Intra-portfolio systemic contagion
Basic aspects and comments on current regulation

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Abstract
Traditional approaches to credit risk evaluation have looked at a portfolio's obligors as separate elements. However, daily bank practice suggests that there can be contagion effects between obligors, a fact that through the current normative has been explicitly acknowledged by EU regulation authorities. The "group of connected clients" is the key-concept for this revolutionary change: EBA requires banks firstly to identify such groups according to a set of different criteria and then to treat each of them as a single risk unit. This normative challenges banks to adopt concepts and methods rather new with respect to its professional background and practice. Here, its conceptual and practical implications are discussed, and some of its main flaws are evidenced: its framework remains static instead of dynamic, local instead of systemic, threshold-based instead of continuous variations. Therefore, if on one side this normative introduces the revolutionary concept of the groups of connected clients among risk evaluation criteria, on the other side it remains still entrapped into the traditional view and leaves untouched the risk evaluation of "non-dominated" clients. Hence, it should be considered as a step towards a full new paradigm, which had to look at portfolios as inter-organizational networks, more or less subjected to "failure cascades" depending on its specific structures. To this aim, it is required to design a new rating system with which single obligor's risk evaluation should be measured precisely and in relation with the position they cover within the whole portfolio.

Keywords: credit risk evaluation, complexity economics, economic dependency, economic networks, failure cascades, financial contagion, groups of connected clients, inter-firm networks, network interconnectedness.

JEL codes: G28, L14, O16.

1. Introduction

The issue of credit risk evaluation methods has a long history and a rich scientific literature, which produced advanced operational methods, recently enhanced also with modern computational techniques, like Monte Carlo simulation models, machine learning, and genetic algorithms. Further, these methods now can be fed by new data sources and therefore they are becoming a flourishing field of application of big data analysis. These fin-tech innovations are expected to produce dramatic improvements with beneficial effects on the performance of financial operators. Actually, the dramatic underestimation of some harmful bankruptcies (Lieven, 2016) casted serious doubts on the effectiveness of prevalent methods (BCBS, 2000, 2005; ESMA, 2015; FSB, 2014; Hemraj, 2015; Jeon & Lovo, 2013; Lieven, 2016; Malik, 2014; Mattarocci, 2014; McClintock Ekins & Calabria, 2012; White, 2010).

In this perspective, the economic crisis has not determined but only accentuated a chronic inadequacy or incompleteness of standard methods. Financial contagion processes have been rightly indicated as a major cause of the persisting crisis, and a new economic literature is studying this phenomenon and systemic failures of the credit system (Capponi & Chen, 2015; Glasserman & Peyton Young, 2015, 2016; Zamami *et al.*, 2014; Zheng, 2013, to name just a few). It has been underlined that the dominant idea that more interdependence between credit operators would have hindered contagion effects by "splitting" a single operator's default over many others was wrong - or at least too simplistic (Battiston *et al.*, 2012; Chinazzi *et al.*, 2013; Lorenz *et al.*, 2009; Nier *et al.*, 2007; Sachs, 2014).

However, albeit in delay with respect to the speed of global propagation of financial crisis, the attention for themes like contagion and failure cascades is growing very fast but so far, limited to the credit system level. Now it is time to go a step further by recognizing that financial contagion

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processes do occur at not only inter-bank (or credit system) level, but also at intra-bank level, because in a portfolio most obligors are likely connected to a significant degree. In other words, a bank portfolio should be seen as a *network of interconnected obligors*, and thus, since networks can channel contagions, their risk evaluation should not focus only on single obligors, but rather should take into account their connections. At least, when they are critical. Leaving aside retail or individuals-obligors, a firms-obligors' portfolio is most likely a (more or less dense) network, whose connections are constituted by trade, equity capital flows, and other types of relationship, which are at the same time the channels through which contagion can propagate. The proposal of looking at a portfolio as an obligors' network is treated in the next section of this paper, where it is argued that, consequently, a portfolio is an inter-organizational network characterized, to some extent, by aspects common to other types of this class of objects, like industrial clusters and industries, but it has also its very peculiar aspects.

Then, in section three, I discuss more deeply the complexity that characterizes these types of networks, namely, its nature of multi-layer interconnected networks. It is underlined why and how this property makes very difficult building analytical models, especially if purposed for reliable predictions. Further, in the same section I show the ways in which intra- and inter-portfolio contagion can occur. We will see that there are two main situations: through multibanking and inter-firm relationships. Finally, in the last section, the normative recently emanated by EBA, and currently under implementation, will be summarized specifically for what concerns the *groups of connected clients*, which introduces a crucial novelty with respect to the traditional approaches to credit risk evaluation. In fact, even if that regulation does not yet fully acknowledge a portfolio's network nature, it makes a remarkable step forward in that direction, because it explicitly admits that some clients could be (strongly) connected and that such connections matter for credit risk evaluation. Therefore, driven by the international authorities of regulation, the EU banking system is pushed towards a paradigm change in credit risk evaluation. The compliance of EBA regulation is a big challenge, because it requires adding new methods and views. Banks will need a lot of support to design and develop them, even because, so far, authorities have been not very prescriptive regards how to accomplish these tasks. However, as I will show in the last section, this normative is not without flaws and limitations, especially because it is trapped into a static and local approach to contagion and runs rather approximate distinctions between strongly and weakly connected clients. These criticisms are followed by a brief outline of a new rating system that, based on the concept of positional risk analysis, can overcome the flaws of the new current regulation.

2. What are the main drivers of intra-portfolio contagion?

If a portfolio is a set of (more or less densely connected) organizations, then it should be seen as an inter-organizational network, made presumably for the most part by companies. Consequently, its structure and dynamics are matter of study into that research field, which is old and vast (Knoke, 2012; Parmigiani & Rivera-Santos, 2001; Provan *et al.*, 2007). This is a good news, because finally we know where to turn or gaze to face with its understanding and, consequently, with the risk evaluation of each client and portfolio. In addition, this is a true news because, so far, this field was totally stranger to the background of people working on banking and finance. Now, it becomes clear that this professional profile and scientific background should be housed into banking and finance institutions too. It is a radical innovation in the way to approach problems and in the recruitment criteria of managers and officers at either bank or regulating institutions level. In the final section, I will come back on this point.

The bad news is that we do not have a sound, effective and shared theory of inter-firm networks – even less of inter-organizational networks, which is a broader field[i]. Though this research area has received a tremendous speed up during the last three decades, we still lack a *good* theory about why and how firms build networks, and about what kind of networks are most likely to be formed depending on the type of company, technology, industry, etc. As well, we do not *precisely* know a lot

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of other issues: i) how these networks are supposed to evolve or fail, ii) which is the role played by leader companies or universities, iii) how all these aspects are related to the social and institutional context, iv) which role is played by innovations and how specific technological aspects influence all this; etc. Further, a portfolio network is a very peculiar inter-organizational network, especially in the case of medium-large banks. In fact, its nodes (obligors) have a huge variety, not only respect with structural-economic-financial parameters, let say, technology, size, turnover, export, assets, cash flow, etc., but also respect with a portfolio composition in terms of industrial sectors. In fact, it likely will be more heterogeneous than in an industrial cluster, whose companies, by definition, are rather specialized into one or few industries. The two objects – bank portfolios and industrial clusters - could be perhaps not so different when considering local banks operating just into geographical areas characterized by a significant presence of one or few industrial clusters (Karlsson, 2008; Karlsson *et al.*, 2005).

The state of the art is that, instead of a sound (theoretically and empirically tested), consistent, and integrated theory, we have indeed two or three "main theories" - as transaction cost economics, resource-based theory and evolutionary economics - and a lot of "pieces" of theory, more or less tested or just at the stage of reasonable hypotheses. This variety is enriched (and complicated) by a number of empirical studies, most of them often reciprocally incomparable, because too much heterogeneous in terms of concepts and methods[ii]. This situation makes very difficult building a model of portfolio network, because it had to be at the same time a model of inter-organizational networks, which, in turn, implies a consistent – if not yet widely accepted and detailed - theory.

In this rather discomforting landscape, there are, however, some concepts that are emerging as widely shared and that seem to resist to empirical proofs, even though not sufficiently extensive. One concept is that of dependence and its reverse extreme: control. These two concepts have a long story, as witnessed by the first anti-trust law settled in US in 1890 with the Sherman Act. The aim was just identifying situations of power concentration, and thus of control of a (likely monopolist or oligopolistic) company over consumers and/or economically dependent companies. Since then, the normative evolved through a much more sophisticated and articulated set of parameters, not focusing on the simple 50% threshold of market or production share. In short, over time it became evident that the rule of majority shares is too simple and trivial to accomplish the need to understand control and dependence relationships. Much more appropriately, especially into the research stream related to approaches based on social network analysis, it is used the more moderate (but more realistic and effective) concept of influence power, which can be measured in various ways (see the handbooks of Lewis, 2009; Newman, 2010; Wasserman & Faust, 1994, to name the most diffused).

The difference between these two concepts – control and influence – becomes clear when referred to the one-century long story of the concept of control when applied to the problem of controlling the decision power of a company by controlling its shares. Most current normative are still stranded – with country differences - into the majority threshold criterion, which is downgraded when concerning public companies. However, here too it seems too strict. Every person concretely working into this field knows very well that through a system of "Chinese boxes" it is possible to achieve strong control by holding much less than 50%, sometimes even few percentage points. Further, if a company is placed into a very central position, then, with small shares of direct control, its power could be much higher than that it would get in a different position but with larger shares of control. This is a well-known difference between direct and indirect centrality measures: they indicate different forms of influence power, and the indirect one could be, ceteris paribus, much stronger than the direct one. Both situations could be easily demonstrated numerically and formally through network analysis: a scarcely visible company can hold a huge control (or at least, influence) power according to the position that it covers into an ownership network[iii].

Another set of concepts on which we can capitalize to understand and analyze portfolio networks concerns the channels through which control or influence can occur. Contagion runs alongside these same channels: a dependence relationship implies that when the dominant (or influent) partner fails, it damages the dominated (or influenced) partners. To say channels of influence (contagion) means

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identifying the types of relationships between organizations: trade, equity capital, formal decision making, socially induced decision making, information, knowledge, and other types of critical resources. Using one or the other influence channel is – at least to some extent - a strategic choice, because each channel involves an organization's different type of resources and (dis)advantages: hence, depending on a company's capabilities, resources, and strategies, a specific channel will be chosen.

There are no studies on banks portfolio networks, and thus, we do not know its typical topology and how does it vary according to a bank attributes. However, a visual inspection can help understanding the most general relationship between a portfolio network topology and failure contagion. If the topology were similar to that of fig. 1, then there would be no room for contagion, at least in its true dynamic sense, because in a network fragmented in so many components contagion would be "entrapped" into very small groups of companies. It would not propagate through the portfolio, because the direction of links does not allow moving beyond one or two steps. The topology represented in fig. 1 is the main component of the ownership network of the EU aerospace industry (Biggiero & Magnuszewski, 2019). It tells us that a failure of a company, even if of large size and with many directed links - that is, many controlled subsidiaries - would damage just its subsidiaries, but it would not propagate through the rest of the industry. This form could be called a "static contagion", which indeed is a sort of oxymoron, but it makes sense when contagion is flowing just one-step forward, that is, a contagion of a company towards its neighbors.

As we will see in the last section, current EBA regulation adopts a static approach to contagion. In fact, even though more than one-step is admitted – and, in principle, there might be unlimited steps through "vertical and lateral" paths - the role played by cycles (recursive paths) is substantially neglected. This could have the effect of hiding risky connections under seemingly irrelevant or innocuous connections. *Overlooking recursive paths means overlooking the possibility to bring "the same" contagion – the contagion triggered by a given company - back many times to the same companies*. As I will demonstrate in the last section, it means focusing only on the most immediately and highly dangerous risk positions. To visualize recursive paths, let us look now at fig. 2, where an ownership network of 168 nodes[iv] is shown. At an intuitive visual inspection, a high number recursive contagion processes can be detected.

When contagion is not entrapped into networks of the type shown in fig. 1, it can produce large scale and disruptive effects called cascades (or avalanches), on which there is a huge and fast growing literature (Lorenz *et al.*, 2009; Wang *et al.*, 2016). Most of them focus on the various forms of the snowball effect, that is, on the amplification occurring during the various steps of a contagion process. However, as far as I know, there is no any application on portfolio networks. Indeed, we do not lack studies on financial (Battiston *et al.*, 2012; Chen & He, 2012; Chen *et al.*, 2015; Elliott *et al.*, 2014; Gai & Capadia, 2010; George, 2013; Glasserman & Peyton Young, 2015, 2016; Kauê Dal'Maso Peron *et al.*, 2012; Li & Sui, 2016; Nier *et al.*, 2007; Sachs, 2014), credit risk or inter-bank contagion at system level (Gonzàlez-Avella *et al.*, 2015; Halaj & Kok, 2013; Kanno, 2015; Lenzu & Tedeschi, 2012; Li, 2011; Memmel & Sachs, 2013; Steinbacher *et al.*, 2014; Teteryatnikova, 2014; Upper, 2011; Vallascas & Kevin, 2012), but rather we lack them referred at single portfolios level. At least, not on real assets, like clients represented by companies or not-for-profit organizations. This is probably due to the fact that the view of a portfolio as a network is definitely new and that the ontology of these economic phenomena is rather different from natural or artificial phenomena.

To give a clear insight on such difference, let us remind to the snowball effect: the amount of snow contained in a triggering small ball adds to all the following impacted piles, thus exponentially increasing the following impacts. The snowball does not "go back" to previous places, that is, there are no recursive paths. In epidemiology, there are many models of disease contagion, with or without recursive paths, and in general, a key parameter is the original or acquired immunity of individuals. However, the characteristics of the impacting agent tend to remain relatively stable over time. In electrical engineering, the generation of cascades within electricity grids and the risk of blackout is studied since long and here there are recursive paths with variation of the quantity of the impacting

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agent. However, again, there are many and substantial ontological differences with economic phenomena: the speed of contagion is incomparably higher and the reaction capacity of "nodes" (electric plants) incomparably lower than that of economic agents. Moreover, in most of these cases there is only one carrier of contagion: snow, virus or bacteria, electricity, etc.

When we deal with contagion within economic networks, most likely, we are facing with recursive paths and different carriers of contagion, and many nodes have a significant capacity to react to contagion channeled by one or more carriers. This capacity can give total or partial "immunity": for instance, a company might identify and change some or even all of its most risky suppliers or buyers. Alternatively, a company could try to control in various ways the sources of its uncertainty, especially when they concern critical resources. From merge and acquisition - which involve a great financial, managerial and strategic effort - to much "lighter" strategies, like informal agreements, there is a vast spectrum of choices. Therefore, economic agents differ from natural or artificial agents in terms of their much higher complexity and much broader capacity of strategic actions. Further, there is one more aspect that distinguishes economic agents: their huge variety. For instance, companies can differ one another in terms of size, performance, degree of diversification, strategy, structure, internal processes, and products, just to name the most important aspects. Hence, this extreme heterogeneity makes building models of contagion much more difficult than in other fields, where the variety of nodes and its topology is not so high.

What I am arguing, in short, is that, despite the many models that have been already published or are in progress into the fields of natural or artificial sciences, the ontological specificities of economic phenomena require specific models. They are just at the beginning, particularly into the phenomenal domain of inter-organizational network dynamics, which requires its own specific models, because specific are the contagion processes and the nature of nodes and topologies involved. An inter-bond network cannot be treated as an inter-firm network. Which aspects and mechanisms are common to different phenomenal domains will be likely identified with future studies, especially after that portfolio networks will be known and analyzed.

Fig. 1 Contagion entrapped into a highly fragmented network

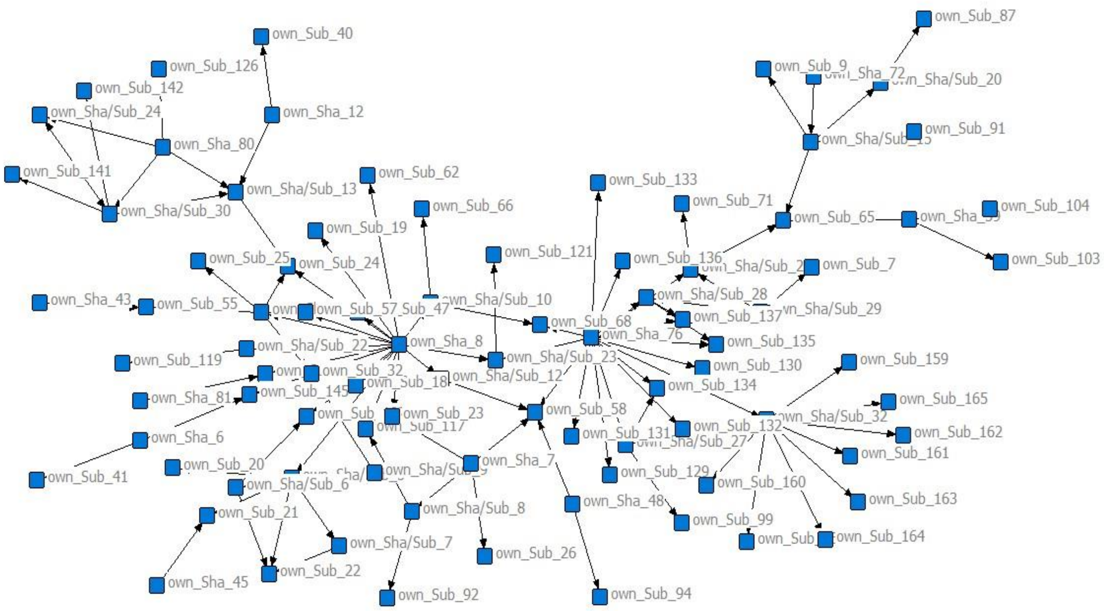

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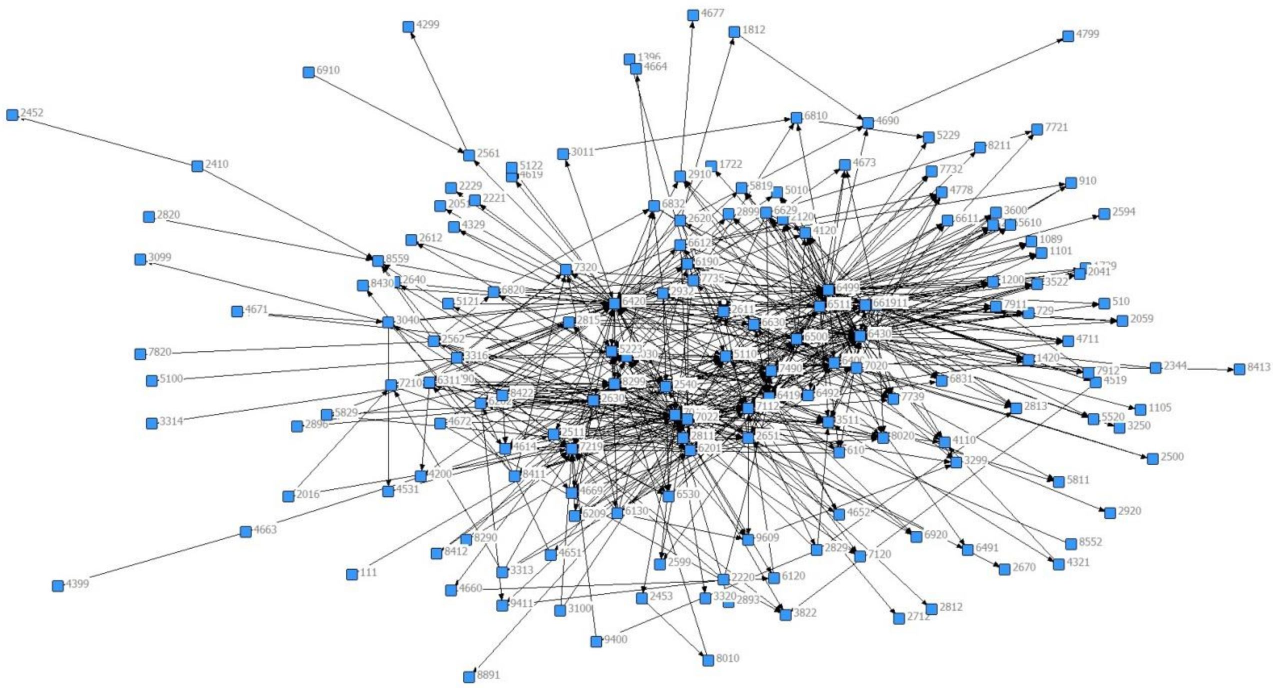
Fig. 2 Contagion flowing through recursive paths



3. Bank portfolio as a credit system layer

A credit system should be seen as a *complex multi-layer multiplex, made of interdependent networks*. Let us unveil the meaning of the single parts of this definition. About the meaning and measures of complexity, a huge and never-ending literature grew during last decades. It is not possible to summarize here that debate, but few remarks are useful. Common sense and a large part of systems and network literature hang the property of complexity to that of size: large networks are ipso facto complex networks. This is not so true, because highly fragmented and sparse networks can be very large but not really complex[v]. Even more if such networks were lacking (or poor of) cycles[vi]. In fact, it is the presence of cycles that, as a determinant of complexity, prevails on size: if characterized by a significant number of cycles, even a small network should be considered as complex. The reason is that, especially in a dynamic perspective, cycles mean recursivity, that is, the possibility that any impulse starting from a point of the cycle flows repeatedly until its effects extinct or, as it happens in many cases, destroy the network itself. Recursivity is the condition required to have positive feedback mechanisms, self-reference or self-organization, and many forms of nonlinearity[vii]. Recursivity is the true powerful "poison of complexity", which makes complex also the networks that, at first sight, might seem simple. In a credit system, banks and other financial operators interact through direct and indirect relationships, forming many cycles. For credit systems are recursive networks, because they are full of cycles and even reciprocity[viii], they are complex networks.

Multi-layer (Kivelä *et al.*, 2014) means that a network is made of different levels of aggregation that interact one another. For example, a network of individuals, who are also gathered into groups, is a multi-layer network of individuals and groups, which influence each other, because group behavior can affect that of its individual elements, and vice versa. In a credit system, banks are the nodes, which can be aggregated into a national credit system and this latter into a regional or global level. Therefore, the supra-level behavior influences what happens in the inferior level, and vice versa. The level-specific networks co-evolve alongside a vertical axis (fig. 3), and its bottom-up dynamics produces the so-called emergent properties, that is, behaviors that are unexpected and largely unpredictable because of nonlinear and recursive mechanisms. In the top-down direction, aggregate behaviors constrain and orient the behavior of the elements situated and interacting into the underlying networks. This is the form of complexity usually addressed to as the so-called micro-

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macro interaction (Arthur, 2014; Manzo, 2014; Squazzoni, 2012), which can be properly (albeit still limitedly) understood through agent-based simulation modeling (Arthur, 2014; Biggiero, 2016c).

A network is called "multiplex" – sometimes it is used the same word "multi-layer" for this different aspect too – when its nodes do interact through more than one type of link. For example, banks are connected each other directly by exchanging inter-bank loans and the many types of bonds and obligations, peoples (managers/directors) mobility, and information flow. Therefore, in principle, each of these types of connection generates a specific topology. In other words, if we looked at a bank network focusing on inter-bank loans we would get a topology likely rather different from that corresponding to, let say, information or obligations network. Now, the crucial point to be stressed here is that the structure associated to (generate by) a given *type* of link influences the structure associated to another type. In other words, the type of link X (suppose, inter-bank loan) connecting, let say, bank A and B, could influence the interaction between these same two banks in terms of another type of link Y, let say, some kind of bond. For instance, the wish or availability to exchange a given amount of Y bonds could be influenced by the inter-bank loan X.

Further, there is also a mutual influence between the behavior and performance of a bank and the position that it covers within the topology corresponding to each type of link, and consequently with the position that it covers into the whole multiplex, once taking into account all the different topologies with which the multiplex is constituted. And this type of influence is mutual, because it goes – usually through a recursive process – from the (dis)advantages related to the position to the bank's behavior and performance, and vice versa. The mutual influence between different types of links and that between a node's position and its performance are two tremendous sources of network complexity, which add to that of recursivity, the irregularity of links distribution, and the large size[ix]. All these five sources of complexity occur in a credit system and in each of its layers.

Finally, the phenomenon of network interdependence (or interconnectedness) means that two or more networks co-evolve alongside the horizontal axis of the fig. 2, that is, within the same level of aggregation[x]. The difference with the previous concept of multiplex is that a multiplex is a network whose nodes are the same but connected, accordingly to the different types of links, in various ways. Conversely, two (or more) networks are interdependent when they have one or more nodes in common, but in the remaining parts, they are different and evolve with partially independent dynamics (Zhang & Modiano, 2017). Why partially? Well, because the common nodes make the networks not completely independent, and thus, interdependent. In principle, one of the two could be dependent and the other independent, but in practice, this situation is supposed to be rare among socio-economic networks. For example, a credit system-network is interconnected with the various industry networks, which are made by firms and various types of not-for-profit or semi-public organizations. Hence, a given industry (or sector of activity) has its own dynamics, which is not completely independent on the credit system, and indeed, it is usually very much dependent on that. On its own, a credit system is also relatively independent on the industry structure and dynamics of its clients. Therefore, a credit system and the industries of its clients are interconnected networks[xi].

In short, a credit system is a very complex system, which co-evolves vertically through different layers and horizontally in each layer through the mutual influence of different types of links and through its interdependency with other types of networks. Bank portfolios constitute a layer in the credit system, thereby influencing - and being influenced by - the credit system. Regulatory institutions are at a superior level with respect of the credit system. They influence the credit system with normative and decisions enforced directly on the credit system or on the (lower) level of single banks. A portfolio is a complex network, because: i) among its nodes (clients) occur complex relationships with mutual influence between links and positions; ii) its nodes have a huge heterogeneity in terms of economic-financial-territorial-juridical attributes; iii) it could be extremely large; iv) it is supposed to be characterized by many recursive paths. Further, a bank portfolio is a multiplex, because among its nodes occur all the types of relationships that characterize inter-organizational networks. Finally, a bank portfolio is part of various interdependent networks, namely,

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other portfolios through multi-banking clients, industrial and public administration sectors through all of its clients.

Fig. 3 Multi-layer socio-economic networks

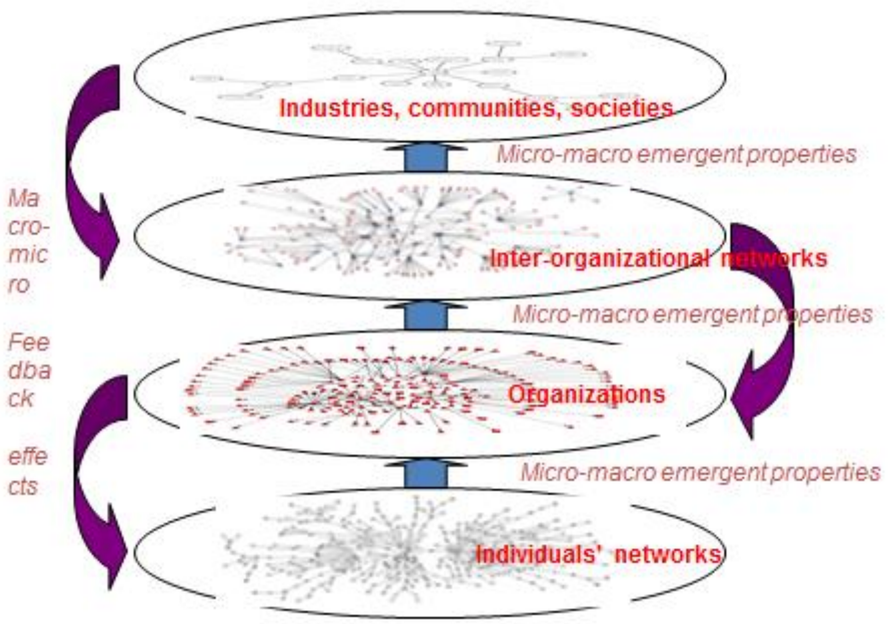
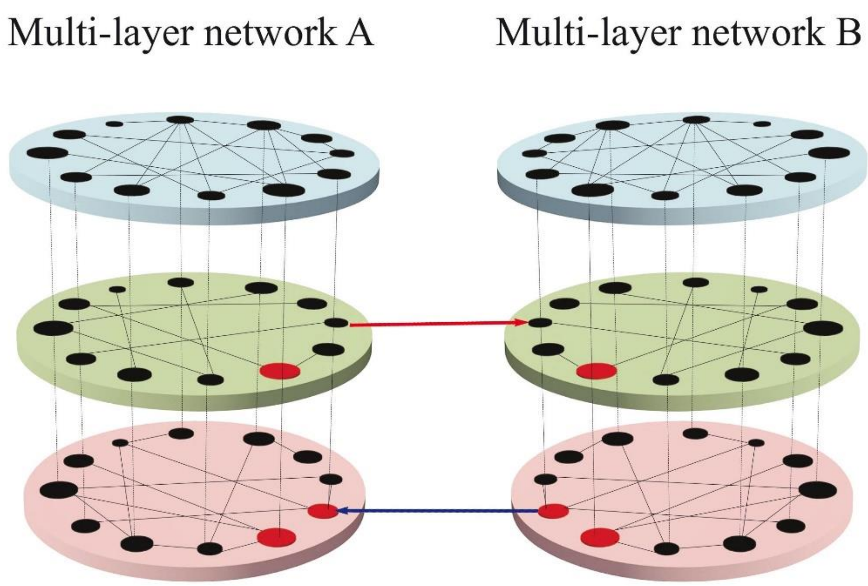


Fig. 4 An example of multi-layer interconnected networks



4. How intra- and inter-portfolio systemic contagion are connected?

The following three figures help us understanding the relationships between failure or crisis contagion at credit system and single portfolio level. As well-known, pushed by the evidence and violence of the world financial crisis triggered by US sub-prime bonds, the ideas of financial contagion and banks (or other operators) interconnectedness as its prerequisite and facilitator have been raised and developed about 10 years ago. As frankly and clearly acknowledged by Stiglitz and others (Battiston

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et al., 2012; Delli Gatti *et al.*, 2006, 2009, 2010), economists not only did not anticipate the danger of that situation, but indeed delayed so much to acknowledge it because of a delay that was firstly theoretical, and then consequently empirical. Finally, such delay became applicative with respect to the policy intervention side (Schweitzer *et al.*, 2009)[xii]. As Stiglitz noted, economic theory was traditionally underestimating the role of networks. More specifically, into the specificity of financial-credit system, the mainstream view was that a high interconnectedness – what in network analysis is measured as network density and direct or indirect reciprocity – were a positive and not negative aspect. In fact, it was retained that, when challenged by a bank failure, the higher was the interconnectedness of the credit system, the lower the negative effects, because they would have been split over a major number of operators. Let say, a simple application of the basic principle of risk diversification. Into this view, however, there is a clear misunderstanding of the deep nature of complex networks: that is, looking not just at a single node's neighbors, but rather at the neighbors of neighbors and so on at the whole network view[xiii]. Further, that myopic view was accompanied also by a typical static approach, which underestimates just the contagion effects. As we will see in the last section of this paper, both these forms of myopia are still affecting, albeit in a weaker degree, the new EBA's regulation.

Fig. 5a shows a bank A's portfolio as part of a credit system, whose network can allow financial contagion via inter-banks direct relationships: i.e. funds and bonds borrowed between them. As well, obligors' network at portfolio level can generate failure (or crisis) contagion triggered and/or channeled through one or more of the types of relationships holding between them. However, so far, the two levels seem relatively independent: they communicate just because a crisis of a single portfolio can trigger a crisis of the corresponding bank, which in turn can trigger a crisis into the credit system level.

Fig. 5b shows the phenomenon of multi-banking as a way to transmit contagion at credit system level through the obligors indebted with more than one bank. The red link shows that a given obligor is at the same time client of bank A and B, and thus, if it were impacted by a failure contagion within bank A, with its failure that obligor would bring contagion into bank B. Then, by means of that bank, into another access point of the credit system level. Hence, we see that what happens at the micro-level of a single node (obligor) of a bank portfolio affects the structure and behavior of the credit system macro-level. This is another example of the vertical (bottom-up, micro-macro) co-evolving process indicated in fig. 3.

Finally, fig. 5c shows that a credit system contagion can be triggered also by connections between companies that are clients of different banks. Here we see that the portfolios A and B represent two interconnected inter-firm networks, which therefore co-evolve and, in so doing, its co-evolution influences the credit system level by affecting two banks. This is the horizontal co-evolutionary process depicted in fig. 3. This process has multiple effects also on the credit system level, hence again in the vertical direction micro-macro: from a lower system level to its superior level. So far, we have evidenced two ways to bring contagion from single portfolios to the credit system level.

All these co-evolutionary network processes work also in the opposite direction, that is, from the macro- to the micro-level. Crises that originate autonomously into the credit system can drive some of its nodes (banks) to fail or to adopt wrong credit policy or sudden changes that can trigger the crisis of (some of) its obligors. These latter could, in turn, trigger or reinforce new contagion processes in one of the three ways above underlined. It is worth noticing, once more, that these are all recursive processes, either at credit system level or at portfolio level and in the way that they interact bi-directionally between levels.

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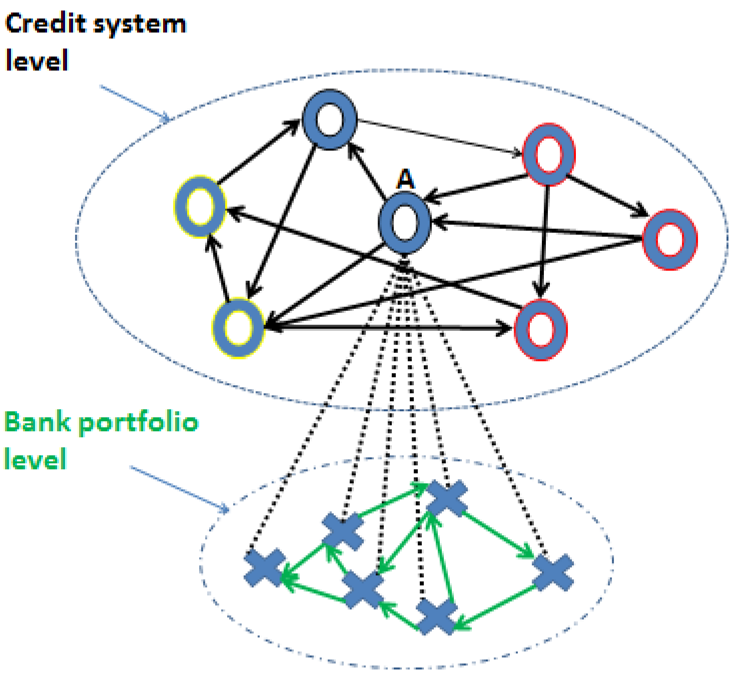
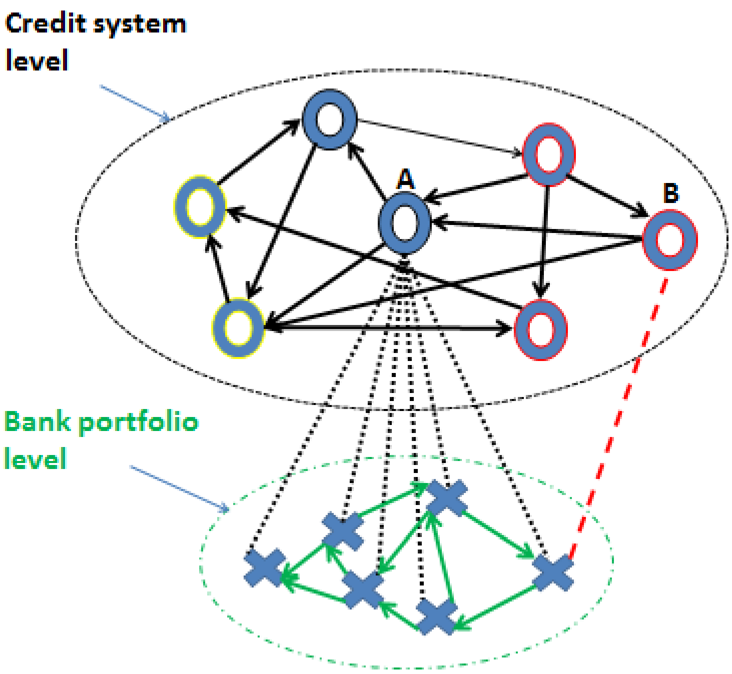
Fig. 5a



Legend
Black links: channels for propagating possible systemic risk contagion through inter-bank links at credit system level
Green links: channels for propagating possible systemic risk contagion through inter-firm links at portfolio level

Fig. 5b



Legend
Red link: channels for propagating possible systemic risk contagion through firms' multi-banking

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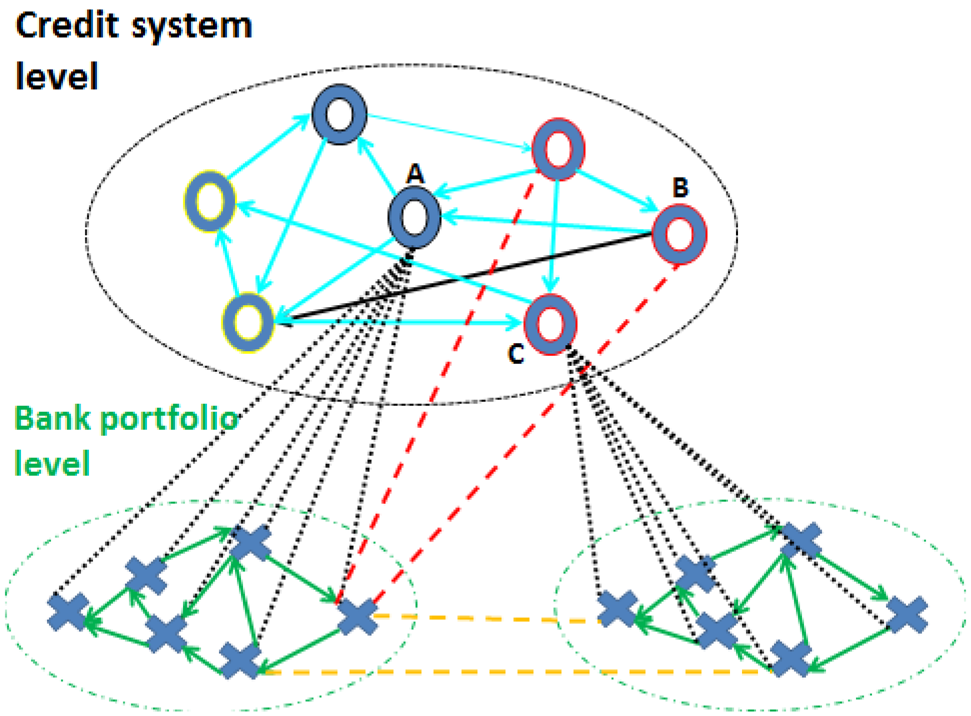
Fig. 5c



Legend
Beige links: channels for propagating possible systemic risk contagion through inter-firm connections

5. Progress and limitations of current European regulation

This section is divided into three parts: in the first one the conceptual and methodological framework of EBA regulation is outlined, in the second one some of its main flaws are discussed, and finally, in the last part, it is prospected a way to overcome such flaws by designing and implementing a new complete paradigm change.

5.1 Conceptual and methodological framework of EBA regulation.

Besides establishing reference criteria of standard attributive methods of credit risk evaluation, EU Regulation No 575/2013 of European Parliament treats the concept of *groups of connected clients* (GCC), which had been previously introduced in 2009[xiv]. In the following years, further documents have been produced by EBA as Guidelines on Connected Clients and then Final Guidelines, aimed to clarify and specify what should be meant with this concept and, supposedly, how to measure it. Finally, central banks of member countries supported further documents to help banks' understanding. The growing efforts currently employed by all these institutions is due to the fact that the GCC concept, though not yet a complete paradigm change, introduces a new view by leaving the focus only on single independent clients to embrace a collective and relational approach. Because traditional credit risk methods were always based on looking at clients as "monads", that is, as disconnected one another[xv], the GCC concept marks a relevant change: the focus is on *connections*, which are also distinguished into different types. It is a conceptual and, even more, methodological revolution, because it posits a discontinuity with the past by disclosing that, beyond the conventional "attributive dimension" of risk evaluation, there is a network dimension, even if limited to "special cases". The former refers to the only existing approach, which is based on evaluating a client's economic-financial attributes, possibly accompanied by information concerning other types of attributes, like the accountability and adequateness of a client's management and property or the economic cycle in general or the attractiveness or profitability of its sector of activity. They are all attributes of the client and its environment. Conversely, the latter – the network dimension – presumes that a portfolio is a network and refers credit risk evaluation to the specific position that a client covers

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within its close pattern of relationships or the whole portfolio. EBA's new regulation addresses to this latter approach. Being stranger to the cultural and professional background of the banking and finance world, the adoption of this view – and for sure, a fortiori, its application in banking practices – needs substantial supports from either regulation institutions, associations or consultancy companies.

Let us go deeper into the GCC concept. The basic idea is that, *if one or more companies substantially depend on company A, so that A's failure would crucially harm their repayment capacity or their economic survival, then the group of dependent companies had to be treated as a whole with A and be assigned the same of A's risk degree*. Therefore, the risk degree of dependent companies becomes, in a certain sense, irrelevant: what matters is their dependence on a controlling or dominant company and the risk degree of this latter. Here the innovative approach lies: risk evaluation depends on the connections with others and the connection patterns can prevail (or even make irrelevant) the individual risk evaluation measured as if that company were isolated. Thus, a proper and effective risk evaluation should not overlook, at least in some circumstances, the structure of relationships in which a client is embedded. This is the seed of a paradigm change, even if, as we will see below, it has been not yet fully developed into a consistent new system.

Even though not explicitly discussed or anchored to scientific literature, it seems that EBA's normative distinguishes two main classes of dominance (or dependence, if looked from the other side): *control relationships* and *economic dependencies*. The key-point is that, whenever one or both types of connections holds between clients, then such *strong* connections constitute an "idiosyncratic risk factor" and thus, those clients should be treated as a single risk. Indeed, GCC had to be properly called GSCC, groups of strongly connected clients. What should be meant for "strong" is a matter of discussion. EBA's document speaks in terms of "significant" intensity of connection, such that it can indicate a dominance relationship. However, this approach leaves a high uncertainty and freedom of interpretation, which, if on the scientific side could be appreciated and left to future deepening, on the practice side becomes rather uncomfortable and opens to hard disputes between regulation and surveillance authorities and credit operators. Indeed, provided that in some cases, like the voting rights, what matters is the absolute majority rule, this is the position taken in some documents of national banking regulation authorities.

As for control relationships, EBA requires that banks identify situations in which a "controlling person/entity has legally enforceable rights to establish a strong form of financial dependency on the controlling person/entity by the controlled entity". EBA refers to these situations as those in which a controlling company exerts a central government over a controlled one(s). Notice that in this class of dominance relationships, the perspective from which EBA looks at the various situations is, in semantic terms, just that of the central government, that is, the dominating company. The regulation provides a non-exhaustive list of seven forms to exert control, which could be grouped into the following:

i) the majority of equity capital;
ii) the majority of voting rights into the board of directors (or analogue organism for non-corporate organizations);
iii) any other contract-based form of majority or dominance in strategic decision-making.

So far, EBA's innovation would be not so radical, because the issue of holdings risk evaluation was well present in banks management also in the past, and the related economic literature was quite familiar in the professional and scientific background of people working into regulation institutions. EBA's normative goes on and points at the analogous situation of dependence from a dominant company even when it concerns economic dependencies, defined as the situations in which "the financial difficulties or the failure of a client would lead to funding or repayment difficulties for another client". Even for this second class of dominance relationships EBA provides a non-exhaustive list of many - eight, in this case - forms of dependence, among which trade (supplier-buyer) relationships and a high concentration of crucial resources on a single source - be them funds or some special constraint – seem to be the most important ones. Here, EBA employs the concept of

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dependence instead of control, somehow reversing the perspective from the controlling to the controlled[xvi]. Actually, the meaning is not exactly the same, because in the former case the dominance is established by some law enforcement, while in the latter it comes from economic power. In practice, the two situations sometimes overlap or occur into indistinguishable forms, but in principle, they can be distinguished. According to the scientific research tradition of the American sociology of organizations[xvii], trades, assets, debts, suppliers and buyers are all forms of uncertain resources with which organizations should face. Even if it belongs to a different research tradition, EBA's framework on economic dependencies is perfectly consistent with that perspective.
Remarkably, EBA invites banks to collect information also on the currently-non-clients, because it is aware that dominance could come from outside the portfolio or that some (many?) of those non-clients could be essential parts of some GCC. However, acknowledging that it could be very hard or impossible to get the necessary information, when the presence of such non-clients is significant within a group of client, this would legitimate the bank to overlook the identification of the given GCC[xviii].

5.2 Flaws of EBA regulation

Despite the substantial progress and innovation above acknowledged, the GCC approach designed so far by the banking authorities suffers, however, of the following five flaws[xix]:

i) it is static and local instead of dynamic and systemic;
ii) the threshold logic required to select strong connections produces very approximate results;
iii) quantitative criteria and thresholds required to identify a GCC operating in a small market niche are not provided yet;
iv) the problem of multi-banking clients and the consequent incompleteness of the portfolio knowledge is insufficiently treated;
v) standard (attributive) methods of risk evaluation are not questioned and left unaltered.

Static approach. The true nature of contagion is dynamic, not only because of the simple reason that it takes time to produce damages, but for the more important reason that the "infected" might change its function and state, and thus, over time, contagion can produce new different effects. Now, as already discussed in section 2, if there were no cycles, the role of time would be restraint to the former case: just the time to produce damage to the adjacent node and from them, in turn, react and transfer the impact. However, if there were cycles, then contagion can come back to a previously infected but survived node, which now could be further weakened or definitely destroyed. Due to the complexity of large recursive networks, without analyzing these propagation processes it is impossible to know who will be only impacted and who will be definitely destroyed. A static approach in presence of recursive paths implies the exclusion or overlook of those groups of clients that are connected only through weak links. To demonstrate the relevance of this neglect, let see the following simulation.

An exemplificative simulation. To demonstrate the radical difference between a static and a dynamic approach to contagion, the following example and simulation shows the consequences of overlooking weak connections, when adopted a dynamic contagion perspective. Let the network of fig. 6 be a group of 10 clients, and its connections be trade relationships: a supplier-buyer network. At first sight, it is clear that nine of them are connected and then we are potentially into the situation of economic dependency addressed by current normative. Still at first sight, if one follows the paths connecting clients, let say, the various supply chains that constitute this supplier-buyer network, it appears clear that they are recursive. In tab. 1, clients' turnover are reported, while in tab. 2, the structure connecting such clients: namely, its topology.
As we can see, trade connections are so small that they do not identify a GSCC, because the flow of money incoming to each company (ORG) is lower – and in general much lower – that the 50% of turnover of the receiving company. Further, let suppose that they do not have any ownership

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connection, neither any voting rights relationships, nor any exposure in terms of financial or any other kind of resources. In short, they are not a GCC according to current, and thus, the bank should not consider them (or any sub-sets of them) as a single risk position. However, if we (properly) approached contagion risk in a dynamic perspective, we would see that they, excepted of course client 10, which is disconnected from all the rest, had to be considered as a GCC, because they are potentially highly contagious and destructive each other. Through the IFCOP software[xx] (Inter-Firm COntagion Program), I have run a simulation by supposing a failure of ORG9 (tab. 3).

Tab. 1 Values of clients' turnover

companies	turnover
ORG1	30
ORG2	20
ORG3	20
ORG4	20
ORG5	25
ORG6	15
ORG7	15
ORG8	18
ORG9	30
ORG10	10

Tab. 2 Link distribution between clients

	ORG1	ORG2	ORG3	ORG4	ORG5	ORG6	ORG7	ORG8	ORG9	ORG10
ORG1	0	1	7	0	0	0	0	0	0	0
ORG2	0	0	2	0	0	0	5	0	0	0
ORG3	0	0	0	3	8	0	0	0	0	0
ORG4	6	0	0	0	4	0	0	5	0	0
ORG5	0	6	0	0	0	0	1	0	0	0
ORG6	8	4	0	0	0	0	0	0	0	0
ORG7	0	0	0	0	0	0	0	2	0	0
ORG8	0	0	0	0	0	3	0	0	10	0
ORG9	0	0	7	9	9	0	0	0	0	0
ORG10	0	0	0	0	0	0	0	0	0	0

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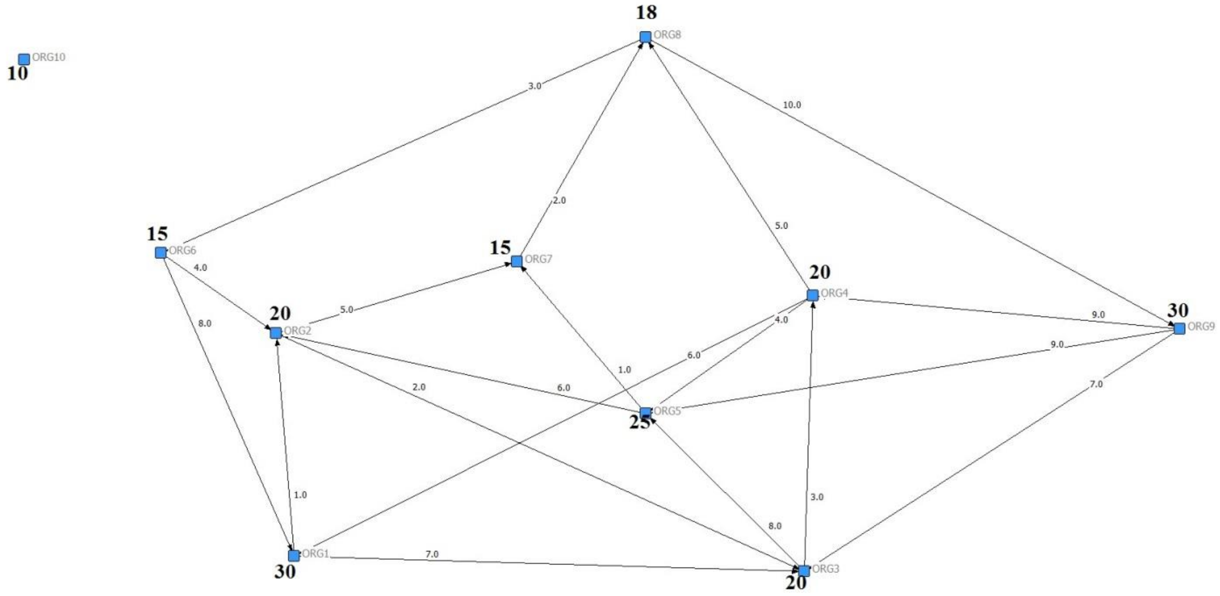
Fig. 6



Each step represents a time interval, which could mean a month or a shorter/longer time span, depending on the type of products represented in the model. This length, in fact, varies with the type of each specific economic activity, but we can reasonably assume a month, which is the production-sale cycle length of many commodities. The outcome shows that within 5 months all the other eight connected clients do fail. Clearly, none of them fails at the first impact: it is just the dynamic (repetitive) contagion that initially only damages each client and then, after some (few) repeated impact, provokes the failure. In addition, clearly, not all of them fail at the same time: most failures happen in the last steps, because the clients have been weakened during the previous ones. In short, if the bank checked the situation of this group of clients in January and recorded a highly risk position for company ORG9, the bank would not be alarmed for any of the other companies. However, if ORG9 actually failed, it might likely happen that the whole group of clients (excepted ORG10) failed before June.

Of course, there are a number of suppositions at the base of this simulation model, as for any model indeed. Let us list the most important ones:

i) clients are supposed to be unable to find alternative customers;
ii) clients keep invariant the same position within the network;
iii) clients keep invariant the same economic characteristics;
iv) there is a uniform degree of resilience to turnover reduction before failure;
v) turnover reduction is split proportionally among a client's customers;
vi) an impact becomes irrelevant under a sensitivity threshold.

The last three conditions are already parametrized in this current version of this simulation model, while the parametrization of the others should be still implemented. However, as for the invariance assumption, it should be argued that in the short run – that is, 1 or 2 years, as usually agreed – it is difficult to employ significant changes in most sectors. Therefore, this experiment sounds realistic because its dynamics implies less than one year. Further, this experiment looks reasonable – indeed, prudential - also for the parameter of resilience, which has been set up at 0.5, which means that all the companies of this group can resist until a turnover loss of 50% before failing. A higher degree would further shorten the survival of this group.

Indeed, to improve the model and make it more realistic and reliable, still other aspects had to be designed and implemented, namely:

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a) applying contagion propagations also to equity capital connections, as it is suggested by current normative[xxi];
b) including some important economic-financial parameters that could influence a client's resilience degree and that could be influenced by the amount and number of its exchanges and position within the network[xxii];
c) considering clients' strategic capabilities; and so on.

Indeed, the road to build a truly satisfying agent-based model of inter-firm networks and its evolution is still long. Some models are already available and provide good suggestions to enrich this or other models for evaluating inter-firm contagion processes and its effects on firms' positional risk[xxiii].
Anyway, the results of this experiment shows that, by using a simulation model like this one, a bank could explore the effects of specific failures combinations that, according to its own information, are considered more likely or pernicious than others are. Moreover, the identification of the sequence followed by contagions provides precious information for planning possible interventions. Actually, the lack of considering the contagious effects of multiple (simultaneous and/or alternated) failures is another defect that derives from the static perspective: what resists a single impact could be not enough resistant to impacts coming from multiple triggers. In fact, due to the complexity of large and recursive networks, propagation processes can follow rather different paths according to which and how many clients fail, and on when such failures happen.

Tab. 3 Simulation with ORG9 as trigger
Step 1: *ORG9*
Step 2: ORG3, *ORG4*, ORG5
Step 3: ORG1, ORG2, *ORG5*, ORG7, *ORG8*
Step 4: *ORG2*, *ORG3*, *ORG6*, ORG7
Step 5: *ORG1*, *ORG7*

Local instead of systemic approach. By applying EBA's (implicit) conceptual and methodological framework, a portfolio would resemble the upper part of fig. 7: a landscape of mountain peaks representing GSCC. The other clients – possibly members of groups of (weakly) connected clients - should be considered, at least from the point of view of risk evaluation, as separated entities. From the point of view of the portfolio structure, the connections between such clients are "hidden under the clouds". The flaw of this approach is that this way we will overlook the entire landscape, as shown in fig. 7b., thus missing the knowledge of the paths connecting peaks. Conversely, especially in a dynamic perspective, the structure underlying and connecting peaks definitely matters, because contagion runs through those ways.

Fig. 7a Peaks selection in a portfolio quasi-smooth landscape

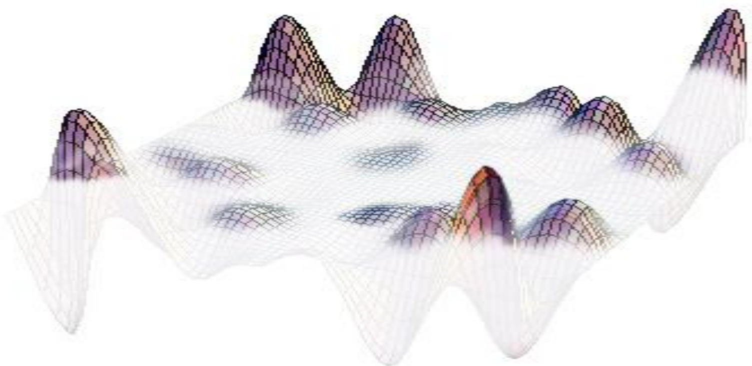

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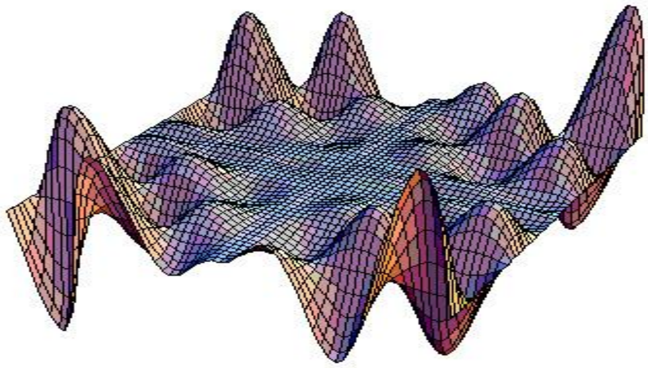
Fig. 7b The quasi-smooth landscape of the portfolio in its entireness



Distorting effects of threshold logics. Instead of simply overlooking clients' connections, the choice to assign – when dependency is strong - to dependent clients the risk of the dominant client is a remarkable step forward. However, at a closer sight, it is a rather approximate method, because of two main problems:

i) it does not allow to make risk degree distinctions among dependent clients;
ii) it neglects a client's connections pattern when no one of them is critical - over the majority threshold. This on/off approach is weak and full of possible bad consequences. For instance, let suppose three clients - A, B and C – having the following situations: A is disconnected from any other client, B is weakly connected with some, and C is right below the threshold for all the types of connection. According to current normative, these three clients should be treated in the same way as being not member of any GSCC. Thus, none of them receives the risk evaluation measured for its dominant client. However, they are clearly in three different conditions.

Lack of quantitative criteria for niche detection. Rightly, EBA addresses to market niches as contexts of shared and competing resources between clients, so that such clients should be treated as a GSCC. However, currently we lack concrete conceptual and methodological indications on how to discover these situations and how to measure the corresponding "niche's risk". It is worth noting that the huge literature on industrial clusters/districts is still inconclusive respect with the similar problem of finding objective and effective criteria to identify clusters/districts. Over time, the question revealed harder than was expected decades ago. Hence, it is perfectly understandable that we still miss criteria to measure a niche's risk, because before that had to be found criteria to identify niches.

The problem of portfolio network completion. A bank has a complete knowledge of its portfolio only with regards of its mono-banking clients, which are supposed to be a small share. Monetary flows among multi-banking clients are unknown for the portion that is intermediated through other banks. It means that the large majority of connections between clients are unknown to a given bank. However, the presence or absence of such connections can decide whether a group of clients is strongly or weakly connected. Neglecting the majority of links – at whole portfolio level – will likely make most groups of clients weakly instead of strongly connected. Consequently, there should be a dramatic underestimation of risk evaluations. Further, in a dynamic perspective, we would lack most paths that contagion can follow.
This problem of unknown connections is particularly severe for trade relationships, because currently there are no sources of this type of data. There are only two solutions. One is that of estimating such unknown connections through very complex and advanced statistical methods applied to networks.

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This field is called link prediction and there are recent interesting developments[xxiv]. This seems the best way to approach the problem, while in perspective the second (and hopefully definitive) solution could be that of strengthening and enriching the Open Banking normative to make this data available for banks.

5.3 Overcoming the flaws by completing the paradigm change

These five flaws make current normative rather imperfect, with heavy consequences on the whole portfolio risk evaluation and the following assessment of a bank's solidity. In fact, the whole portfolio risk evaluation will be substantially increased or decreased according to the net effect of the gap between the risk level and the corresponding amount of credit of dominant and dominated clients. If the risk level of the former is, in average, higher than that of the latter, then the whole portfolio risk evaluation will be substantially increased, and vice versa.

Therefore, we would need an approach able to:

i) take into account dynamic contagion, meaning the effects of repeated contagions. This would be particularly important when multiple clients default in simultaneous or alternate times. Indeed, this is exactly what happens during times of severe economic crisis;
ii) consider the portfolio as a unity, meaning a systemic instead of local approach;
iii) measure single credit risk positions in reference to the risk positions of all others, thus avoiding distortive threshold logics.

The final purpose would that of building a new rating system based on a *positional credit risk analysis*. It could take into account the (dis)advantages of the position covered by each client (or GCC) within the portfolio and allow calculating a network-based VAR.

Conclusions

Standard methods of credit risk evaluation are receiving a tremendous improvement from the recent growing diffusion of advanced computational techniques. However, conceptual and methodological approaches remain based on focusing each obligor as a monad, whose risk level depends only on its individual characteristics, sometimes adjusted with sectoral or macroeconomic coefficients. Conversely, a portfolio should be considered a network, because most likely a substantial part of its nodes is connected each other by many kinds of relationships, like trade, ownership, long-term agreements, information, knowledge, and people's mobility. This fact makes a portfolio network an inter-organizational network, prevalently constituted by companies.

Unfortunately, we lack a sound and complete theory of inter-organizational networks, either at network level or at single organizations level, because these are very complex objects of study. However, besides the acknowledgment of the existence of various types of connections, we know that there are complex relations either between performance and connection patterns of single companies or between the various types of relationships. In other words, the position an organization covers into the network affects its performance: better positions that are (more advantageous) are likely to enhance better performance, and vice versa. Further, in a multi-layer network as the ones we are dealing with, an organization could cover a good position with respect to a given type of relationship but not with respect to another one. In short, we are beginning to understand what ingredients make inter-organizational networks so complex, but we cannot yet well explain how they behave.

We do not know yet what type of topology is prevalent in portfolio networks, for the simple reason that we lack empirical studies on this matter. However, grounding on what we already know about economic networks, it could be taken for granted that many recursive paths should characterize them, which makes them complex networks. Actually, a portfolio network, not differently from most (perhaps all) socio-economic networks is a multiplex interconnected with other networks: horizontally with the sectors and/or industrial clusters to which its companies belong to and with the other banks from which multi-banking companies borrow money, and vertically with the credit

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system of which a bank is a member. Therefore, banks and its portfolio networks are complex large networks that co-evolve through the credit system and its single clients and sectors. Because we know that contagion processes, which in fact occur either vertically or horizontally through the various types of relationships, it comes clearly that a bank portfolio, characterize co-evolving complex networks is likely to generate intra-portfolio contagion processes.

This acknowledgment requires a paradigm change in credit risk evaluation methods, which had to be extended also to the whole portfolio level. The EU normative launched in 2013 and currently under application has moved a first step in this direction, because it explicitly addresses to the existence of connections between clients and states that when such connections are strong they create unilateral or reciprocal dependence. In these cases, EBA states that, from the risk profile, each group of strongly connected clients should be treated as a whole and be assigned the risk level of the dominant client. This acknowledgment breaks the historically consolidated view that a risk profile should be measured by looking at single clients as individuals. In this sense, this normative is revolutionary. Among the various types of relationships through which clients might be connected, the following four are the most relevant: ownership, voting rights, trade, financial - and other crucial - resources exposure.

This approach posits a hard cultural and methodological challenge to single banks, which are traditionally stranger to these issues. Each European bank is invited to accomplish to the following fundamental tasks:

a) identifying the groups of clients that are connected;
b) selecting those that are strongly connected;
c) treating each of them as a unit risk position by assigning the risk of the dominant client with respect to the most risky relationship;
d) calculating the consequences in terms of the whole risk portfolio;
e) reporting all these data to EBA.

However, this normative suffers of some flaws, which will be overcome when a systematic positional credit risk analysis will be implemented and structured into a dedicated rating system for both single clients and whole portfolios. The main flaws are represented by a static and local approach to contagion. In fact, if the dynamic dimension of contagion is neglect, then only the most risky situations are identified and consequently the whole portfolio network topology is overlooked. Hence, it is lost the knowledge of the paths connecting the groups of clients, be they strongly or weakly connected. Further, current normative adopts an on/off (threshold) approach that seems quite approximate for evaluating groups of connected clients. There will be too many "intermediate" positions that would be improperly evaluated, especially when considering the multiplicity of types of relationships – that is, the multiplicity of dependence relationships (i.e. contagion channels). Finally, it is not said how to identify and measure the situations of niche resources shared by a given group of clients, nor how to face with the network completion problem, which makes all the previous analyses affected and weakened by the neglect of unknown connections. In conclusion, the new normative under implementation is revolutionary respect with the previous one, but still too mild and moderate. It is necessary a full acknowledgment of the network nature of a portfolio and a consequent positional credit risk analysis generating a related rating system.

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[i] Just to have an idea of the complexity and fragmentation of this research field, see the handbook by Cropper et al. (2008).

[ii] Concepts could be often based on incompatible assumptions and methods of gathering data and the types of data itself can be too different.

[iii] An example of application to ownership networks can be found into the forthcoming paper by Biggiero & Magnuszewski (2019).

[iv] Here nodes represent the industries involved as shareholders or subsidiaries into the ownership structure of the EU aerospace industry.

[v] However, in practice, the argument that large size implies complexity becomes true because, most often, when networks grow and become large, they "generate" cycles. There are either ontological or statistical reasons for this phenomenon. Anyway, whatever the reason, it is very likely that, if a network is large, then it has also recursive paths, and thus, it is complex.

[vi] In network analysis there is the paradigmatic class of DAGs - directed acyclic networks – that characterized by the lack of any cycle. A cycle is defined as a path that starts and ends with the same node (see Newman, 2010; Wasserman & Faust, 1994; or any handbook on graph theory).

[vii] There is a vast literature on these three issues, largely deriving from systems science (Forrester, 1968) and cybernetics (Ashby, 1956; Foerster, 1982, 1984; Foerster & Zopf, 1962). To not inflate this paper, let me refer only to Bertuglia & Vaio (2005) and Casti (1994), who do not focus explicitly on recursivity or economic networks, but deal also with them while providing a broad view of complexity and nonlinearity. For works more explicitly focusing on those two issues, see Arthur (2014) and Biggiero (2001, 2016 a, 2016b, 2018, 2019).

[viii] Reciprocal connections can be seen as one-step cycles, and thus, reciprocity can be seen as the strongest form of recursivity.

[ix] Traditionally, network scientists have referred network complexity more to the size and the irregularity in nodes' degree distribution (Dorogovtsev, 2010; Lewis, 2009; Newman, 2010; Vega-Redondo, 2007). Social network scientists have started to investigate also the mutual influence between either types of links or nodes' position with its performance (Carrington et al., 2005; Friedkin & Johnsen, 2011; Goyal, 2007; Jackson, 2008).

[x] The reference book on this issue is D'Agostino & Scala (2014). Further contributions are Castet & Saleh (2013) and Danziger et al. (2014).

[xi] Perhaps, It is worth noting that the study of cascades in interconnected networks has been started only recently (Fu *et al*., 2014; Saulo *et al*., 2014; Vespignani, 2010).

[xii] It is worth noting the lapidary judgment that an eminent economist like Arrow (2009) gave 10 years ago on network theory: "[it] … may not be all that useful or needed".

[xiii] Though a branch of economics – and even more of management and organization sciences – are adopting and fast developing a network approach, there are very important reasons that make difficult for mainstream economics to acknowledge the network nature of socio-economic phenomena. See Jackson (Jackson, 2008, 2010, 2014a, b) and Carvalho (2014) for a critical view "from within" economics and Biggiero (2016a) for criticisms pointing at the epistemological and methodological foundations of mainstream economics.

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[xiv] It was introduced in a document of the Committee of European Banking Supervisors (CEBS) titled "Guidelines on the implementation of the revised large exposures regime".

[xv] Current standard methods attempt to capture the collective dimension when calculating the VAR (Value at Risk) of the whole portfolio. However, at a closer view, it is clear that they do not look at the structure of the portfolio, that is, at the relationships between clients. They only look for correlations between them, so to classify them into risk classes, calculate actual whole risk, and hopefully estimate its down- or up-grade risk development. Besides the fundamental – but very subtle and complex – difference between correlations and interconnections, which is a matter that of course cannot be treated here, it is enough underlining that such methods deal anyway with the whole portfolio and leave untouched the evaluation of credit risk of the single clients. Until the normative that we are commenting in this section and, more generally, the radically innovative view of a portfolio as a network of clients, that evaluation remains based on the view of isolated clients.

[xvi] Indeed, even the visualization of the connections into the scenarios in the Annex of the Final Guidelines changes according to the cases of control or dependence: in the former the connections lack orientation, while in the latter case the orientation runs from the dependent to the dominant company. This perspective change results a little bit confusing, therefore it is better to be aware of it.

[xvii] The excellent book by Pfeffer and Salancik (1978) is a point of reference, because it framed the whole matter in the perspective of the sociology of organizations. Its title is enlightening in itself: The external control of organizations.

[xviii] See the last scenario (Mm1) presented in the Final Guidelines.

[xix] There is indeed some further problem of lack of clarity, like that concerning some combinations (connections) of GCC disclosed according to different types of connections, let say, trade and ownership. For example, if client A in terms of ownership and client B in terms of trade dominate a given client C, and if risk assessment of A and B are different, then which risk assessment should be given to C? This and other more complicated situations are not discussed in EBA's documents.

[xx] I did this software with the purposes of: (1) disclosing and measuring potential contagions via trade relationships within an inter-firm network; (2) measuring the consequent positional risk rating; (3) identifying contagion paths; (4) clustering firms into risk classes.

[xxi] Indeed, this inclusion would require modeling how trade and ownership connections influence one another – a task that would imply to have a sound and effective theory of inter-firm networks, a theory that, now, we lack.

[xxii] In fact, resilience threshold can be considered as a synthetic parameter to take into account some of these other variables. For instance, the longer debt rotation or the higher commercial credits, the higher the resilience capacity (and the lower the threshold).

[xxiii] A partial literature review can be found in Biggiero (2016a), while the problems and trade-offs between models richness and usefulness in comparison with other types of relational methods are discussed by Biggiero (2016c) and in the specialized literature on agent-based and computational modeling (Battiston *et al*. 2007; Fujiwara, 2008; Gilbert, 2008; Epstein, 2007; Squazzoni, 2012). Waiting for further improvements, the current release of IFCOP seems able to produce more (and more sophisticated) outcomes than those required to accomplish EBA requirements. In fact, its version dedicated to bank portfolio networks does measure positional risk analysis to build an entire rating system and a number of other information to cluster clients in different risk levels, and to identify the organizations that currently are non-clients but whose potential failure would substantially damage one or more clients.

[xxiv] For instance, by means of Exponential Random Graph Models (Lusher *et al.*, 2013; Harris, 2014) it could be possible to estimate unknown links grounding on the perfectly known and on a presumably highly known portion of the network. Insights on the origins and development of these models into social network analysis, on how to employ them for inter-firm networks and, more generally, for economic analysis can be found in Biggiero (2016a).

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