groups with no banks nor conglomerates.

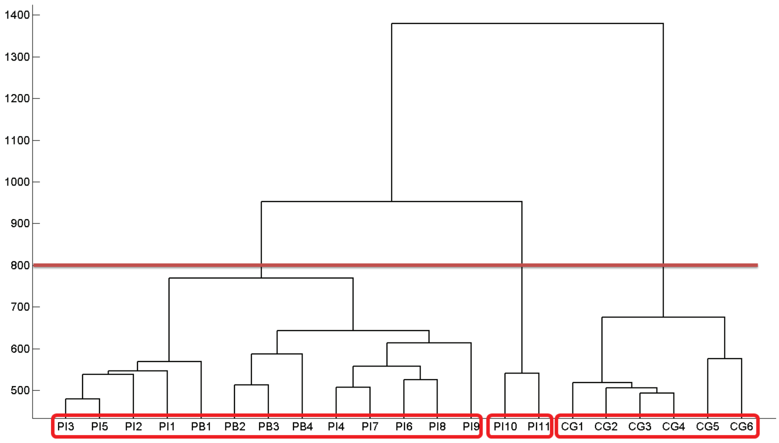
The three panels of Figure 4 provides the following findings. First, conglomerates are specific players on the asset side (volume and risk taking) but are close to banks in terms of funding. In contrast, pure insurers are characterized with their funding strategy while on their asset side appear as close to pure banks.

The substitutability analysis provides additional insights with respect to the integration analysis. For volumes (see Figure 5.a), four clusters can be identified: one with five conglomerates, another one with three banks, one with six insurers and one that mixes one conglomerates with one bank and five insurers. For credit risk (see Figure 5.b), the six conglomerates form an homogeneous group, relatively close to a duo of two insurers while pure banks and pure insurers tends to shape two different communities. For funding risk (see Figure 5.c), the picture is less clear. Conglomerates appear specific and some insurers tend to form an homogeneous group. The blurry features of the result can be interpreted as a diversity among portfolio choices.

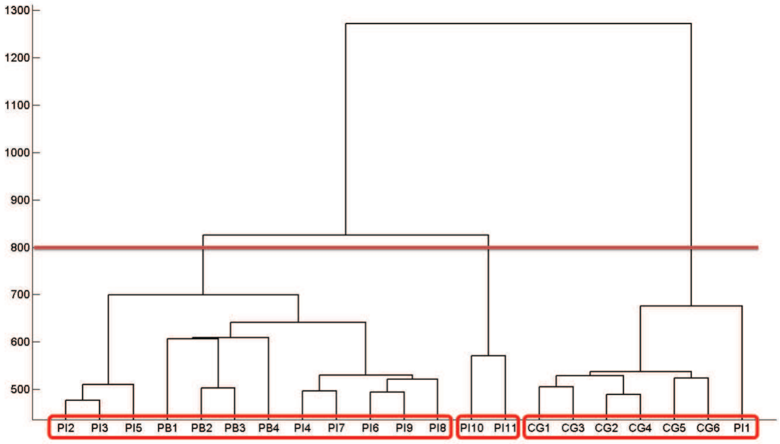
In conclusion, conglomerates form a typical group that tends to be exposed similarly both on their asset sides and on their liability sides. This similarity appear only when combining a size analysis and an allocation analysis (Figures 4 and 5). Pure insurers and pure banks appear to invest similarly at first glance (Figures 4.a and b) but they differ in the allocation of these exposures (Figures 5.a and b). Insurers are characterized from their relying on the network to get funding (Figures 4.c) even if some of them can have funding mixes similar to other financial institutions (Figure 5.c).

5 Network Structure Identification

In this section, we compare the genuine network with various network structures studied in the literature. Stylized networks can result from theoretical models and from strong feature stemming from empirical analysis. The overall objective of this section is not to identify a specific structure but to derive a measure of interconnectedness from the structure identification. In contrast with previous methodology based on pair-wise



a) Volume

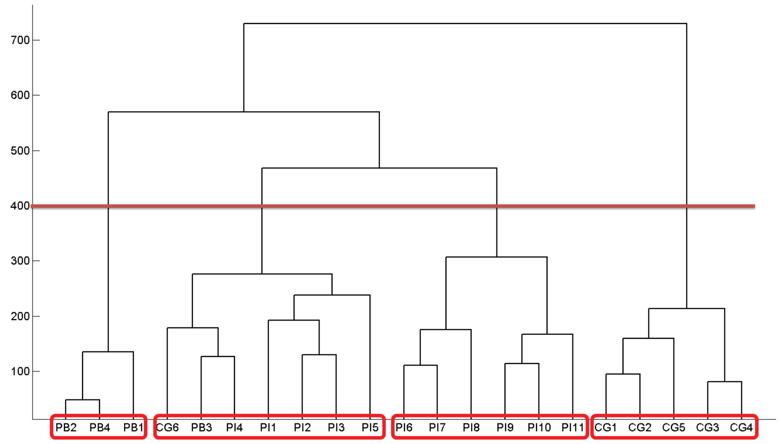


b) Credit Risk

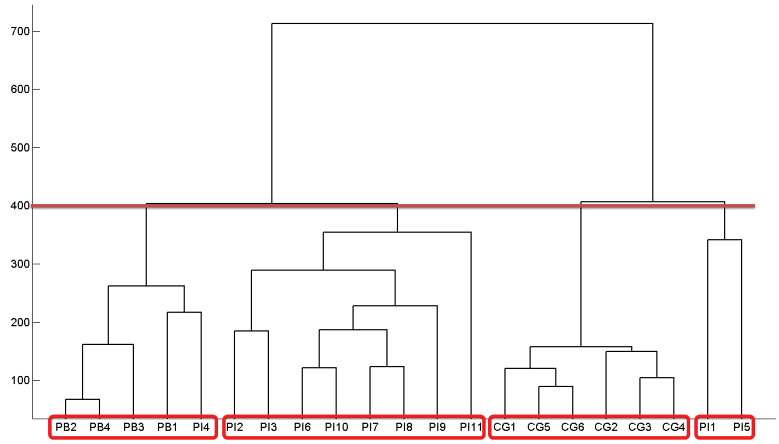
c) Funding Risk

Source: ACPR data, authors' calculation.

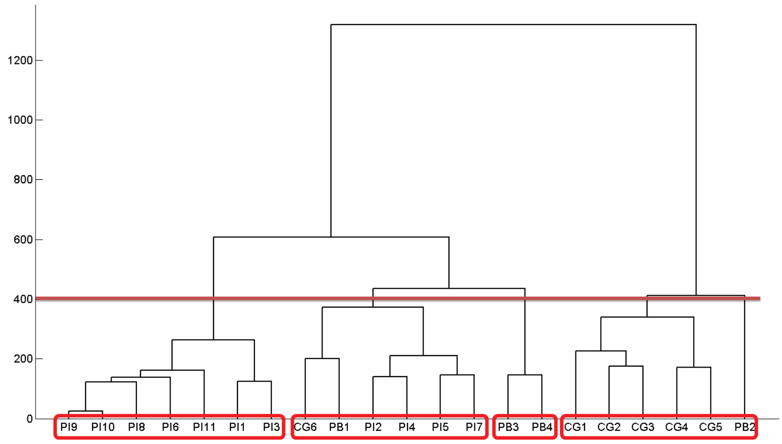
Figure 4: Dendrograms for Integration



a) Volume



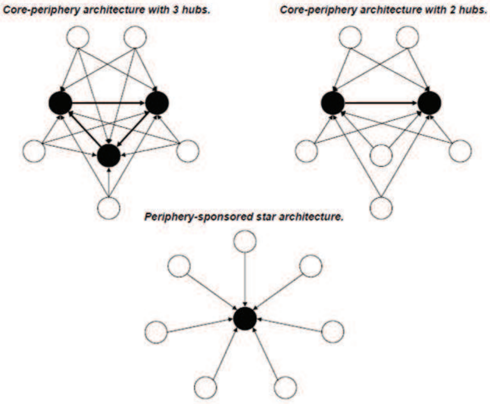
b) Credit Risk



c) Funding Risk

Source: ACPR data, authors' calculation.

Figure 5: Dendrograms for substitutability



Source: Galeotti and Goyal (2010).

Figure 6: Core-Periphery structure *à la* Galeotti and Goyal (2010)

comparisons, network structure identification techniques rely on the whole mapping of exposures between all institutions.
After presenting two "textbook" network structures, we calibrate them on our database to draw conclusions on interconnectedness.

5.1 Review of stylized networks

The economic literature provides stylized networks corresponding to various incentives to network formation.

5.1.1 Theoretical perspective: complete core-periphery structure

Game theorists have analyzed how the setup of pay-off between players leads to the formation of network. In game theory, networks are usually unweighted (i.e. there is no size attached to a link) and undirected (i.e. a link is both ways). For instance, Galeotti and Goyal (2010) analyze the resulting network for a set of players who benefit from their own efforts and from the efforts of their counterparts. They also introduce a cost associated to link formation. Therefore for each player there is a trade-off between doing on its own knowing that this effort provides a positive externality to its counterparts, and getting interconnected. The authors show that the equilibrium structure is composed of two sets of players. The first set is called the core: all members, called hubs, are completely interconnected between themselves. The second set is called the periphery: peripheral player are connected only to all core-players (see Figure 6). When the core is reduced to one player, the network is star-shaped. Galeotti et al. (2006) propose a similar analysis with heterogeneous players and show that other network shapes may emerge. In particular, some players can be intermediaries between local hubs (see Figure 7). Usually, game theorists have in mind network based on cooperation (friendship for social application, R&D partnership for firms...) even if financial framework is new field of application [Acemoglu et al. (2013) or Elliott et al. (2013)].

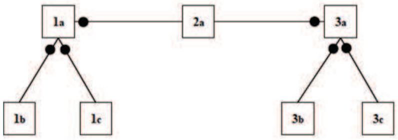


Figure 4: Single Intermediary Between Two Center-Sponsored Stars

Source: Galeotti et al. (2006).

Figure 7: Intermediation between local hubs

	Germany	Netherlands	United-Kingdom	Italy
Number of banks	≈ 1800	≈ 100	≈ 150	≈ 150-200
Density	≈ 0.61%	8%	3.2%	10%-20%
Size of the core	45	≈ 15	≈ 15	≈ 20-50
Distance (%)	≈ 12	≈ 29	≈ 5	≈ 40

Source: Craig and von Peter (2014) for Germany, van Lelyveld and Veld (2012) for the Netherlands, Langfield et al. (2012) for United-Kingdom and Fricke and Lux (2014) for Italy.
Note: the distance measures the quality of the fit of a core-periphery structure à la Craig and von Peter (2014). A low distance indicates a good fit while a large distance indicates a poor fit.

Table 9: Core-Periphery Structure Identification in National Banking Systems

5.1.2 Empirical (banking) perspective: light core-periphery structure

Empirical analysis of banking system points to a core-periphery structure [see Craig and von Peter (2014)]. This core-periphery structure is similar but different to the one introduced by Galeotti and Goyal (2010). In banking framework, the core banks are fully interconnected as in game theory, but peripheral banks are connected to at least one core banks and not necessarily to all, contrasting with the results from game theory. Moreover, links are directed: the lender is distinguished from the borrower. We distinguish a *complete* core-periphery network in line with Galeotti and Goyal (2010) from a *light* core-periphery network that corresponds to Craig and von Peter (2014). Considering the two potential structures makes our work directly comparable to others papers [see van Lelyveld and Veld (2012), Squartini et al. (2013), Craig and von Peter (2014) or Fricke and Lux (2014) for instance] and increases the robustness of our results. This core-periphery pattern has been observed in various countries for their domestic banking system (see Table 9). However, to our best knowledge, insurance companies have never been included.

Our methodology borrows significantly from the method developed in Craig and von Peter (2014). The first step is to convert an exposure matrix into an adjacency matrix. An adjacency matrix is composed of 0 and 1: the coefficient (i, j) is 1 if and only if the coefficient (i, j) of the exposure matrix is strictly positive. The basic idea of the procedure is to count the number of discrepancies between two adjacency matrices. The first adjacency matrix is the observed one whereas the second one is the idealistic one corresponding to the tested stylized network. One drawback of using adjacency matrices is the loss of information on exposures' size: a significant exposure has the same weight as a small one. To deal with this aspect, we adopt two strategies. The first feature is to consider three exposures matrices : the volume exposure matrix E^T, the credit risk exposure matrix CR^T and the funding risk exposure matrix FR^T. The second feature is to censored exposures that are considered. We include in the optimization program the choice of a censoring threshold.[7] The outcome of the procedure is the best selection of the identification of the core institutions and the peripheral ones, over the censoring threshold.

The complete methodology of identification is presented in Appendix B.

5.2 Identification of complete core-periphery network

Results of the complete core-periphery structure identification are presented in Table 10 where a check mark indicates that the institution is part of the core. The best fitting is obtain by considering only exposure higher than €1.5bn. The core is composed of 5 conglomerates and 1 pure insurer. The complete core-periphery structure is very plausible since there is only 3.6% of errors between the observed adjacency matrix and the theoretical one.

When looking at the structure from the joint of view of credit risk, the picture is different. If only exposures representing more than 1% of the equity of the lender are concerned, the complete core-periphery has a distance about 16%. Five conglomerates, three pure banks and two insurers are part of the core. However, when the threshold increases, the fitting is poor since error rate is between 30% and 71%. Similar results are got when looking at funding risk.

Comparing these results shows that the complete core-periphery structure is a suitable stylized network shape for the French financial network, but only when considering raw exposures. In that case, the core is composed of conglomerates and one pure insurers. In contrast, when exposures are normalized by the size either of the lender or of the borrower, the complete core-periphery structure disappears. One interpretation is that five conglomerates and the pure insurers are in tight commercial relationships, with large volume of exposures. But these exposures do not represent an area prone to contagion either in terms of solvency (credit risk) or in terms liquidity (funding risk).

5.3 Identification of light core-periphery network

Basically, the results with a light core-periphery structure does not differ significantly from results with a complete core-periphery structure (Table 11). The core-periphery structure is clear when considering gross exposures. The lowest distance of 3.6% achieved for exposures higher than €1.5 bn is comparatively very good ; for comparison, Craig and von Peter (2014) have distance about 12% on the German interbank market (see Table 9). The core is composed of five conglomerates only contrasting with the previous structure where one pure insurer was also spotted. The funding risk perspective exhibits no core-periphery structure. Meanwhile, credit risk exposure (above

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[7] We adopt a grid with a step of €0.5bn for the total exposure matrix, a step of 1% for the credit risk exposure matrix and a step of 0.1% for the funding risk matrix.

	Volume	Credit Risk	Funding Risk
CG1	✓	✓	✓
CG2	✓	✓	✓
CG3	✓	✓	✓
CG4	✓	✓	✓
CG5	✓	✓	✓
CG6			
PB1		✓	✓
PB2			
PB3		✓	
PB4		✓	
PI1		✓	✓
PI2			✓
PI3		✓	✓
PI4		✓	✓
PI5	✓		✓
PI6			
PI7			✓
PI8			
PI9			
PI10			
PI11			
Distance (%)	3.6	16.2	14.6
Censoring threshold	€1.5bn	1%	0.1%

Source: ACPR Data, authors' computations.
Note: The fifth pure insurer (PI5) is identified as member of the core for the analysis in volume and in funding risk but as member of the periphery for the analysis in credit risk. The best fitting of the structure for exposures in volume is obtained for a censoring threshold of €1.5bn and the distance between the theoretical adjacency matrix and the observed adjacency matrix is 3.6%.

Table 10: Complete Core-Periphery Structure Identification

	Volume	Credit Risk	Funding Risk
CG1	✓	✓	✓
CG2	✓	✓	
CG3	✓	✓	✓
CG4	✓	✓	
CG5	✓	✓	
CG6			
PB1		✓	
PB2			
PB3		✓	
PB4		✓	
PI1		✓	
PI2			
PI3		✓	
PI4			
PI5			
PI6			
PI7			
PI8			
PI9			
PI10			
PI11			
Distance (%)	5.0	15.7	71.4
#Core	5	10	2
Threshold	€1.5bn	1%	0.1%

Source: ACPR Data, authors' computations.
Note: The third pure insurer (PI3) is identified as member of the core for the analysis in credit risk but as member of the periphery for the analysis in volume and in funding risk. The best fitting of the structure for exposures in volume is obtained for a censoring threshold of €1.5bn and the distance between the theoretical adjacency matrix and the observed adjacency matrix is 5%.

Table 11: Light Core-Periphery Structure Identification

1%) includes several institutions on top of the same five conglomerates.
These results confirm the main finding of the complete core-periphery structure identification. Five conglomerates represent the bulk of the volumes of financial exposures. However, in terms of risk, the partition is much blurrier. The funding risk seems to be very diffuse with no compact set of highly interconnected institutions. The credit risk perspective do not provide good fitting when avoiding exposure lower than 1%. When taking into account these modest exposures, the core (in both model) represent about half of the sector.

5.4 Conclusion

The first finding is that the core-periphery structure, usually applied to banks, is also relevant when including insurance companies. We found similar quality of adjustment

than those obtains by research on banks only.
The second finding is that the "core" is mostly composed of conglomerates when considering the volume of exposures. However, controlling for size makes the core-periphery structure no longer a good candidate (even after an optimization step on the censoring threshold). Controlling for size is adopting a risk perspective rather than a flow perspective. Financial conglomerates make up the "core" of the volume network but are not as central when we control for size. Conglomerates play a pivotal role to gather and distribute financial assets (*i.e.* inter financial institution assets) but not to gather and distribute risk. Risk is not concentrated into a few players, but rather diversified among many players. From this perspective, evidence points to a resilient network.
Thirdly, there is no conclusive results as regard to choose between the complete core-periphery structure and the light core-periphery structure. Adjustment quality are qualitatively similar.

6 Systemic importance and systemic fragility

Spotting interconnectedness as a dimension of systemicity is considering contagion risk. Albeit informative, previous analyses are not specifically focused on contagion risk. In this section, we derive interconnectedness measures from network stress test techniques which are specifically designed to handle contagion risk. We first represent the methodology deriving two measure of interconnectedness: *systemic importance* and *systemic fragility*.

6.1 Methodology

A network stress-test is defined by specifying the contagion model and the design of external shocks. We use the contagion model proposed in Gourieroux et al. (2012). This structural model extends the Eisenberg and Noe (2001)'s model by distinguishing between contagion through shares and bonds. For the shock, we consider the impact of the individual default of each institution. The initial default of institution X is defined as the wiping out of all the external assets of institution X. Since we have 21 institutions, we have 21 scenarios of individual defaults. These scenarios lead to measure two dimensions of interconnectedness: *systemic importance* and *systemic fragility*. The systemic importance of institution X is the impact of institution X's default on the network whereas its systemic fragility is how many times X is likely to be affected by the defaults of other institutions. Alves et al. (2013) propose to measure the systemic importance of institution X with the number of institutions in default due to institution X's default and to measure systemic fragility of institution X with the the number of scenarios where institution X is in default. Applying these definitions, we find too few distinctions between institutions. We consider a much more conservative approach by looking at contagion links where losses are larger than 10% of initial equity. Thus, the systemic importance of institution X with the number of institutions suffering from a loss higher than 10% of their initial equities following institution X's default. Similarly, the systemic fragility of institution X is the number of scenarios where institution X

suffers from losses larger than 10% of its initial equity. We use a threshold at 10% for simplicity; our results are robust to other threshold (see Appendix C for a sensitivity analysis). Since the Gourieroux et al. (2012)'s model considers contagion through equity, a loss propagation may exist even if no default occurs.
Note that we do not analyze the probability of contagion. We rather adopt a conditional perspective: we assess the spread of contagion conditionally to the default of one institution.

6.2 Results

Table 12 reports the scores of each institution. Three groups are identified: one group is composed of institutions prone to be systemically important, another group is composed of institutions prone to be systemically fragile and the last group gathers institutions that are neither systematically important nor fragile. Note that we find no institution with significant systemic importance and significant systemic fragility. To limit the impact of using a threshold (10% of equity), we simply consider groups and not exact figures. Considering higher thresholds would globally decrease the figures of systemic importance and systemic fragility (see Appendix C). Figure 8 reports the number of institutions with specific level of systemic importance and systemic fragility, with the three groups identified. The three groups do not completely match the distinction between conglomerates, pure banks and pure insurers. However, there is a strong – but imperfect– link between conglomerates and systemic important institutions: five out of six conglomerates are part of it and only one important institution is not a conglomerate. Since the French financial conglomerates are the biggest players of the considered perimeter, this results is not surprising.

7 Policy perspectives

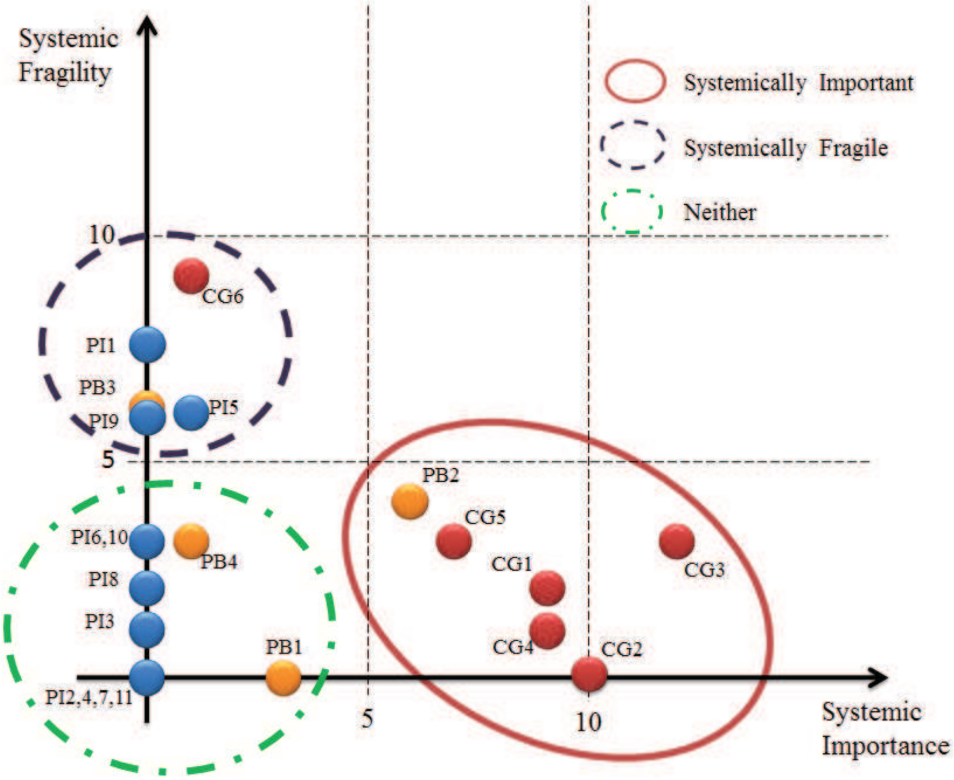
We reviewed several strategies to assess interconnectedness of financial institutions: statistical closeness in Section 4, topological structure identification in Section 5, as well as analysis of systemic importance and systemic fragility in Section 6. It is natural to search for linking the network structure to its sensitivity to contagion. There is no much arguing that the contagion depends on the structure, but there is room for debate on the capacity of current tools to measure the structure are sufficient to proxy contagion. The methods we reviewed are heterogeneous in resources to be run (computation time, algorithm complexity, data, etc.). From a practical point of view, there is a potential trade-off between the different strategies. In this section, we compare the results of the various methods and then suggest some guidelines for supervisory tools.

Interconnectedness measuring strategies based on hierarchical clustering and topological structure identification agree on a clear distinction between conglomerates and others institutions when considering volume exposures. However, core-periphery identification does not give insights on riskiness whereas hierarchical clustering provide a few elements for integration and for substitutability. One explanation of this discrepancy

	Importance	Fragility
CG1	9	2
CG2	10	0
CG3	12	3
CG4	9	1
CG5	7	3
CG6	1	9
PB1	3	0
PB2	6	4
PB3	0	6
PB4	1	3
PI1	0	7
PI2	0	0
PI3	0	1
PI4	0	0
PI5	1	6
PI6	0	3
PI7	0	0
PI8	0	2
PI9	0	6
PI10	0	3
PI11	0	0

Source: ACPR data, authors' computations.
Note: The table indicates under the "importance" heading the number of institutions failing after the failure of institution in the first column. The last column reports the number of scenarios when the institution would fail. For instance, the default of CG1 leads 9 others institutions to lose more than 10% of their equity. Only two institutions through their defaults generate loses for CG1 higher than 10% of its equity.

Table 12: Systemic Importance and Systemic Fragility Scores.



Source: ACPR data, authors' computations.
Note: The default of CG1 leads 9 others institutions to lose more than 10% of their equity. Only two institutions through their defaults generate loses for CG1 higher than 10% of its equity.

Figure 8: Systemic Importance and Systemic Fragility. 12/31/2011.

is the binary aspect of the core-periphery identification (even considering the optimization on the censoring threshold). Moreover hierarchical clustering provides insights on all the institutions while core-periphery distinguishes only two groups of institutions. Keeping the core-periphery structure identification may be paramount because it draw a broad picture. Identifying the core can help identify systemic institutions that may be the source of wide-spread contagion phenomena. On a methodological point of view, we may advocate that hierarchical clustering tools, such as integration and substitutability measures, may help to make a diagnosis to neutralize the risk of contagion. The identification of a core-periphery structure involves interconnectedness features as well as size effects.

The focus of supervisors about interconnectedness is contagion risk. In that respect, we consider that the measures derived from stress-test framework can be considered as a the most relevant. Therefore, we assess the ability of other methods to predict the three groups identified with systemic importance and fragility. To do so, we run exact Fisher test[8] on the contingency table build on one group identified by contagion-based measures and one group identified by any other method.

Table 13 reports the quality of adjustment between the interconnectedness measures. The main result is that no measure is able to identify systematically fragile institutions whereas most methods are able to identify systematically important institutions. This mismatch may be structural for the core-periphery since one partition is composed of two groups while the other is composed of three. But even when the two partitions are composed of three groups, there is no detecting the fragile institutions. Therefore, there is only a partial overlapping of the information brought by substitutability/integration analysis and the contagion analysis. Substitutability and integration analyses are run on a pair-wise basis. Therefore, results indicate that two institutions have similar interconnectdeness but do not provide the scale of this common level. On the contrary, contagion based analysis provides directly the levels of interconnectedness for each institution.

We presented several strategies to measure interconnectedness. Even if some reveal themselves failing to be perfectly in line with supervisory focus, we do not think that they should be thrown away from a supervisory toolbox. Interconnectedness is in all likelihood a multi-faceted concept that requires therefore several measure to be accounted for. The general characteristics of each strategy as well as potential supervisory use is detailed below and summarized in Table 14.

First at all, we recommend picking interconnectedness measure with parsimony to avoid unnecessary complexity. Provided a volume exposure matrix, we recommend deriving a credit risk matrix and a funding risk matrix. Descriptive statistics on risk matrices are very informative to have a broad, albeit crude, picture of interconnections. Comparing pair-wise institution along substitutability and integration is useful to assess similarities between institutions, or to detect outliers. However, this strategy does

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[8] Since our sample is small (with only 21 observations), considering exact Fisher test is more robust than usual chi-2 test.

		Importance	Fragility	Neither
Volume	substitutability	++	.	++
	Integration	+++	.	+++
	Core	+++	.	.
	Periphery	.	.	+++
Credit Risk	substitutability	.	.	.
	Integration	+++	.	++
	Core	+	.	.
	Periphery	.	.	.
Funding Risk	substitutability	+++	.	++
	Integration	.	.	.
	Core	.	.	.
	Periphery	.	.	.

Source: ACPR data, authors' computations.

Legend: "+++" indicates a p-value lower than 1% for the exact Fisher test between at least one group of the method in line and the group identified in column. Similarly, "++" for a p-value lower than 5%, "+" lower than 10%.

Table 13: Comparison of interconnectedness measures. 12/31/2011.

Tool	Summary Statistics	Integration & substitutability	Core-Periphery Identification	Systemic importance Systemic fragility
Design	continuous individual	continuous pair-wise	binary system-wide	continuous system-wide
Measure	quantitative	none	qualitative	quantitative
Complexity	easy	easy	complex	complex
Potential bias			size effect	model dependence
Policy concern	usual monitoring	cross-market comparison	SIFIs identification	SIFIs identification

Table 14: Tools and Policy Concerns

not provide individual scores of interconnectedness.

Identifying core-periphery structure is to be handled with care. Our results are contrasted. They suggest that this method is easily corrupted by size effects. A formal identification of the core of a network helps to see where volumes dwell but does not necessarily pinpoint riskiness. Moreover, note that the results are binary rating of interconnectedness –either in the core or in the periphery– giving no scale of interconnectedness.

Contagion models provide two clear measures of interconnectedness: systemic importance representing the contagion risk generated by the institution and systemic fragility catching the exposure to contagion risk. These last measures provide scores and robustness check can easily been carried out. Nevertheless, these measures depend on the model used, in particular the contagion channels that are included. Therefore, scores should be read keeping in mind the limits of the underlying model.

8 A closer look at conglomerates

All analysis tools used in this paper have pinpointed conglomerates as specific players. They constitute one specificity of the French financial sector: the biggest institutions are active both in the banking sector and in the insurance sector. Many questions are often raised when considering conglomerates [see van Lelyveld and Schilder (2003)]. After describing the global structure of French financial conglomerates, we consider three questions: Are insurers within a conglomerate different from a pure insurers? Are conglomerates contagion walkway between insurance and banking sectors? Are conglomerates improving resilience?

8.1 Data set

In the data collection process, we are able to disentangle the banking component from the insurance component of a financial conglomerates. We distinguish intra-group exposures (from one component to the other component) from extra-group exposures (from one component to another financial institution). The network is therefore composed of 27 nodes: six banking components of conglomerates, six insurance components of conglomerates, four pure banks and eleven pure insurers.

The French financial conglomerates are banking-dominant. The equity associated to the banking components represent about 90% of the total equity of the group. Therefore, we assume that the banking component is the parent company of the insurance component. Consequently, the exposure of the banking component on the insurance component is composed of equity. Overall, the exposures from one component to another are more-or-less balanced. In a majority of cases, the insurance component is slightly more exposed to the banking component than the banking component to the insurance component. In any case, the main difference between the intra-group exposure is the instrument: bank component holds equity issued by the insurance component whereas the insurance component holds debt instruments from the banking component.

8.2 Are insurers within a conglomerate different from a pure insurers?

To assess the impact of being part of a conglomerate, we examine whether an insurance part of conglomerate differs from a pure insurer. To do so, we use the methodology presented in Section 4 to assess the likeliness of exposures of the 27 institutions. Let us emphasize that we are focus here on the exposure to the French financial sector, not on the whole balance sheets.

Concerning integration (see Figure 9), the analysis differ for the asset side with volume and credit risk (see Figures 9.a and 9.b) and for the liability side (see Figure 9.c). For the asset side, the insurance components are very close to the banking components. The parts of conglomerates shape an homogeneous group distinct from a second group that mixes pure insurers and pure banks. The picture is similar to what we observe in

Section 3 (see Figures 4.a and 4.b), except that the conglomerates are now split into banking components and insurance components. Contrary to the asset side analysis, the liability side analysis with funding risk (see Figure 9.c) depends on the status. The banking components shapes a clear group distinct from every other institutions. Insurances components form two homogeneous groups which are relatively close to pure insurance.

Concerning substitutability of volumes (see Figure 10.a), nine (out of twelve) components of conglomerates form a cluster. A second cluster is clearly composed of pure insurers. Last clusters are small and mix different institutions. In that perspective, insurance components of conglomerates tend to lend similar amount to the same counterparties as their banking homologous do. This proximity disappear when examining credit risk (see Figure 10.b). Except for few exceptions, three groups are identifieds: a group form a banking components and pure banks, a group of pure insurer and a group of insurance components. For funding risk (see Figure 10.c), we identify clearly the banking components, the insurers components but the last group mix pure insurers and pure banks. The sectoral reading is partial.

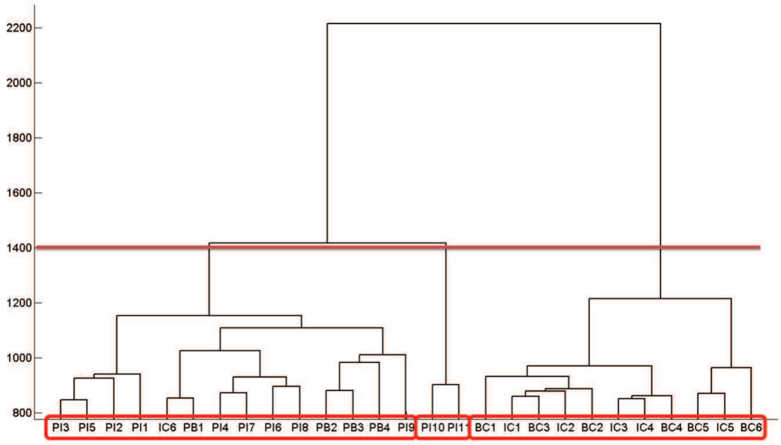
Comparing the results on substitutability and the results on integration, we draw four stylized facts. On the asset side, financial conglomerates appear to have the similar exposures for their banking components and their insurance components. This portfolio closenness may come from a scale of economics in counterparty risk monitoring. However, the portfolio allocation differ. Insurance components have a clear profile distinct from their homologous and distinct from pure insurers. This feature may be explained by a diversification constraint at a group level: the portfolio of the banking component and of the insurance component should not excessively overlap. On the liability side the nature of activity is a clear discriminant. Insurance components' funding strategy is much more alike pure insurers than its banking homologous.

From this analysis of the intra-system financial assets and liabilities, insurers that are part of a conglomerates differ clearly and moderately from pure insurers. Insurance components tends to be more exposed than pure insurers but their exposures seem diversified from their banking homologous in order to avoid a concentration risk at a group level. There is a clear insurance profile on the liability side. Insurance components appear to have a funding strategy similar to any pure insurers.

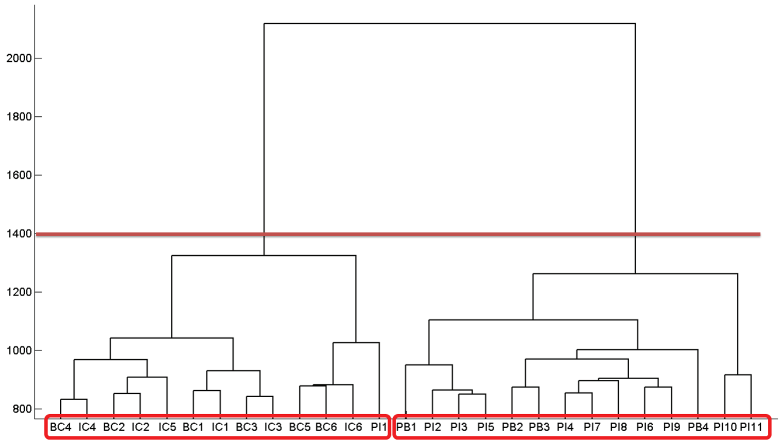
8.3 Are conglomerates contagion walkway between insurance and banking sectors?

Since conglomerates are active in the banking sector and the insurance sector, a natural concern is the risk that they facilitate the propagation of a crisis from one sector to another.

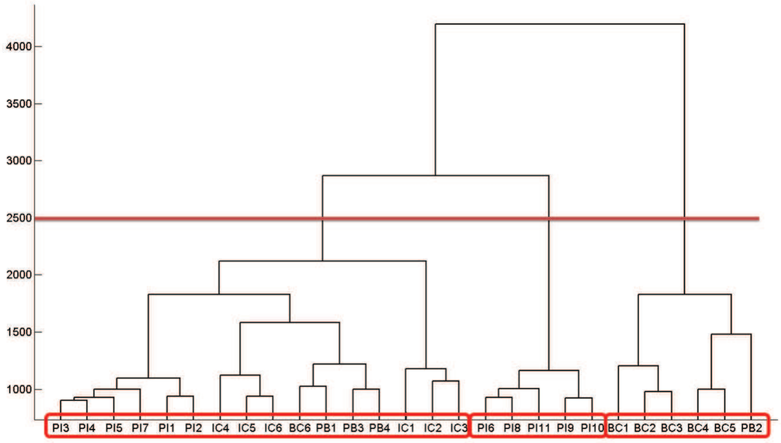
We consider the idiosyncratic default (with a minimal recovery rate) of each component of the 6 conglomerates. For four of them, the default of the banking component implies the default of the insurance component. On the contrary, the default of the



a) Volume



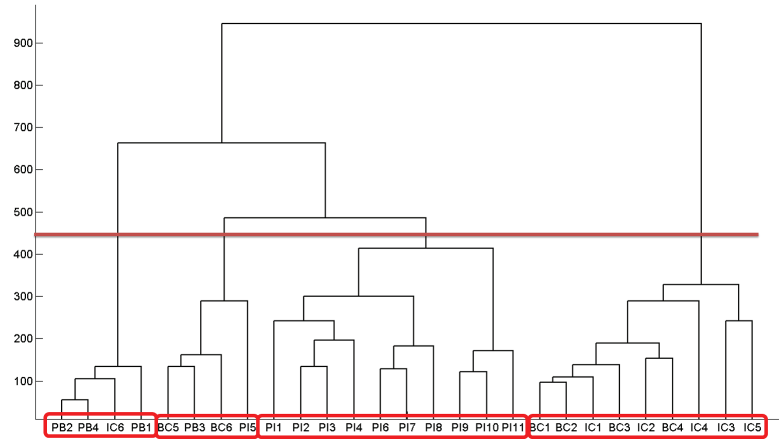
b) Credit Risk



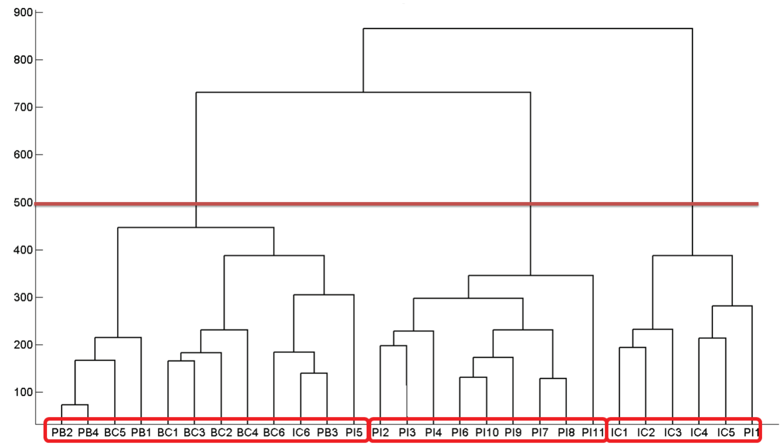
c) Funding Risk

Source: ACPR data, authors' calculation.

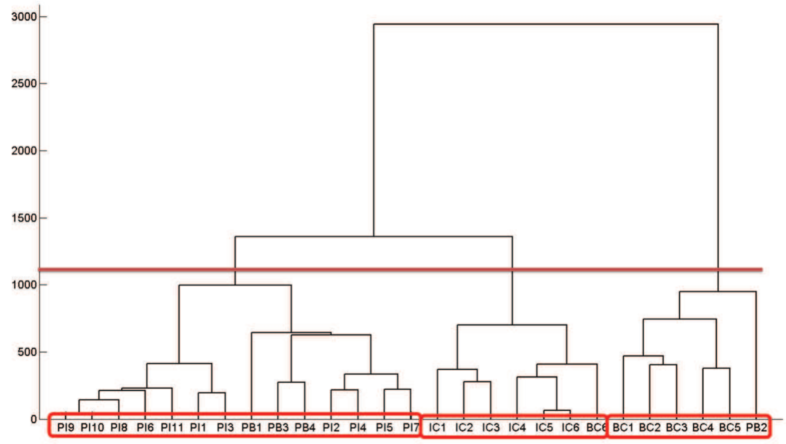
Figure 9: Dendrograms for Integration When Conglomerate are Split



a) Volume



b) Credit Risk



c) Funding Risk

Source: ACPR data, authors' calculation.

Figure 10: Dendrograms for Substitutability When Conglomerate are Split

insurance component never triggers the default of the banking component. This result is in line with the fact that the banking component is much more important than the insurance component for the French conglomerates.

8.4 Are conglomerates improving resilience?

One way to assess the relevance of conglomerates is to examine whether they improve or not the resilience of the financial institutions they are constituted of. In that perspective, we complete our data set by the sovereign exposures of the 27 institutions on Germany, Spain, France, United-Kingdom, Ireland, Italy, Portugal and United-States of America.[9] These exposures are common to the banking and the insurance sectors. Indeed, they are not told to resume all source of risk but sovereign risk is today one major concern. We define one scenario by country by assuming that all institutions suffer a loss of half their respective exposures to the considered country. For each scenario, we compare the situation where financial conglomerates are split and the situation where financial conglomerate are one group. In the first situation, the two components of one conglomerates are considered as different entities –albeit exposed one to another– whereas in the second situation they share their fates. There is no general argument to tell which situation is the most resilient.

Except for France and Italy, the impaired losses do not lead any institutions to default, whatever the situation. For Italy, one insurance component is in default (with a recovery rate of 98%), but on a fully consolidated basis, no institution is in default. For France, all insurance components and one banking component are is default (with an average recovery rate of 91%), whereas on a fully consolidated basis, only one conglomerate is in default (with a recovery rate of 98%). For pure insurers, the France scenario triggers the default of four of them (with an average recovery rate of 95%). With respect to these scenarios, financial conglomerate strengthen the resilience of the French financial sector since policyholders, who are debt holders, are less likely to suffer losses.

8.5 Conclusion

Financial conglomerates are no usual financial institutions and they raise debates. We bring insights to shed light on some specific aspects of these discussions. First, we compare insurance components of financial conglomerates to pure insurers. On the liability side, we canot distinguish insurance components from pure insurers. On the asset side, insurance components appear more exposed than pure insurers but this higher level if offset by diversification effect at group level. Second, we analyze the contagion risk. We show that for French conglomerates, which are banking dominated, the insurance component is exposed to the banking component whereas the banking component does not depend on the insurance component. However, when considering common shocks that affects both components, conglomerates appear in general more

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[9] The exposures are based on Large Exposures reports for banks and TCEP reports for insurers

resilient than a separated structure. Our insights do not wound up debates about conglomerates but support such financial structures.

9 Concluding remarks

As interconnectedness becomes a major concern for systemic risk supervision, being able to measure interconnectedness is paramount. Interconnectedness is a multi-faceted concept that no unique measure may summarize. Using a unique database of bilateral exposures between banks, insurers and financial conglomerates, we review several strategies to measure interconnectedness. We show the pro and cons of each measure, and analyze how they overlap. Methodological results are complemented with empirical results with a particular focus on conglomerates. This approach leads to formulate potential policy recommendations.

First, we measure the degree of interconnection along the network-*substitutability* and network-*integration* concepts. This strategy provides continuous results based on a pairwise approach. This strategy is a good match to run cross-market comparison. Conglomerates appear as an homogeneous population sharing common features. Banks and insurers are distinct from conglomerates but are not easily distinguishable among themselves.

Second, we calibrate a *core-periphery* structure, usually applied to banking networks. This approach enable us to consider the whole system but only on a qualitative base. This stylized structure is still relevant for a network composed of insurance companies in addition to banks. However, it appears that this structure is more likely to be driven by institutions' sizes than by their levels of interconnectedness. Conglomerates are core institutions with respect to volumes of exposures but the total risk of the system is much more diversified among much more institutions. In terms of supervision of systemic risk, our results call for a clear distinction between size dimension and interconnectedness dimension.

Third, we study *systemic fragility* and *systemic importance* of institutions based on a contagion risk assessment. The informative content of this last method is complementary to the previous analyses. In particular, we show that contagion models are necessary to spot fragile institutions, which are significantly exposed to contagion risk.

The uniqueness of our database stems from being the first set of bilateral exposures between banks, insurers and financial conglomerates. Financial conglomerates are particular institutions active on both banking sector and insurance sector. We find that insurers from conglomerates are similar to pure insurers when looking at the funding part on the liability side. The intra-financial assets portfolio differs between pure insurers and insurers from conglomerates in a very specific way, that can be explained by being part of a financial group. Moreover, the concern that conglomerates generates a risk of contagion between sectors appear limited. Our partial results shows that the group structure of conglomerates components strengthen resilient.

Interconnectedness concern and network analysis shape a growing literature. Complementing our work by additional interconnectedness measures, such as measures based on market data (Billio et al. (2011)) is a way to go. Moreover, the current method used to identify stylized structures relies on a specific matrix distance. As explained in Craig and von Peter (2014), a theoretical grounding of such a distance, as well as empirical characteristics, would be welcome. Last, introducing a time dimension applying the same methodology to the same sample at different date would enrich the analysis.

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A Building data set

A.1 Defining nodes

The very first step is to define the 27 nodes shaping the network.

For conglomerates, we use the detail list of the entities of the group (consolidation perimeter in the annual reports or regulatory "Implantat" Reports). This list of all subsidiaries includes information such as name, activity code, country, size, interest control, voting control... We define the sub-group "insurance activity" as the combination of all subsidiary whose activity code is directly insurance. In contrast, we define the sub-group "banking activity" as all the remaining entities in the list (that are not in the sub-group "insurance activity"). We keep track of the interest control in case of entities that are not fully controlled by the head.

For pure banks, we use the same information as for conglomerates. However, all entities in the list of consolidation perimeter are considered part of the node (regardless of the activity code).

For pure insurance, we consider all insurers that are part of the group we consider.

A.2 Collecting balance sheet data

French banks are required to report to the Autorité de Contrôle Prudentiel et de Résolution a detailed balance sheet ("FINREP Report") at a consolidated level. This consolidation level is suitable for pure banks but for conglomerates, this report encompasses the banking and the insurance activity. We split the assets and the liability using the ratio of the required capital for banking activity on the total required capital (for banking activity and insurance activity) provided by an auxiliary report ("Conglomerat" Report).

Insurance supervision is on a solo basis. Therefore, supervisory reports for insurance companies are not directly providing consolidated balance sheet. We use the public annual reports of the 11 insurances we consider.

A.3 Collecting data from banks on extra-group exposures

French banks are also required to report all the large extra-group exposures ("Large Exposure" Report). In the Large Exposure report, the financial institution consider the exposures of all its banking subsidiaries (i.e. excluding any potential insurance subsidiary) that exceed 10% of its capital or more than 300 millions of Euros. The counterpart are consolidated. With Large Exposure report, we can reconstruct the exposure of all the pure banks and all the banking nodes of the conglomerates toward all the others nodes.
Large Exposure report declaration perimeter has few exceptions: in particular, expo-

sures that are deduced in the computation of the regulatory capital are not reported. We check with off-site supervision teams the deduced elements and incorporate them.

A.4 Collecting data from insurers on extra-group and intra-group exposures

French insurance companies reports a highly detailed balance sheet (TCEP report) at a solo basis (i.e. without including any subsidiary). Going security by security on the asset side, one can reconstruct exposures to nodes using the very first step about defining nodes. In contrast of Large Exposure reports, TCEP has no exceptions but is on a solo basis. Therefore, we are underestimating the exposures of insurers by neglecting the exposures of the non-domestic entities. This bias is expected to be insignificant for insurers whose activity are only in France and more pronounced for globally active insurers.

The TCEP is very useful to assess the structure of exposures to a conglomerate. For each insurance company, the TCEP distinguishes the exposures to the sub-group "insurance activity" from the exposures to the sub-group "banking activity". We observe that almost all exposures are reported to the the sub-group "banking activity". For simplicity, whatever the nature of the reporting institutions (conglomerate, pure bank or pure insurer) we consider that any exposures to a conglomerate is actually an exposure to the sub-group "banking activity".

B Structure Identification

Craig and von Peter (2014) propose the methodology in the light core-periphery structure identification. Our contribution is to introduce in the optimization program a censoring threshold involved in the definition of the observed adjacency matrix. We transpose the methodology in the case of the complete core-periphery structure.

B.1 Identification of the complete core-periphery structure

Complete core-periphery structure refers to the structure proposed in Galeotti and Goyal (2010). Let us denote h the size of the core (h for hubs). If the core institutions are firstly indexed, the theoretical adjacency matrix $A^{ccp}(h)$ presents a block structure:

$$A^{ccp}(h) = \left(\begin{array}{c|c} A^{ccp}_{1,1} & A^{ccp}_{1,2} \\ \hline A^{ccp}_{2,1} & A^{ccp}_{2,2} \end{array} \right),$$

where all the off-diagonal coefficients of $A^{ccp}_{1,1} \in \mathcal{M}_{h,h}(0,1)$, $A^{ccp}_{1,2} \in \mathcal{M}_{h,n-h}(0,1)$ and $A^{ccp}_{2,1} \in \mathcal{M}_{n-h,h}(0,1)$ are equal to one, and all the coefficients of $A^{ccp}_{2,2} \in \mathcal{M}_{n-h,n-h}(0,1)$ are zeros. $A^{ccp}(h)$ is a symmetric matrix since Galeotti and Goyal (2010) consider undirected links. For example, a network of 8 institutions with 3 core institutions is characterized by:

$$A^{ccp}(3) = \left(\begin{array}{ccc|ccccc} 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 0 & 1 & 1 & 1 & 1 & 1 \\ \hline 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \end{array}\right).$$

To compare this structure with our observation, the first step is to define a distance measure. Let us for instance consider the $(n,n)-$exposure matrix E, a censoring threshold θ and a sub-set of indexes c. We denote $\tilde{E}(c)$ the matrix obtained by reordering the lines and rows of E so that the first indexes correspond to c:

$$\forall (i,j) \in [1;n]^2, \tilde{E}_{i,j}(c) = \begin{cases} E_{c(i),c(j)} & \text{if } (i,j) \in c^2, \\ E_{c(i),\overline{c}(j-\#c)} & \text{if } (i,j) \in c \times \overline{c}, \\ E_{\overline{c}(i-\#c),c(j)} & \text{if } (i,j) \in \overline{c} \times c, \\ E_{\overline{c}(i-\#c),\overline{c}(j-\#c)} & \text{if } (i,j) \in \overline{c} \times \overline{c}, \end{cases}$$

where $\overline{c}$ is the complement of c to $1,...,n$. The observed adjacency matrix, labeled $A(c,\theta)$, is defined as:

$$\forall (i,j) \in [1;n]^2, A(c,\theta)_{i,j} = \begin{cases} 1 & \text{if } \tilde{E}_{i,j}(c) > \theta, \\ 0 & \text{otherswise.} \end{cases}$$

To build a distance measure, we aggregate the number of pairwise error analyzing the $|A(c,\theta)_{i,j} - A^{ccp}(\#c)|$ in a block perspective. Based on $A(c,\theta)$ and $A^{ccp}(\#c)$, the aggregate error matrix is defined as:

$$E^{ccp}\left(A(c,\theta)\right) = \begin{pmatrix} \#c(\#c-1) - \sum_{i=1}^{\#c}\sum_{j=1}^{\#} cA_{i,j}(c,\theta) & \#c(n-\#c) - \sum_{i=1}^{\#c}\sum_{j=\#c+1}^{n} A_{i,j}(c,\theta) \\ \#c(n-\#c) - \sum_{i=\#c+1}^{n}\sum_{j=1}^{\#} cA_{i,j}(c,\theta) & \sum_{i=\#c+1}^{n}\sum_{j=\#c+1}^{n} A_{i,j}(c,\theta) \end{pmatrix}.$$

The distance is the sum of the coefficients of the error matrix over the number of links:

$$d^{ccp}\left(A(c,\theta)\right) = \sum_{i=1}^{2}\sum_{j=1}^{2} E^{ccp}\left(A(c,\theta)\right)_{i,j} \Big/ \sum_{i=1}^{n}\sum_{j=1}^{n} A_{i,j}(c,\theta).$$

Determining which institutions are in the core and which ones are in the periphery is seeking the partition which minimizes the distance $d^{lcp}\left(A(c,\theta)\right)$ over all partitions of the institutions c and all the censoring threshold θ.

B.2 Identification of the light core-periphery structure

"Light core-periphery network" refers to the structure proposed in Craig and von Peter (2014). Let us denote h the size of the core (h for hubs). If the core institutions are firstly indexed, the theoretical adjacency matrix A^{lcp} presents a block structure:

$$A^{lcp}(h) = \left(\begin{array}{c|c} A^{lcp}_{1,1} & A^{lcp}_{1,2} \\ \hline A^{lcp}_{2,1} & A^{lcp}_{2,2} \end{array}\right),$$

where all the off-diagonal coefficients of $A^{lcp}_{1,1} \in \mathcal{M}_{h,h}(0,1)$, there is at least one non-zero coefficient in each line of $A^{lcp}_{1,2} \in \mathcal{M}_{h,n-h}(0,1)$, there is at least one non-zero coefficient in each row of $A^{lcp}_{2,1} \in \mathcal{M}_{n-h,h}(0,1)$ and all the coefficients of $A^{lcp}_{2,2} \in \mathcal{M}_{n-h,n-h}(0,1)$ are zeros. Contrary to the complete core-periphery structure, A^{lcp} is not necessary symmetric. For example, a network of 8 institutions with 4 core institutions may be characterized by:

$$A^{lcp}(4) = \left(\begin{array}{cccc|cccc} 0 & 1 & 1 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 & 0 & 0 & 0 & 1 \\ 1 & 1 & 0 & 1 & 0 & 1 & 0 & 0 \\ 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{array}\right).$$

In the case of a light core-periphery structure, the aggregate error matrix for an observed adjacency matrix $A(c,\theta)$:

$$E^{lcp}\left(A(c,\theta)\right) = \left(\begin{array}{cc} \#c(\#c-1) - \sum_{i=1}^{\#c}\sum_{j=1}^{\#c} A_{i,j}(c,\theta) & (n-\#c)\sum_{i=1}^{\#c} max\left(0; 1 - \sum_{j=\#c+1}^{n} A_{i,j}(c,\theta)\right) \\ (n-\#c)\sum_{j=1}^{\#c} max\left(0; 1 - \sum_{i=\#c+1}^{n} A_{i,j}(c,\theta)\right) & \sum_{i=\#c+1}^{n}\sum_{j=\#c+1}^{n} A_{i,j}(c,\theta) \end{array}\right)$$

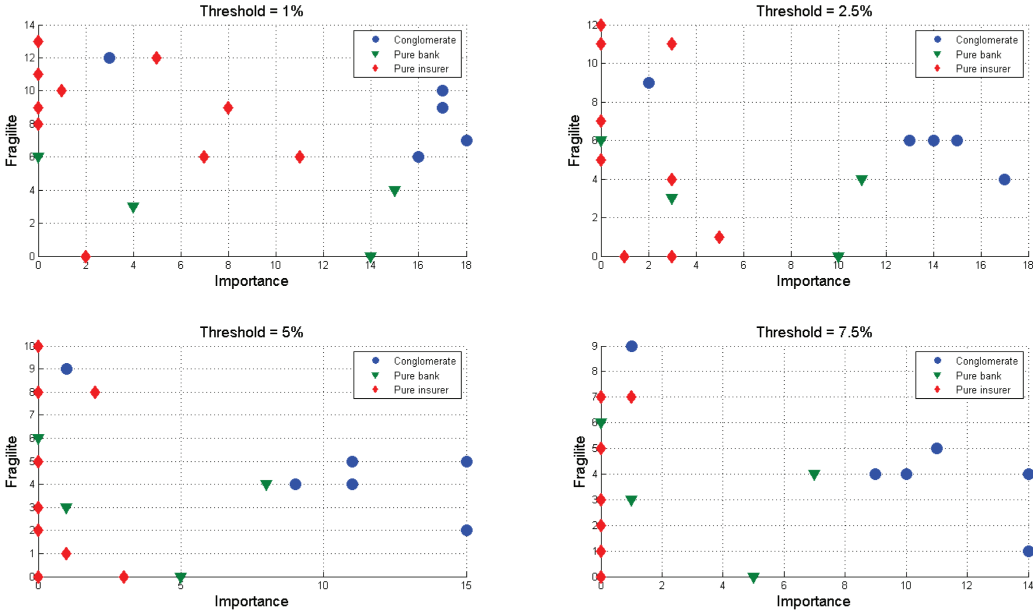
The distance is the sum of the coefficients of the error matrix over the number of links:

$$d^{ccp}\left(A(c,\theta)\right) = \sum_{i=1}^{2}\sum_{j=1}^{2} E^{lcp}\left(A(c,\theta)\right) \Big/ \sum_{i=1}^{n}\sum_{j=1}^{n} A_{i,j}(c,\theta).$$

Determining which institutions are in the core and which ones are in the periphery is seeking the partition which minimizes the distance $d^{ccp}\left(A(c,\theta)\right)$ over all partitions of the institutions c and all the censoring threshold θ.

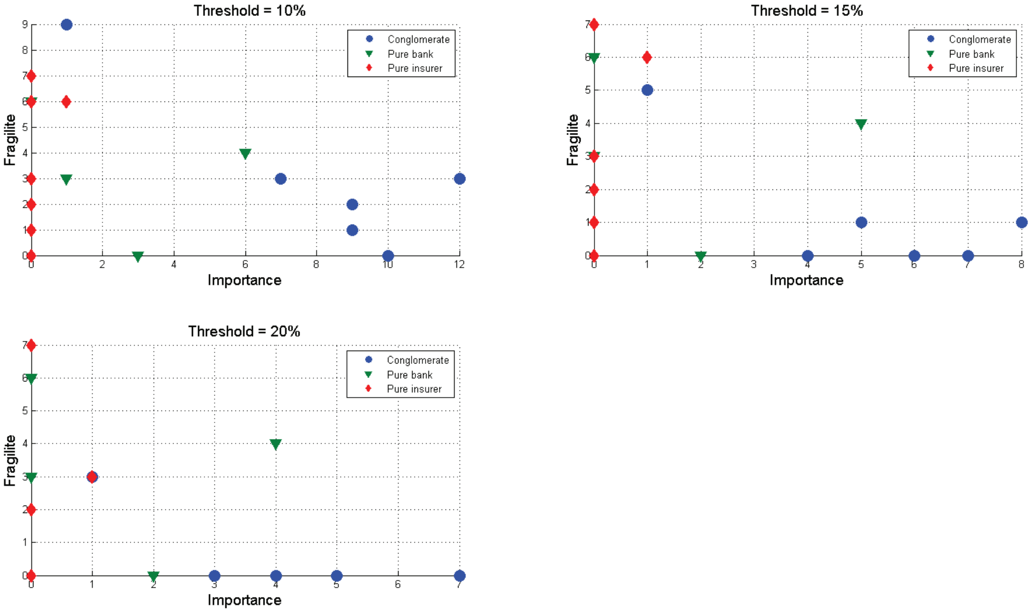
C Sensitivity analysis for systemic importance and systemic fragility

Figures 11 and 12 are similar to Figure 8 except that the threshold used to compute the scores of systemic fragility and systemic importance vary from 1% to 20%.



Source: ACPR data, authors' computations.

Figure 11: Sensitivity Analysis of Importance and Fragility (1/2). 12/31/2011.



Source: ACPR data, authors' computations.

Figure 12: Sensitivity Analysis of Importance and Fragility (2/2). 12/31/2011.

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