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Systemic Importance of Financial Institutions: From a *Global* to a *Local* Perspective? A Network Theory Approach

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After the systemic effects of bank defaults during the recent financial crisis, and despite a huge amount of literature over the last years to detect systemic risk, no standard methodologies have been set up until now. We aim to build a concise but comprehensive picture of the state of the art, illustrating the open issues, and outlining pathways for future research. In particular, we propose the analysis of some examples of local systems that attract the attention of the financial sector. This work is directed to both academic researchers and practitioners.

Keywords: Systemic Risk, Counterparty Risk, Financial Networks, Basel Regulations, European Market Infrastructure Regulation.

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1 Introduction

The financial meltdown that started in 2007, where the financial system was at the same time a source and a victim of the crisis, has highlighted the weakness of international regulations concerning the banking risk supervision. Indeed, in Europe before the crisis, Basel 2 framework did not properly address several crucial points, such as the *liquidity risk*, the *counterparty spread* risk (Credit Valuation Adjustment risk) and the *systemic risk* (related to a system-wide perspective of the banking system as a whole). After the global crisis, the classical statement "too big to fail" has then often replaced by "too interconnected to fail" or "too complex to fail" (e. g. Bastos et al. (2009) and Strahan (2013)).

The banking system represents a cornerstone in the analysis of systemic risk due to its important role in the propagation of shocks to the economy. As emphasized by the recent financial crisis, bank failures weaken the financial system and spread financial distress. Financial institutions whose bankrupt may trigger the failure of other institutions need more rigorous supervision by regulators and should hold higher levels of capital requirements. Hence, the new Basel 3 regulatory setting tries to address these points (BCBS (2013b)). However, a huge debate over the methodologies, the measures, the effectiveness of the rules about the systemic risk is taking place in the banking and academic community.

Past regulation on bank capital requirements followed a *micro-prudential* approach: each bank was assessed on the basis of its own portfolio and its own risk. Regulatory capital had to be large enough to face bank's risk level. Hence, the debate focused mainly on which adequate risk measure should be adopted (*Value at Risk* vs. the *Expected Shortfall*). Similarly, setting up an effective capital requirement for the systemic risk implies a robust definition of what does systemic risk mean. In the international debate the *resilience* of a banking system had been largely scrutinized. What happens to the remaining banks of the system when a big bank fails? This question leads naturally to a *Loss Given Default* approach. Hence, the systemic features of a bank are linked to the losses that it can cause by some contagion mechanism determined by its default. The purpose is that the banking system, by new capital constraints, should be more resilient to such a shock, exactly as an hydric network damaged by a hole into its structure. Alternatively, one could adopt an ex-ante risk contribution approach, e.g. estimate the *ComponentVaR* contribution of the single bank to the global systemic risk.

In the scientific literature, the network theory has been widely adopted in the recent years for many applications, such as the web, social networks, airport design, traffic flows and so on. Therefore, once the relationships among banks (e.g. inter-banking market, OTC derivatives, etc.) are modeled as a *network*, where banks are the nodes and their bilateral exposures are the oriented links, we could exploit network theory tools and indicators to estimate and possibly anticipate systemic risk.

The lack of a complete data set about bilateral exposures does not allow an accurate and granular description of the network system (nodes, edges, weights, attributes) at a given state. In particular, at a local level practitioners (banks) can work with their *peer-to-peer* banking links where all bilateral data are available, while the scientific community has studied the aggregate global statistics (e. g. BIS statistics and DTCC (2013)) and some partial network information in order to investigate the network features and/or behavior by some simulations. New regulations, such as the European Market Infrastructure Regulation (EMIR) and the *Trade Repository* implemented by the European Securities and Markets Authority (ESMA) in 2014, could give new relevant insights on the network structure.

The work is structured as follows[1]. Section 2 is a short overview of the systemic risk regulatory framework, mainly the Basel 3 and the EMIR principles. This section provides also an example of a *macro-prudential* tool applied by the European Systemic Risk Board. In Section 3, we describe the existing bridge between the systemic risk and complex networks theory, and we point out some approaches in the literature where the network representation is combined with some probabilistic structures to study the network dynamics. In particular, we recall some network indicators recently introduced by Cont et al. (2010). In Section 4, we present some hints for improving systemic risk network measures and making this scientific field more suitable to effective applications in the financial industry. Moreover, we discuss some more empirical issues, related to the segmentation of products and markets, and we focus on the choice about an enlarged network (containing also different objects) vs. local and specialized networks. Extensions on local networks are shown, with the particular perspective of the Italian market. The Section 5 provides conclusions.

2 An Overview on the New Regulatory Framework

2.1 The Basel 3 General Framework and the Systemic Risk Measurement

In response to the financial crisis, the recent Basel 2.5 and the just started Basel 3 regulations state new principles in order to ensure a new stability paradigm for the financial institutions. Specifically, the Basel 3 principles are a quite complex recipe of several new rules, splitted in very many definitive or consultation papers (e. g. BCBS (2011, 2013a,b,d)).

[1] For a deepening on some of these aspects, the interested reader can refer to Bonollo et al. (2014)

Our goal here is not to review the whole new Basel 3 framework, but to point out its leading principles.

By conceiving the bank own capital exactly as a wall against wildfire (the unexpected losses due to the risks), the new regulation can be summarized as follows:

- **Higher minimum capital requirements**. This is stated mainly in the common equity tier 1 level (CET1), that increases from 2% to 4.5%. This is exactly as a higher (or more robust) minimum level for the firewall
- **New risk, new indicators, more rigorous treatment** of some classical risks. We refer mainly to the coverage of *liquidity risk*, to the new measures for the *counterparty risk* (CVA) and market risk (*IRC*, *stressed VaR*), to the *leverage* risk.

The above usual *micro prudential* tools (where the bank is measured by its own risk level) have been enriched by the Systemic Risk capital buffer. This is an innovative *macro-prudential* approach in the supervisory mechanism.

It is worth to remember that the improvement of the framework for "*more resilient banks and banking systems*" (quoting from the Basel 3 paper title) is becoming a continuous time process. In fact some further innovations are scheduled for the next few years, a lot of them mainly in the market risk area (BIS (2013d)).

Since the systemic risk is a macroeconomic risk deriving from the fact that banks belong to a financial network, the Basel Committee along with the Authorities, such as ESMA and the European Financial Stability Board (ESFB), combines new constraints on capital requirements and operational tools.

A first strategy to reduce the systemic interconnections is through the incentive to clear OTC derivatives by means of central counterparties (CCPs, see also the following subsection). To enforce this goal The Basel 3 rules state a small risk-weight of 2%, which must be applied to exposures to CCPs which respond to several conditions.

We recall that the "usual" risk weight in the Basel framework are 0% (Govies exposures, multilateral banks), 20% (excellent rating exposures), 50% (good rating) and so on.

Furthermore, the Basel Committee has developed a methodology for assessing the systemic importance of those financial institutions whose failure would represent a serious problem for the whole system. These institutions are called Global Systemically Important Banks, G-SIBs, or Global Systemically Important Financial Institutions, G-SIFIs. Against a possible moral hazard, these banks are obliged to satisfy an additional tier 1 common equity capital requirement, within a range of 1% − 3.5%, according to their systemic relevance as explained below.

The proposed methodology is grounded on a measurement system based on multiple indicators, grouped into 5 categories (BCBS (2013b)). These indicators reflect different aspects of what creates negative externalities and makes a bank relevant to the stability of the financial system. The approach introduced by the Basel Committee seeks to investigate the effects that the failure of an institution has on the economic system, rather than on the risk of it happening. The underlying rationale of this approach is that a new capital requirement reduces the default probability of the bank and it must be applied across a range of different values depending on the single bank systemic relevance.

For each of the 5 identified categories an equal weight of 20% is assigned, and, except for the size, in turn, each category is constituted by more indicators of equal weight. In most cases, the value of the single indicator is calculated as the ratio between the measured value for the individual institution and the total value measured for the set of institutions which constitute the sample reference group. The categories are as follows:

1. *Cross-jurisdictional activity*: 2 indicators of weight 10% each (cross-jurisdictional claims and cross-jurisdictional liabilities). The aim of this category of indicators is to quantify the international importance of the bank. The two indicators measure the significance of bank's activities outside its home jurisdiction compared to overall operations of the other banks in the sample.
2. *Size*: One indicator of weight 20% (total exposures as defined for use in the Basel 3 Leverage Ratio, see paragraphs 157-164 in BCBS (2011)). The larger the bank, the more difficult the chance that its activities can be replaced by other institutions and therefore the higher the probability that its troubles or failure cause financial distress in the financial markets in which it operates.
3. *Interconnectedness*: 3 indicators of weight 6.67% each (intra-financial system assets and intra-financial system liabilities, Securities outstanding). The financial difficulties of a single institution can significantly increase the likelihood that other institutions come into distress, given the network of contractual obligations that characterizes financial systems.
4. *Substitutability/financial institution infrastructure*: 3 indicators of weight 6.67% each (assets under custody, payments activity, underwritten transactions in debt and equity markets).
5. *Complexity*. 3 indicators of weight 6.67% each (notional amount of OTC derivatives, *level 3* assets, trading and available-for-sale securities). The systemic impact of the difficulties or failure of a bank should be positively correlated to the overall complexity of the bank itself, i.e. its business, structural and operational complexity.

For each bank, the score for a particular indicator is calculated by dividing the individual bank value by the aggregate amount for the indicator summed across all banks in the sample. This value is then multiplied by 10.000 to express the indicator score in terms of basis points. Each category score for each bank is determined by taking a simple average of the indicator scores in that category. The overall score for each bank is then calculated by taking a simple average of its five category scores.

The systemically important banks are grouped classifying them according to the score calculated on the basis of the above multiple indicators. Then banks will be affected by different requirements for greater capacity to cope losses, depending on the intensity of their systemic importance. The institutions will be periodically evaluated in order to allow a possible revision and migration from one group to another as well as, from time to time, the measurement methodology and the thresholds will be revised in order to adapt them to market changes and evaluation technologies. Institutions can migrate *in* and *out* of G-SIB status, and between categories of systemic importance, over time. This aspect is of great importance, as being a G-SIB is not a permanent status.

Tab. 1 G-SIBs as of November 2013 allocated to buckets corresponding to required level of additional loss absorbency (Source: FSB)

Bucket	G-SIBs in alphabetical order within each bucket
3.5%	(Empty)
2.5%	HSBC, JP Morgan Chase
2%	Barclays, BNP Paribas, Citigroup, Deutsche Bank
1.5%	Bank of America, Credit Suisse, Goldman Sachs, Group Crédit Agricole, Mitsubishi UFJFG, Morgan Stanley, Royal Bank of Scotland, UBS
1%	Bank of China, Bank of New York Mellon, BBVA, Groupe BPCE, Industrial and Commercial Bank of China, ING Bank, Mizuho FG, Nordea, Santander, Société Générale, Standard Chartered, State Street, Sumitomo Mitsui FG, Unicredit Group, Wells Fargo

The buckets currently identified by the Basel Committee are 4, which correspond to additional capital requirement of: 1%, 1.5%, 2% and 2.5% respectively. Moreover, above these buckets it has been provisionally placed an empty level which corresponds to a requirement of 3.5%, to push financial institutions to avoid worsening their position migrating to this class more burdensome (see Tab. 1).

Not all the required information for the indicators can be easily extracted from the asset and liabilities balance sheet or from the profit and loss report. To this end, the Basel Committee defined a standard template where institutions collect all data across the large banks and specify all the details (Bcbs (2014)). If we get a look at the official template, and we exclude some further sub-total indicators, we have about 85 variables that banks have to calculate, coherently with their financial reports.

The deadline for the effective application of the rules on G-SIBs is scheduled for 2019.

2.2 European Market Infrastructure Regulation (EMIR) and Trade Repository

While the Basel 3 regulation for the systemic risk refers to some heuristic indicators, a more quantitative approach could allow to have a deeper control of the financial system dynamics and related risks. Referring to the OTC derivatives market, until now the reporting (BIS, ISDA, CFTC), has shown an *aggregated* style, as it has been based on a pooling of data coming from national central banks or from some leading *reporting dealers*. Due to the lack of information or to the difficulty to check adequately their quality, it is very hard to measure (or to estimate) the amount and type of bilateral exposures, netting agreements, and collateral positions between two counterparties.

Recently regulators are implementing ways to solve the problem of the scarce availability of data. In Europe, the creation of the ESMA and the ESRB are also motivated by the need to enforce the availability of data in order to improve the supervision and the restraint of the systemic risk. In particular, the EMIR regulation was established with the Regulation No. 648/2012 by the European Parliament. Roughly speaking, the main purposes of the EMIR are to reduce or to control the counterparty credit risk, the systemic risk and the market abuse.

Hereinafter we give respectively a general overview of the pillars that compose the EMIR and some details about the *Trade Repository* which represents the challenging tool that should allow all market players to get useful data in order to analyze the systemic risk. As a *byproduct* of the new regulation, the trade repository should imply a higher quality data level of the international derivatives statistics (e.g. BIS, DTCC, OCC (2014)).

The Pillars of the EMIR Architecture. In recent times, it has become quite common to split every new financial regulation or international framework in some logical *pillars*. The EMIR may be synthesized in the following pillars:

- Pillar I: Every *eligible* OTC derivative must be cleared by some Central Counterparty (CCP).
- Pillar II: Every *non-eligible* OTC derivative deal must be collateralized by some suited cash or security guarantee, with standard contracts.
- Pillar III: The required OTC and listed derivatives data must be reported to the Trade Repository, the so called reporting obligation.

In principle, the three pillars look very simple, but in the practical application some hundreds of FAQs have arisen (ESMA (2013)) and several releases of QAs and technical standards have been published.

Regarding the market players that must apply the EMIR, specific obligations are defined for different operators; namely: Financial Institutions (banks, asset managers, funds), Non Financial Corporations Plus (NFC+ in the EMIR definition), and the other Non Financial Corporations (NFC)[2].

More explicitly, the Pillars I and II are mandatory only for financial institutions and NFC+, the pillar III for all the market players. Regarding to the Pillar III, of course some retail or private operators will not submit their contracts to the trade repository, since the bank will submit the deal data and the mirrored "customer side" data on behalf of him or her.

The Pillar I aims to reduce the credit counterparty risk by replacing the *peer-to-peer* classical OTC derivatives relationships with some robust hubs, such as the CCPs (see Fig. 1). The CCPs must in fact satisfy very strong requirements, both for capitalization level and for organizational constraints.

Strictly speaking, the CCPs are the clearing houses located in each stock exchange: in the IDEM (Italian Derivatives Market) in Milan the clearing house is the "Cassa Compensazione Garanzia", in the Eurex market in Frankfurt the clearing house is the "EC EurexClearing " and so on. In the EMIR regulation (and also in Basel III), the CCP concept is broader, and all OTC clearing houses that match the requirements can ask for the registration.

[2] The NFC+ are different from NFC according to a volume threshold; the volume is define by the gross notional value, and it ranges from 1 to 3 billions of euros, separated from different asset classes (equity, interest, Forex, credit, commodities).

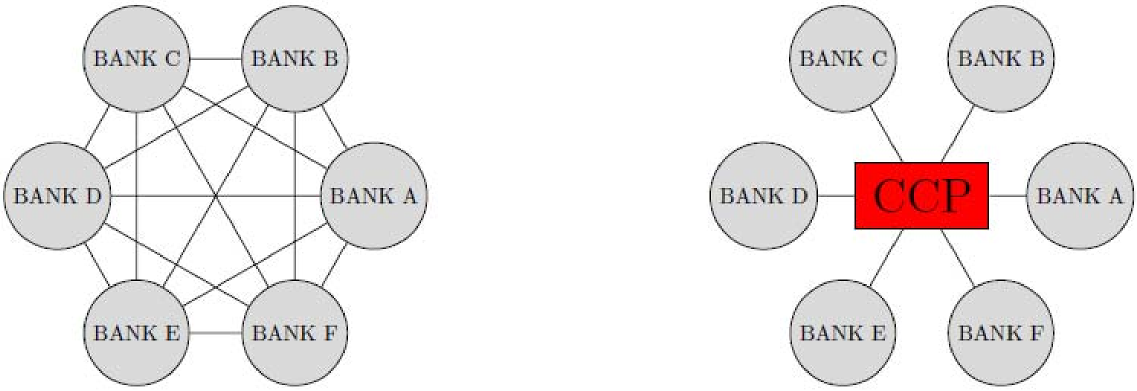

Fig 1: From the left to the right the passage to the network structure with CCPs as hubs of the network.

As we discuss in other sections of the paper, one can wonder if the new topology given by a CCP implies or not a reduction. In fact a CCP reduces the default probability of the single exposure but it increases the loss given default effetct. What happens when a CCP fails? What if one of its major clearing members defaults? Furthermore, if specific derivatives classes are cleared by many separate CCPs (Duffie et al. (2011)), which is the impact on netting capacity and collateral demands?

The Pillar II again aims to reduce the counterparty risk by a *collateral* risk mitigation. Even though there are no doubts about to the effectiveness of the measure, from a business perspective a high collateral level with a frequent margining process could cancel the *leverage effect*. Hence, one of the main incentive to make a new deal might be hampered.

Finally, the Pillar III is meant to monitor the systemic risk, the market abuse, and to get more reliable derivatives statistics. This aspect will be discussed in the next paragraph.

The Trade Repository (TR). As we said above, the main scope of the trade repository is to disseminate high quality information in order to have a comprehensive view of the market and to monitor the systemic risk and market abuse phenomena. Who will have the full information available? Quoting from the EU regulation 648/2012 "… to ESMA, the relevant competent authorities, the European Systemic Risk Board (ESRB) and the relevant central banks of the European System of Central Banks (ESCB)...".

Full availability means at the highest level of *granularity*: ESMA and the other allowed subjects will be able to drill down any deal of counterparty A with counterparty B, exactly as reported by both counterparties A and B.

In this sense, the Pillar III of EMIR looks like the Pillar III of the Basel regulation, the *disclosure* pillar. In the same manner, only regulators can access the detailed data related to the exposures and the risks of the banks, but all market participants can compare at a more aggregated level the risks of the different banks by mean of a set of standardized tables that banks are obliged to publish in their own website.

More specifically, the regulation 151/2013 designs three different levels of granularity: the *Transaction* level, the most detailed one, the *Position* level, with details by counterparty and product/underlying, and the *Aggregate* level, with details by product/underlying, but no counterparty information. The authorities and regulators can get the first two levels depending on their mandate, while the other market players will work only at the aggregate level.

The practical implementation of the TR requires many details. First of all, the banks and the others subjects do not report directly to the ESMA, as they are intermediated by some Trade Repository Services, called *Trade Repositories* (TRs). The TRs must register to ESMA. The activation of the reporting started on 2014, February 12. All new contracts must be reported, along with all contracts with trade date after 2012, August 16 by a *backload* process.

The data that must be reported are splitted in two main categories: the specific counterparty data and the *common* data (e.g. trade date, notional, underlying data, collateral, etc.), for a full list of (26 + 59) = 85 variables (fields). The TRs will apply a strict data quality process in order to ensure the reliability of granular data as a preliminary requirement for the aggregated statistics, hence they must match the data dispatched by the two counterparties.

Due to EMIR, in order to match and compare the data before their publication, banks now must adopt several common *identifiers* and taxonomy codes. Among them, the most important are: *UTI*, Unique Trade Identifier (the deal identifier), *LEI*, Legal Entity Identifier, and *UPI*, Unique Product Identifier.

The report obligation to the TR must be satisfied daily, in the sense that any new deal is reported within one working day. Several events must be reported, such as the new deal, its expiry, early exercise, coupon payment and so on. In addition, the general 85-dimensions data requirement is quite different depending from the *asset class* of the deal, namely: interest, equity, forex, credit, commodity, exchange traded derivatives (ETDs).

Anyway, in spite of the huge effort that the whole financial and ICT industry is performing to feed data, the TRs will undoubtedly give a lot of tractable empirical data along with new ideas and directions useful to define the systemic risk field. After a “phase-in period”, we expect that the systemic risk research based on the TRs might slightly change the very heuristic approach to the systemic risk concerning the SIFIs Basel 3 regulation.

2.3 The ESRB Quantitative Systemic Risk Indicators

There is a long distance between the academic systemic risk indicators proposals vs. the regulatory framework. At an intermediate level, one can wonder about the systemic risk monitoring organized by the authorities. An outstanding example is the *Risk Dashboard* published by the ESRB with a monthly frequency (e. g. ESRB (2014)).

Before getting into the details of the risk dashboard, it is worth to note the disclaimer in the cover page of the report “*DISCLAIMER: The risk dashboard is a set of quantitative indicators and not an early-warning system. Users may not rely on the indicators as a basis for any mechanical form of inference”*. In other words, just a descriptive meaning is assigned to the indicators, without any inferential property.

Coming now to the contents, a first indicator is the *Composite Indicator of Systemic Stress* (CISS). See Fig.2 for an example and Holló et al. (2012) for the details. The CISS aims to measure the current state of instability of the financial system, and authors define the *systemic stress* as the part of the systemic risk already materialized.

The calculation schema of CISS is the following:

1. Selection of 15 raw-indices belonging to 5 sectors/markets (money, bond, equity, forex, banking);
2. Aggregation of them by a vector of weights and a correlation matrix;
3. Standardization, so that the CISS is unit-free in the range [0,1].

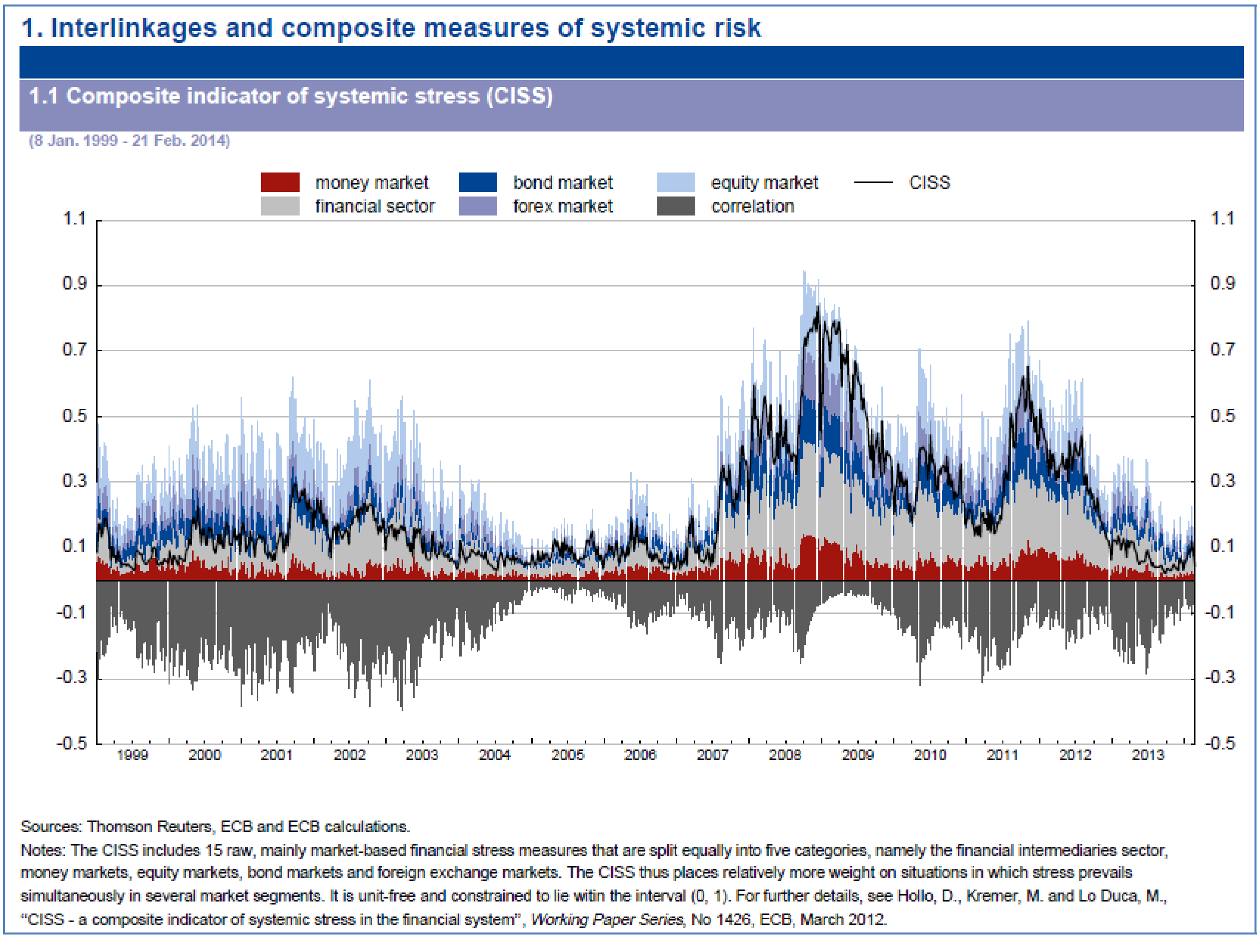

Fig. 2: CISS as of February, 2014

We have some doubts about the kind of risk that the *CISS* captures. If we examine the 15 sub-indicators that build the synthetic *CISS* index, most of them are related to the *volatility* of different asset classes (money market, bond market and so on). The remaining sub-indices are calculated by several *spread* and *yield* indicators for the different sectors. Hence, are we measuring systemic risk or the financial volatility and risk premium (the spread)? Moreover, the authors point out that the systemic events should be captured by a "sizeable increase" or "unusually high level" of the CISS. To this end, it is not clear how to set up these concepts for implementing a *backtesting* process in order to evaluate the explanation/forecasting properties of the CISS indicator. Hence we think that more empirical test are needed.

Finally, we observe that this approach to systemic risk measure by market indicators can be defined a *top down* approach, where one seeks for a satisfactory statistical fitting, while the network approach belongs to the *bottom-up* approach, where a structural link between the financial network and the systemic risk is sought.

The second indicator in the dashboard is the *CoVaR* as proposed in Adrian et al. (2011). Namely, “Co” stands for *co*nditional, *co*movement, *co*ntagion. More explicitly, one captures the Δ*CoVAR*. The *i*-th ΔCoVaR is the difference between the *VaR* of the whole financial system being the *i*-th bank in distress, and the *VaR* of the system when the bank *i* is in median conditions.

Again, the estimation of the indicator is based on market data, such as spread curves, yield curves, market volatility such as the *VIX* index. Practically, the *ESRB* dashboard refers to the banks belonging to the Stoxx600 european index, currently about 50 financial institutions. We have the same doubts about the CISS indicator. *CoVaR* is of course a very appealing indicator, but it does not explain the mechanics of the systemic risk and its contagion issues.

3 A Network approach for Measuring the Systemic Risk

3.1 Available Data and Construction of the Network: One Comprehensive Network or Several Segmented Sub-networks?

Typically, network theory describes financial institutions as a set of nodes while the matrix of bilateral exposure E gives, for each pair $(i; j)$ of nodes, the exposure E_{ij} of node i to node j. Usually, widely applied measures to describe a network are out-degree and in-degree of each node, connectivity, degree distribution, assortativity, network size, out-strength and in-strength of each node and related normalized quantities and correlation, distance and “weighted" distance between two nodes and indicators of resilience.

Since the difficulty to obtain reliable data about the effective exposures, many authors focus only on domestic market and investigate the structure of interbank exposures to describe the system. Usually, reports provided by banks to supervisors represent the main source of bilateral expositions: for instance, Boss et al. (2004), Guerrero-Gòmez and Lopez-Gallo (2004), Lublóy (2005), Cont et al. (2010) and Langfield et al. (2012) investigate respectively Austrian, Mexican, Hungarian, Brazilian and UK data sets, while Mistrulli (2007), Iori et al. (2008), Iazzetta and Manna (2009) and Delpini et al. (2013) describe Italian interbank networks.

Few studies use actual exposures, thus highlighting the difficulty to define the real structure of the financial system. Unfortunately, incomplete data sets are likely to determine biases on contagion estimates. Typically, the lack of data is dealt with the maximization entropy of exposures matrix[3]. According to this procedure, researchers do not impose any structure on the system, but rely only on

[3] See Sheldon and Maurer (1998) for the use of maximum entropy in financial networks.

the bilateral exposures resulting in the balance sheets[4]. Basically, authors assume that banks spread their exposures as evenly as possible, and use balance sheet data to infer the entire matrix of expositions. This procedure implies that banks share the same portfolio of interbank exposures and that incomplete and disconnected systems are difficult to be simulated. This in turn fails to reproduce some stylized properties of financial networks, such as sparseness of the exposures matrix and tiering. In particular, the banks have expositions only with a (relatively) small number of counterparties due e.g. fixed costs. As suggested by Upper (2011), these pitfalls may lead to an underestimation of the possibility for contagion and an overestimation of its severity.

A particular interest from an operational point of view is related to the work of Langfield et al. (2012). Authors exploit a very granular data set provided by the Financial Services Authority (FSA) collecting data for 176 UK banks plus 314 non-UK banks which are counterparties for at least one UK bank (in spite of the lack of actual bilateral exposures regarding foreign counterparties which usually induces researchers to impose contagion caused only by domestic exposures). In particular, they analyze two networks: the exposures network (relevant for solvency) and the funding network (relevant for liquidity). The classes of financial instruments are the following:

- **Exposures network**: “unsecured interbank lending”, “marketable securities”, “net CDS sold”, “securities financing transactions (after collateral)” and “off-balance sheet derivatives exposures”;
- **Funding network**: “unsecured interbank lending” and “repos (before collateral)”.

For a network theory perspective, the application of “segmentation” in terms of markets and products may lead to an over enrichment of attributes for both nodes and edges. In particular, considering the various set of instruments in which a financial institution is involved there is the serious possibility that the resulting system appears over-detailed. This may induce practitioners to define separate networks, focusing on a particular sub-set of variables useful to detect specific operational needs. Authors describe the structure of the networks by considering classes of instruments, maturity, type of bank and country, showing how the structure and the properties of the network vary significantly by asset class and banks features. Moreover, authors apply clustering methodologies in order to split banks in groups ordered by risk characteristics and they also consider the heterogeneity of the nodes by studying the network of exposures divided by Core Tier One

[4] Alternatively, the so-called Stochastic Block Modeling of networks is characterized by link predictions algorithms applied to create missing links by simulating a large number of networks based on underlying exposure data and imposing behavioral features. See for instance Lu and Zhou (2010).

capital (CT1), where the exposure of i to j is divided by CT1 of i, and the funding network divided by the liabilities, where the exposure of i to j is divided by the total liabilities of j.

According to the Bank of England templates used to fill information about banks activities, financial institutions have to report a detailed set of information based e.g. on asset classes, type of financial instrument and counterparties, maturity and exposures limits with an higher level of details for large banks. Adopting a similar approach one might focus on the analysis of financial networks related to specific markets or geographical areas. This could be reconciled with the distinction between "global" systemic risk and "local" systemic risk. For instance, a separated description of the financial system could provide insights whether a bank is systemically risky in a particular market and not in another, or how its locally central position in a particular area or market is related to a greater risk contribution to the overall systemic risk and, in general, if global periphery nodes could sometimes play the role of local systemic important institutions.

Finally, calibrations and estimations deeply exploit historical data in order to investigate financial system features. Bisias et al. (2012) argue that these approaches typically rely on the assumption of stationarity. However, if the structure is not stable over time, it might be not adequate to infer the properties of the system from past observations. In particular, one might argue that the lack of stationarity represents one of the main sources of systemic risk and that financial innovations affect the stability of the system reducing transparency and increasing complexity.

3.2 Network Structure and Distress Propagation

Systemic risk is related to the relationship between the structure of the financial network and the event of financial contagion. Using the methodology of the network theory much effort has been spent in detecting patterns able to describe the tendency to contagion.

A pioneering work by Allen and Gale (2000) considers three types of networks in the interbank market: (i) the complete structure, where banks are symmetrically linked to all the other banks; (ii) the incomplete structure, in which banks are directly linked to their neighborhoods and other links are only indirect; and (iii) the disconnected structure characterized by at least one pair of banks not linked either directly or indirectly. Authors show how although complete structures are usually identified to be more likely to spread financial distress, the consequences may be less harsh since losses are shared among more counterparties. In addition, disconnected structures are more prone to contagion but may prevent cascades effects from spreading to all banks. Hence, as the completeness of the network increases, the risk of single default goes asymptotically to zero thanks to risk sharing, thus enforcing the resilience of the system.

From a different perspective, Freixas et al. (2000) define a money center model where the existing exposures are those connecting the money center bank and its counterparties, which are themselves not linked together. Therefore, if the loss is sufficiently high the default of a bank linked to the money center will generate the default of the latter, while a failure of the money center bank may trigger failures of the connected banks even for lower losses.

Some recent studies highlight that too dense interconnections may reduce the stability of the system. Some further studies show a positive relationship between the possibility of systemic collapse and the size of banks' counterparties (Vivier-Lirimont (2006)) and describe how interbank exposures exceeding a threshold may increase the event of contagion (Nier et al. (2007)). In particular, Nier et al. (2007) argue that the increasing degree of the system induces the interbank network to exhibit an M-shaped pattern representing the interplay of two effects determined by more links: firstly, the enforcement of the resiliency of the system, and secondly, an increase in the channels through which contagion may spread. Haldane (2009) conjectures the existence of a trade-off between the resilience of a connected network and the scope for a larger spreading of financial distress in a more connected system. Within a certain range connections enforce shocks absorbing and system robustness, while beyond this range connections may represent a mechanism for propagation and, therefore, fragility may prevail. Battiston et al. (2012) argue that in the presence of a financial accelerator, capturing counterparties' reactions, and of persistence, that is when the variations in the level of financial robustness of institutions tend to persist in time, the probability of default does not decrease monotonically with diversification. As a result, the financial network is most resilient for an intermediate level of connectivity. Similarly, Billio et al. (2012) describe how the increasing level of systemic risk in finance and insurance is positively related to the rising interconnection of financial institutions over the past years. Acemoglu et al. (2013) show that, in the presence of large shocks, interbank exposures may facilitate the spreading of contagion thus determining a more fragile system. From similar perspectives, Gouriéroux et al. (2012) analyze how financial distress spreads in the system through exposures based on debt holding, while Cabrales et al. (2013) describe the relationship between the capacity of greater interconnected system to share the risk and the greater exposures resulting from larger components in the system. Elliot et al. (2013) reflect upon the impacts of the integration (that refers to the level of exposure of organizations to each other) and the diversification (that refers to how exposures are spread out) on the extent of financial contagion, showing that a system is most susceptible to widespread financial contagion when two conditions hold: firstly, integration is intermediate, and secondly, organizations are partly diversified.

Finally, an useful review on simulation methods is given in Upper (2011) who describes the set of general assumptions commonly diffused in literature to study contagion, providing comparisons and analyzes, and shows the most used simulation algorithms, i.e. the one proposed by Eisenberg et al. (2001), where the losses of all banks resulting from the failure of a certain bank are simultaneously computed, and the sequential method introduced by Furfine (2003). Many studies extend the basic framework to incorporate features relevant in real financial networks. Among them, we recall Degryse et al. (2007) (time dimension and simulation), Fender et al. (2010) (international banks and cross-border issues), Müller (2006) (liquidity extensions), Elsinger et al. (2006), who consider the joint effect of interest rate shocks, exchange rate shocks, and prices variations on interbank payment flows. Finally, Cifuentes et al. (2005) describe a network in which links represent portfolio holdings and contagion is caused by changes in asset prices, while Mistrulli (2007) studies bank mergers and their impacts on the resilience of the system.

3.3 Network Quantitative Indicators

As a consequence of the recent financial crisis and the introduction of systemic risk in Basel regulations, financial institutions and academic literature show a growing interest in quantitative measures able to capture systemic risk, in particular as regards the contribution of the single institution.

A wide set of systemic measures have been introduced in the literature. Recently, Bisias et al. (2012) investigate systemic risk measures from different perspectives: macroeconomic measures that focus on various macroeconomic aggregates such as asset price indices and GDP growth rates, network measures based on the modelization of the financial system by nodes (financial institutions) and edges (contractual relationships), forward-looking risk measurement that postulates an evolution dynamics of the financial system along time, cross sectional measures that analyze the co-dependence of institutions on each other (e.g. CoVaR), stress tests and measures of illiquidity and insolvency.

According to the approach followed by Basel Committee, i.e. the above mentioned LGD approach, we discuss some interesting network indicators recently introduced by Cont et al. (2010). Authors suggest a quantitative methodology for the analysis of contagion and systemic risk in a network of interconnected financial institutions and apply it to study the Brazilian financial system.

Bilateral exposures within the system are described by a network $I = (V ; c; E)$ where V represents the set of n financial institutions (nodes), E is the matrix of bilateral exposures (E_{ij} represents the exposure of node i to node j defined by the mark to market value at a certain time, so that it is the maximum loss in the short term for i in case of an immediate default of j) and $c =$

$\{c(i) : i \in V\}$, where $c(i)$ is the bank i's capital which represents the bank i's capacity to absorb losses.

The contagion mechanism of the model implies that the failure of bank i affects the asset values of its creditors. These losses are partially or totally absorbed by creditors' capital. If the loss is greater than bank j's capital, then it will lead to a new default and a new round of losses to the creditors of j. Therefore, a domino effect may happen, thus determining a *loss cascade* which implies to update at each round the losses resulting from previously failed banks.

The *Default Impact* (DI) of a financial institution i is defined as the total loss in capital due to cascade effects generated by the default of i. This measure takes into account the amount of losses determined by the component "default by contagion" and excludes losses of the institution that caused the default cascade. Hence, it allows to measure the systemic impact on the network inflicted by the failure of a certain institution.

Clearly, the DI is related to the sub-graph of contagious exposures. The exposure of node j to i is said "contagious" if j fails in each scenario in which i defaults. Hence, the sub-graph of contagious exposures plays an important role since the wider it is, the greater the extent of contagion. In particular, under stressed market conditions this part of the graph may increase, thus determining a higher risk of cascade effects. This suggests to take into account the effect of correlated shocks that simultaneously reduce the capital of the institutions of the network. Indeed, the DI is based only on the default event, without taking into account the possibility of systemic events, e.g. market shocks, which could hit at the same time all the institutions of the networks. In order to consider the possible presence of systemic events that can affect all the institutions of the network at the same time, Cont et al. (2010) introduce the *Contagion Index* (CI). Assuming a market stress scenario which generates the default of i, the CI measures expected losses inflicted to the network as a consequence of the cascade effects caused by the default of i. Hence, the CI of institution i is defined as its expected DI when the whole network is subject to correlated market shocks that produce the failure of i.

From a policymaker perspective, the above findings allow to build a bridge between regulations and network properties of financial systems. Although they have to be also tested in other financial networks, the systemic risk indicators introduced by Cont et al. (2010) seem promising to us since they well integrate the cascade effect, the credit risk and the market factors.

4 Open Issues and Proposals for Future Research

We conclude this section with the following subsections where we outline some ideas in order to improve theoretical tools and applied research in this field.

4.1 Improvement of the Network Model and Indicators

The indicators introduced by Cont et al. (2010) implicitly hypothesize a static framework. We propose to improve them including a dynamics for the MtM value of the exposition of each node based on some relevant common risk factors plus an idiosyncratic risk factor specific for each node. In addition, a model and a measure for systemic risk should take into account the different types of institutions (the nodes of the network): investment banks, large commercial banks, small banks, branches, large corporates. This in turn could be translated in the way in which the institutions depend on common factors (for instance, using different dependence coefficients). Moreover, network indicators typically rely on the knowledge of the exposure matrix: the more detailed the exposure matrix, the more precise the measure. From the point of view of the single bank or of a researcher, the partition of the MtM value of the whole exposition of a node among the links (in order to obtain the exposure matrix) can be done only using probabilistic tools based on realistic aggregated information (such as, how many equity derivatives, how many interest rate derivatives, some counterparties segmentation, etc.). On the other hand the regulators could be able to know the data at the level of each transaction, by exploiting the very granular information of the trade repositories. Thus, they could consider a dynamics for each link (i, j).

Finally, regarding the common risk factors, we can make distinctions on the basis of the scope of the application. A single bank *front office* department wants to get a very accurate estimation of the MtM of each derivative deal. To this end, the common risk factors could the effective *underlyings* of the derivatives contracts. But for a large bank with several thousands of deals we could reach some thousands of risk factors: it would be impossible to manage them over time and to maintain a clear picture of the risk sources. Moreover, many of these financial underlyings are highly correlated, e.g. the European stock indices (Eurostoxx50, Dax, Cac40, etc.). In a risk management more strategic perspective, one has to move from the underlyings to the *risk drivers*. Risk drivers shape a smaller set (say a few dozen) of background financial factors, from which all worldwide market parameters should depend. A very popular example of risk drivers follows an asset class clustering (equity, interest rate, forex). More explicitly, the list could be:

- Main stock indices;
- For each relevant interest rate curve (EUR, USD, GBP, YEN), 3 buckets points, i.e. short term, medium term, long term interest rate level;
- Forex exchange rates.

Again, these risk drivers might be quite correlated. Hence one can implement a short list selection step (i.e. the most correlated ones are dropped out) or a *PCA* (Principal Component Analysis) process.

4.2 Extensions to *Local* Systemically Important Financial Institutions

The Basel 3 reform covers very large banks whose default can inflict relevant losses on the global financial system, due to their sizes and interconnections.

We guess that the network perspective applied to the systemic risk could be exploited also for further "markets" that can be very different for the size or for the high specialization of the players. In this sense, as we reported in section 3.1, we claim that a set of different segmented networks may be more useful with respect to the too much ambitious project of representing the whole financial system in a unique granular network.

This in turn might lead to the analysis of a set of financial networks which can better fit the range of business activities where banks are involved. From a practical perspective, this might imply the study of the financial system in a variety of markets: asset classes, funding sources, geo segmentation, etc. Due to the novelty of the field and the potential impacts on banking sector, as a promising suggestion we consider the analysis of the following markets, which we briefly illustrate with some examples of local systemic risk.

Regional Banks

This is the simplest example. A small bank with a dominant position in its region can cause a contagion in its local system both to lenders and to borrowers counterparties. For this reason very often the (Italian) Central Bank supports any strategy to merge the distressed bank with other financial institutions. The research issues concern how to monitor the regional systemic role and which data should be exploited.

Crowdfunding Platforms

Crowdfunding is a promising new channel for funding the enterprises. We do not have a sharp definition of what crowdfunding is, but we can distinguish some of its typical aspects:

- The firms are very often start-up or scientific spin-off
- Innovative sector (hi-tech, bio-tech, environmental)
- Very granular funding style, that explains the "crowd" term
- Smart web platforms for an efficient (economic and operational) funding process

- Scientific or technical committee to evaluate the investment proposals

The laws and practices concerning the crowdfunding vary in different countries, and in each region we have a small set of leading platforms[5]. We remember that the first regulation to make feasible the crowdfunding by webportals was defined in Italy. Now we have about 60 platforms, but the funding process is very concentrated.

What happens if we have some failures (fraud, error, default) in one of the nodes that guarantee the funding? Typically the start-up small businesses are quite fragile from a financial perspective, and therefore they could face many problems if the crowdfunding channels stop to run.

How to describe the crowdfunding subjects using a network? Which are the relationships with other financial channels, such as *private equity* and *private debt funds*? Finally, what is the strategy in the geographic segmentation? Several local stand alone networks, due to the different regulations, or a global crowdfunding network, due to both financial and technical efficiency in the funding-lending process?

Although no consolidated statistical literature is available on these topics, the network approach seems to us very adequate for the problem.

MiniBond

The term *minibond* is the Italian commercial name for the bonds issued by small businesses. “Mini” is related to the size (few million of euros) and also to the quick process in order to issue them. These bonds are not subject to the European “Prospect Directive”[6] but, as a protection for the investors, they must receive a rating by some certified agency. The minibond market started in Italy in 2013, due to the “Development Regulation” (“Decreto Sviluppo”) by the Italian Government. Currently, we have several dozens of minibonds listed in the *ExtraMOT Pro* Italian stock exchange market, with a outstanding notional of some hundreds of millions of euros.

The minibond diffusion can reduce the dependence from the banking funding, thus diversifying credit sources and limiting the negative effects of credit crunch. By supporting new types of investors to enter the market (professional investors, asset managers, funds), this in turns enlarge the lenders-borrowers network and may reduce banking dominant position, very relevant in the italian market.

Typically, the advisors of the enterprises in the issue process are regional banks. These banks could default, or they could propagate via the minibond channel their excessive exposures to some defaultable firms.

[5] For a survey of recent success cases see http://www.diaman.it/images/rassegna_stampa/Plus24_26.04.2014.jpg.

[6] See http://www.borsaitaliana.it/obbligazioni/formazione/extramotpro/extramotpro.htm.

Moreover, in the minibond building process the public rating is the key variable for defining the fair interest rate (hence the *risk premium*), while for instance in the mortgages markets the real estate mitigants values are usually strictly correlated with the default probability of the borrower. Therefore, this influences the relationship between credit exposures and the use of collateral, hence suggesting to apply the network approach with the related indicators in the funding-lending schema.

Although it seems clear the positive impact of minibond diffusion on risk sharing and investment enhancement, it is less evident how to measure the systemic effects for the local financial system. Due to the promising volumes of this new market (see the recent very extensive survey by Erzegovesi et al. (2014)), we feel that the network approach for the systemic risk of this specialized market could suggest new interesting insights about its risks.

5 Conclusions

The financial crisis in 2007-2008 highlighted the relevant role of the systemic effects of the single entities' defaults on the stability of the whole financial system. For this reason, the new Basel 3 regulation adopted a methodology in order to face this risk, called systemic risk. However, in spite of the large amount of scientific literature on this topic, the approach proposed by the Committee is heuristically based on some indicators and quite far from being a proper quantitative technique.

There are also other two open issues that are subjects of debate in the literature. One concerns the class of the measure that is more suitable for systemic risk: a "what if " approach (i.e. a "LGD" approach) or a quantile measure or an expected shortfall. The other point regards the most resilient system structure: does the introduction of the CCPs really imply a decrease of the systemic risk or not? Although CCP reduces or cancels the counterparty risk (since it is compensated by the CCP), the size of the loss is bigger if the CCP defaults. There are different points of view concerning which structure is more resilient against contagion and systemic risk. According to us, the above question is still open just because of the absence of a commonly accepted measure for the systemic risk.

Taking into account the current scarce availability of the data and of a well-established applicable methodology, we find acceptable and feasible the indicators-based approach of Basel 3. The selected indicators are chosen to reflect the different aspects of what generates negative externalities and makes an institution critical for the stability of the financial system. The advantages of this approach are its simple logic (although the very large number of input variables required) and the fact that it deals with many aspects of systemic relevance. We suggest to exploit network theory in order to integrate these indicators with measures that consider not only the relationships and the level of exposures of an institution, but also those of its counterparties. It is fundamental not only the position of the single institution in the financial system, but also the positions of its counterparties. Finally, given the difficulty to handle the whole financial system as an unique network, we suggest to investigate the systemic risk in a local perspective, where local means any portion (geographical, market segmentation, ...) of the worldwide financial network.

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