Capital and Contagion in Financial Networks

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Abstract

We implement a novel method to detect systemically important financial institutions in a network. The method consists in a simple model of distress and losses redistribution derived from the interaction of banks' balance-sheets through bilateral exposures. The algorithm goes beyond the traditional default-cascade mechanism, according to which contagion propagates only through banks that actually default. We argue that even in the absence of other defaults, distressed-but-non-defaulting institutions transmit the contagion through channels other than solvency: weakness in their balance sheet reduces the value of their liabilities, thereby negatively affecting their interbank lenders even before a credit event occurs. In this paper, we apply the methodology to a unique dataset covering bilateral exposures among all Italian banks in the period 2008-2012. We find that the systemic impact of individual banks has decreased over time since 2008. The result can be traced back to decreasing volumes in the interbank market and to an intense recapitalization process. We show that the marginal effect of a bank's capital on its contribution to systemic risk in the network is considerably larger when interconnectedness is high (good times): this finding supports the regulatory work on counter-cyclical (macroprudential) capital buffers.

Keywords: Systemic risk; interbank market; contagion; network; feedback centrality.
JEL Classification: C45; D85; G21; G01.

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1. Introduction

Over the last decades, the global financial system has become increasingly large and interconnected. In several countries, a sizable fraction of the growth in the balance sheet of the financial sector before the crisis could be attributed to mutual claims and obligations among financial firms. Interconnectedness has been a key factor in precipitating the crisis as troubles to one financial institution quickly propagated to other entities. In the last quarter of 2008 a number of markets remained dysfunctional for weeks as investors were kept away by uncertainty over the actual structure of exposures. Events showed that contagion may jeopardize the smooth functioning of the global financial system, eventually imposing large social costs to the entire economy and forcing public authorities to step in. In the economic literature, network theory has been used to study the financial sector as a complex system of interlinked agents. Theoretical and empirical works have focused mainly on (i) the assessment of the likelihood of systemic contagion episodes, (ii) different contagion propagation channels and (iii) the link between the network topology and the resilience of the system. The vast majority of contributions investigate the contagion due to direct credit exposure between two counterparties. When bank i defaults, its creditor, say bank j, faces a loss that is proportional to the amount lent to bank i and to a certain recovery rate. Whenever the loss exceeds the equity, bank j also defaults. Bank j propagates the shock to its creditors and this may trigger a cascade of defaults. A measure of the defaulting banks in the cascade represents the systemic risk posed by bank i. This approach (*contagion through default*) fails to predict large contagion episodes. In particular, networks appear to be resilient up to a very high threshold (tipping point), defined in terms of the severity of the initial shock. Systemic events (i.e. a large number of defaults in the cascade) may occur only in the presence of very large exogenous shocks.

This paper proposes a novel method to study contagion in financial systems. The simple idea is that distressed-but-non-defaulting institutions transmit contagion *before* they actually default. In the previous example, only the default of bank i affects the equity of the bank j. However, even before a credit event occurs, bank j's balance sheet might become weaker: as distance-to-default shortens, the value of bank j liabilities - including interbank obligations - declines, thereby negatively affecting the creditors of bank j. As creditor banks themselves become weaker, in turn, they also transmit some degree of contagion to their own counterparties. As a general result, even if no institution actually fails, the overall system may become much more fragile, as a non-negligible portion of the network's equity is likely to be wiped out in a marked-to-market perspective.

Our paper aims at assessing the evolution of systemic risk in the Italian interbank network over the past few years: we analyze a dataset of bilateral exposures obtained from supervisory reports to the Bank of Italy. In doing so, we modify and improve a novel method put forward by Battiston et al. (2012), DebtRank, which implements the contagion through distress idea discussed above. Our measure, DR, is able to measure losses incurred by the network following the default of each participating bank even when no other default occurs. For each bank we compute a synthetic indicator - the DR - that expresses the fraction of the total equity of the network which would be affected by an exogenous shock to the bank. The basic idea underlying the metric is that whenever a debtor institution is weakened, the market value of creditor banks equity is affected even before the debtor institution actually defaults. The DR of an institution proxies its negative externality on the network. The increase over time of the DR of many individual institutions at the same time is a footprint of increased fragility of the network. The method is particularly suited at capturing network externalities as it quantifies systemic risk on a continuous scale and is not limited to the estimation of the tipping point. Therefore, it can be used to evaluate systemically important financial institutions and may also represent a benchmark to implement new stress testing exercises targeting linkages in the financial network other than interbank lending. This is a brief summary of the main results of the paper:

Traditional indicators underestimate contagion risk. DR captures features of a bank systemic importance, such as its positioning in the network´s topology, that would not be apparent under standard default cascades models. In most cases, systemically relevant institutions under DR would pose no threat to the network if losses were computed through standard default cascades models.

The DR of Italian banking groups. Systemic risk in the Italian interbank network has decreased since 2008. The decline is mainly due to decreased interconnectedness in the unsecured interbank market, as opposed to decreased leverage in the system due to banks´ recapitalization process. Decreased interconnectedness can be traced backed to the sovereign bond crisis, which dramatically reduced the amount of wholesale funds reaching the domestic interbank market from international markets. In a sense, a crisis in the interbank market has become less likely over time as another crisis took place in the sovereign bond markets. Such a result suggests the existence of a sort of "interconnectedness cycle": the financial system is intertwined and contagion risk is high in "normal/good " times (in our sample period, before the sovereign debt crisis), the latter decreases with leverage in "bad" times.

Interconnectedness and macroprudential regulation. The evolution over time of the DR of Italian banks offers supports the case for counter-cyclical (macroprudential) capital regulation of banks. Through simple comparative statics, we show that the effect of a bank's capital on its systemic risk is much higher when the financial network is tightly interconnected, which is most likely to happen in good times. Counter-cyclical capital buffers as agreed by the Basel III accord may therefore substantially decrease systemic risk in good times. On the other hand, the release of the buffer in bad times would have a marginal impact on financial stability in the network.

Relationship to the literature. Interconnectedness has an ambiguous effect on the stability of financial systems (Stiglitz (2010)). On the one hand, linkages across agents may improve risk sharing and help allocating risks to those that are better equipped to bear them. On the other hand, such linkages swell complexity and ease the propagation of propagation of contagion if a shock affects the system. Interconnectedness is on the top of the international reform agenda. Over the past few years, researchers across the board have been working on the identification of early warning indicators beyond the micro-prudential risk metrics. Recently the literature proposed different methodologies to measure sources of systemic risk. Shapley values (Drehmann and Tarashev (2011)), the systemic expected shortfall (Acharya et al. (2010)) and CoVaR (Adrian and Brunnermeier (2011)) are among the most relevant proposals for micro-level indicators that do not rely on network analysis. However, several critics argued that these asset prices-based indicators might perform well as thermometers (coincident measures), but not as well as barometers (forward looking indicators). To the extent that they are backward-looking, these risk metrics are typically at their lowest just before financial collapse takes place and have therefore little predictive value.

In many cases, these indicators have been proposed to circumvent the lack of data on the real topology of financial systems and the associated impossibility to identify effective contagion paths among institutions. As an alternative, network analysis based on real data, when available, has been widely employed to explore the resilience of the system to contagion of the financial system. These techniques allow to take into account the simultaneous distribution of risks across agents, beyond the evaluation of the risk-bearing capacity of each of them. Ultimately, however, the success of network techniques is intimately linked to data availability and, in turn, new initiatives on data reporting and collection at both national and international level may be affected by the success of the network approach.

Complex systems in which agents interact can have a simple network representation. In the specific case of financial networks, each financial institution represents a node and bilateral exposures between financial institutions are the links (or edges). Network analysis can be positive or normative. The positive, or static network, analysis allows the characterization of the network topology by means of statistical tools. This helps reaching a better understanding of linkages, hubs and clustering within a financial system. The normative, or dynamic network, analysis consists in the computation of outcomes that follows from an initial network structure that is exogenously perturbed. These exercises provide an assessment of the relationship between the financial system architecture and its stability: results carry relevant information for regulators, to the extent that they help identifying non-linearities due to the network structure.

The interest and the number of contributions on financial networks are expanding considerably. Beyond the well established theoretical literature on financial contagion (Allen and Gale (2000), Freixas et al. (2000), Acemoglu et al. (2012)), the vast majority of empirical contributions finds that the default of an individual institution is typically not able to trigger a domino effect (see, e.g., Boss et al. (2004); Elsinger et al. (2003); Furfine (2003), Mistrulli (2011)[6]). On the basis of the large sequence of contagion episodes of the recent years, the adequacy of procedures used to carry out these contagion simulation exercises is under a severe scrutiny. Recent research tries to fill the gap between the predictions of models of contagion and the evidence from financial crises. More in detail, standard contagion analyses in network economies are characterized by a common, basic idea. An initial shock that hits a region of the network (e.g. a single bank) propagates through interconnected counterparties. In general, different kinds of shocks (default of a single or a group of entities, market freeze, macro shock to common risk factors, ...), contagion channels (direct exposures, fire sales, liquidity hoarding, ...) and indicators to express the systemic importance of individual institutions have been proposed and analyzed.

Cont et al. (2011) propose to complement the idiosyncratic shock with a macro shock that reduces the equity positions of all the banks in the network at the same time, reflecting some sort of common risk exposures. An additional mechanism that may concur to the aggravation of the contagion is the fire sale of assets from distressed institutions (Cifuentes et al. (2005), Caballero and Simsek (2009), Shleifer and Vishny (2011)): such a response is individually rational for a distressed bank, but it imposes a negative externality on other institutions in the network, depressing asset prices and producing an inefficient aggregate outcome (Gai and Kapadia (2010)).

[6]In the specific case of Mistrulli (2011), the paper considers unconsolidated exposures. In other terms, it focuses on individual banks and not on banking group. In this respect, differently from our work, the paper neglects the possibility of internal capital markets to efficiently manage the liquidity of the banking group.

2. Contagion through distress: the DR

Our work proposes a novel method to assess the systemic importance of individual banks. The key idea is that a clear limitation of contagion through default models is their inability to account for the fact that, even when the default does not propagate from a bank to its counterparties, some distress do propagate nevertheless. In this sense, the contagion through default approach implies an underestimation of the intensity of contagion mechanisms. On the other hand, regulatory constraints (such as BCBS rules on Large Exposures) should make the possibility of a default following the failure of a single counterparty highly unlikely. In our work, we explicitly account for the fact that the bank j importing the contagion becomes more fragile even in the case its equity is large enough to withstand the loss. The higher fragility reduces the (market) value of its debt, making (at least) unsecured bank j's claimholders more fragile as well. The idea is fully consistent with the Merton's view on the market value of the bank's debt. As a result, even in the absence of subsequent defaults in the cascade, there can still be a significant systemic impact of an initial adverse shock. The DR is the measure of systemic risk derived from our *contagion through distress* mechanism. It complements traditional methods and provide a measure of the systemic importance of a bank even when default cascades models predict no impact at all. In particular, the DR is an extension of the so-called DebtRank algorithm introduced by Battiston et al. (2012). It is inspired by feedback centrality and takes recursively into account the impact of the distress of an initial node across the whole network.[7]

The DR is a measure of the centrality of the bank in the network and quantifies the propagation and the final outcome in terms of the economic value of the network potentially affected by the initial shock through the cascade of contagion.

Definition 1. *The DR of the bank i expresses the fraction of the total economic value of the network - excluding the bank i - posed at risk by some exogenous shock that hits the bank i. It captures the potential negative externality imposed to the network by the bank, excluding the direct impact of the exogenous shock.*

As an illustrative example, let's compute the DR of the bank i. Consider a simplified chain of unsecured loans granted by bank k to bank j and by bank j to bank i, whose amounts are denoted as x_{kj} and x_{ji}, respectively. Let E_i, E_j and E_k be the equity of the

[7]Feedback centrality measures have found successful applications in many domains like rankings in the world- wide-web (e.g. PageRank). Feedback centrality has a physical analogy with the in-flow in a non-homogeneous diffusion process.

three banks and $E = E_i + E_j + E_k$. In the paper, we use the Tier1 capital. A shock of size s hits the bank i, the targeted bank, that suffers a loss $L_i = s$. Even when $E_i \geq s$, the bank i is still able to transmit some contagion to bank j as the loss L_i erodes its equity and increase the bank i fragility. In particular, the loss for bank j is taken to be proportional to the value x_{ji} (the loan to bank i) and to the factor $h_i = \min[1, L_i/E_i]$.[8]

In this way, the algorithm embeds a type of convexity in the distance to default: the lower the equity E_i, the lower the ability of bank i to absorb the shock, the higher the contagion it transmits to bank j. The rationale is that the value of bank i's obligations decreases as bank i becomes closer to default and the value of its obligations to j declines. Consider the case in which the initial, exogenous shock is large enough ($s > E_i$) and the targeted bank i defaults. The impact on bank j is $W_{ij} = \min[1, x_{ji}/E_j]$, with $W_{ij} = 1$ when the shock that propagates to bank j is large enough to knock the bank j down. The shock propagates along the contagion path and reaches the bank k. The impact on the latter is $W_{jk} = \min[1, W_{ij}x_{kj}/E_k]$. In this simplified case, the DR of bank i is equal to:

$$DR_i = W_{ij}\frac{E_j}{E - E_i} + W_{jk}\frac{E_k}{E - E_i} \tag{1}$$

After simple manipulations we get:

$$DR_i = \frac{1}{E - E_i}\left[x_{ji} + \frac{x_{ji}}{E_j}x_{kj}\right] \tag{2}$$

The first addendum in the brackets is the loss induced to bank j; the second is the loss to bank k, derived as the impact x_{ik}/E_j transmitted by bank j and the exposures of bank k to bank j. The overall loss to the network (the number of the expression in brackets) is divided by the total equity of the system, to have a measure of the relative disruption induced by the bank i on the network. Capital plays as a buffer that smooths the effects of the initial shock to i along the cascade. In general, in a more complex network, bank k may have several debtors that, as bank j, are exposed to the contagion from bank i. Following the initial shock to bank i, at each iteration of the algorithm, some banks down the chain are affected. The sum of the losses occurred to these banks, at each iteration, is used to calculate the DR of the bank i.

One major refinement of our paper is that we explicitly account for a measure of riskiness

[8] Note that when the $L_i > E_i$ the bank i defaults. We assume that in the short run the recovery rate is negligible and the value of its liabilities drops to zero.

of the bank's assets. Indeed, two banks may have the same leverage (ratio of total assets to equity) but the composition of the asset side may differ substantially. More in detail, in the previous example, the impact of bank j to bank k is

$$\hat{W}_{jk} = \min[1, c_j \hat{W}_{ij} x_{kj} / E_k]$$

where

$$c_j = \frac{\text{Average Tier1 ratio}}{\text{Tier1 ratio of bank } j}$$

where, as standard, the Tier1 ratio is defined as the ratio of Tier1 capital to Risk-Weighted Assets. The coefficient c captures the riskiness of the bank relative to an overall average, across banks and time; c acts as a buffer (it is lower than 1) for banks with a Tier1 ratio above the average, and as an amplification mechanism for the others.

Finally, the method gets rid of possible infinite reverberations that can arise due to the presence of loops (i.e. $x_{jk} > 0$ and $x_{kj} > 0$). In these cases, the contagion may bounce several times between bank j and k, potentially until one or both default. To avoid this problem, walks in which one or more edges are repeated more than once are excluded. At each step t (the step is the time when the shock directly or indirectly reaches the node), to the generic bank j we associate a state variable S_j that can take three values *Inactive, Distressed, Undistressed*, so that:

$$S_j(t) = \begin{cases} Inactive & \text{if } S_j(t-1) = Distressed \\ Distressed & \text{if } h_j(t-1) > 0 \text{ and } S_j(t-1) \neq Inactive \\ Undistressed & \text{otherwise} \end{cases} \tag{3}$$

The algorithm stops when all banks are either in the Undistressed or the Inactive state.

3. Data description

Interbank linkages are the plumbing of financial markets. Exposures are surveyed within the supervisory reports submitted monthly to the Bank of Italy. The historical depth of the dataset hinges upon the continuity of data collection method: in principle, all information is available on a monthly basis at least since the early 2000. However, the subsequent adoption of different reporting templates complicates the coherent reconstruction of phenomena, for which it may be necessary an aggregation of different technical forms. Taking into account these difficulties, at this stage we have chosen to focus our preliminary analysis on unsecured interbank relationships, from 2008 on. The resulting representation of the interbank market is a weighted and directed network, namely a set of nodes (banks) that are linked to each other through different types of financial instruments (edges). The direction of the link goes from the bank i having a liability to the bank j claiming the liability, and the weight is the amount of the unsecured liabilities of i towards j. All data are available on a legal entity basis, due to the regulatory purposes of the reporting. However, given the deeply interrelated nature of financial markets and the significant concentration process which has been undergoing in the past decade, both at the Italian and international level, we assume that the economic agents underneath each transaction lie at the group level. For this reason, in the first round of analysis we choose to consolidate individual data, leaving for a later stage the analysis of the groups' internal capital market. Finally, in our exercises we use balance sheet information (e.g. total assets, core tier1 capital,...) from supervisory reports and ad hoc data gathering, that are available both on a solo basis and a banking group level. For a complete description of the Italian interbank network, see Bargigli et al. (2013).

4. The DR of Italian banking groups

4.1. The DR versus contagion through default

We compare our DR measure with the simplest, traditional indicator of systemic risk in financial networks, namely the effects of a default of a bank in terms of other defaults in the cascade. In Figure 1, these effects are measured as the ratio between the total equity of banks that default in the cascade over the equity of the network. Only in few cases the exogenous default of a bank brings about the default of other banks in the network and the overall impact in terms of equity is small (in the worst case, it is about 2% of the total equity of the system, against almost 18% for the DR measure).

Result 1. *The DR differs substantially from indicators based exclusively on contagion-through-default.*

The DR is reported on the vertical axis. The horizontal axis shows the effect to the network of a default of a bank, in terms of the fraction of the total equity of the network that is lost when we restrict to contagion-through-default. Clearly, the DR predicts sizable effects whereas the other measure typically shows no impact at all.

4.2. The DR before and after the sovereign debt crisis

Figures 2-6 report the DR of individual banks from 2008 to 2012. Graphs have a simple interpretation. Each dot represents a banking group (consolidated data have been used, netting out infra-group relationships). The horizontal axis reports the size of the bank, measured with its total assets (in millions of euros). The DR is reported on the vertical axis and, in this case, is expressed as the fraction of the total equity of the system potentially wiped out by an initial shock to a bank. In the DR computation, we exclude the direct effect of the exogenous shock that hits the equity of the targeted bank. In this particular case, we plot the DR of the bank associated to an exogenous shock that brings about the default of the bank. The size of the dot depends on the interbank lending and borrowing of the banking group with the network. Finally, the color of the dot represents the tier1 capital ratio of the banking group.

Result 2. *The DR of Italian banking groups has generally decreased since 2008.*

The decline of the DR is very clear for medium and large banks. It is due to decreasing interbank volumes exchanged in the unsecured market and to a quite intense process of banks recapitalization (Figure 7).

Both phenomena reflect a global trend. However, while the sign of the impact of the two trends on the DR is the same, they have polar opposite interpretations from a financial stability perspective. Indeed, on the one hand, the proper functioning of the unsecured interbank market is essential for an efficient use of liquidity within the financial system. The unsecured interbank market dry-up during the sovereign debt crisis and the migration towards collateralized (often ECB) funding have been a widespread phenomenon in the Euro area periphery. The spike in the spreads between interbank rates and overnight index swap rates almost worldwide is a clear footprint. Acharya and Merrouche (2010) and Christensen et al. (2009) find a precautionary hoarding motive for the sudden dry-up of money markets. Conversely, in Taylor and Williams (2008) the key driver is the sizable increase in counterparty risk. Regardless the underlying cause, a decline in the volume exchanged in the interbank market is generally perceived as the symptom of a disease and represents a major concern for a smooth functioning of funding markets and for the transmission of monetary policy signals. The decreasing activity in the domestic interbank market follows a generalized dry-up of cross border flows, which has been particularly severe for some Euro Area economies over the 2010-2011 period (BIS Quarterly Review, June 2012): Italian institutions were quite dependent on this source of funding that supported a portion of the domestic interbank market and they had to resort to retail funding and to the Eurosystem to replace some of their maturing wholesale liabilities. On the other hand, the regulatory response following the global financial crisis has also pushed for a recapitalization of most institutions. One major example is the European Banking Authority EU-wide capital exercise, that led to an increase of EU banks' capital positions of more than 200 billions of euros. The average leverage levels (core capital) for Italian banks have significantly decreased (increased) over the 2007-2011 period.

A decline of the DR due to stronger balance sheets is desirable; the same conclusion cannot be drawn when the systemic risk declines because the traditional flows of liquidity are impaired and the entire system is more dependent on central bank funding. We disentangle the two effects with a simple comparative statics exercise (Figure 8), running the DR algorithm on two "mixed" networks. The first one is made up with unsecured interbank exposures at Dec-2008 (when they were relatively high) and with banks' capital levels at Dec-2012 (relatively high). In the second exercise, the DR is computed using exposures at Dec-2012 (relatively low) and capital levels at Dec-2008 (relatively low).

We can quantify the impact of more robust balance sheets on systemic risk when banks are more interconnected (Dec. 2008) and compare it with the effect of capital when volume exchanged in the network are lower (Dec. 2012). Comparing the two panels of the left column of Figure 8, the effect of recapitalization on systemic risk is clearly noticeable when the interbank market functions properly, private liquidity flows are significant and interconnectedness is high. On the contrary, comparing the panels of the right column, the effect of higher capital in a low-interconnected network seems much less significant.

4.3. Interconnectedness and macroprudential regulation

A new macroprudential orientation of financial regulation has been undoubtedly one of the key directions of the reform roadmap. Microprudential regulatory frameworks, by focusing on the soundness of financial institutions taken in isolation and disregarding the effects of macroeconomic variables, interlinkages and exposures to common risk factors, have been identified for contributing factors for the run-up of the crisis. In the new perspective, authorities are called to actively manage capital regulation along the business cycle.

In this section, we use our network approach to financial fragility to investigate the link between bank's capital and systemic risk. In particular, we focus on the ability of capital to reduce the systemic risk imposed by the bank to the financial network through contagion. In our view, the results of this section provide a solid argument in favor of a counter-cyclical capital buffer in line with the Basel III Accord. In the spirit of the reform, the buffer would be properly imposed (released) in the expanding (contracting) phase of the business cycle. Our approach captures one particular aspect of the cycle, namely the "interconnectedness cycle": during the crisis many links in the interbank unsecured market have been replaced by central bank funding.

In terms of the algorithm, in all exercises presented so far, in order to compute the DR of the bank, we impose an initial shock that brings about the default of the bank. One undesirable consequence of this approach is that the capital of the bank i, by construction, cannot affect the DR of the bank i: regardless the financial fragility of the bank, the initial shock always induces the default. In this section, we introduce two variations.

1. The initial exogenous perturbation to the bank takes the form of shocks of different size distributed with some probability density function. More in detail, while in the baseline DR computation the initial shock is the default of the targeted bank i, in the exercise presented in this section we hit bank i with a number of shocks, one at a time, and for each shock we run the DR algorithm. Then, to each shock corresponds a number that represents the equity of the network that is potentially wiped out. Finally, we compute a weighted average of these numbers, using the Normal probability density function to obtain the weights (in other terms, the effects of very small and very large shocks have a lower weight). One major effect of this exercise is that the bank i's capital directly affects bank i's DR.
2. We compute the DR of the bank assuming an increase (call it DR+) and a decrease (call it DR-) of the bank's effective capital by the 20%. The outputs are two values, namely DR+ and DR-, for each bank (at each date). The deviation of the DR from the DR+ (DR-) represents the effect of an increase (decrease) of the bank's capital on its systemic risk.

Result 3. *The impact of capital on systemic risk is higher when the network is interconnected. This result supports the desirability of a counter-cyclical capital regulation of banks.*

More in detail, for each bank, we first compute the difference between the DR and DR+. The blue line in Figure 9 represents the evolution over time of the average value of this difference for the top 5 banking groups, where December 2008 is taken as a reference point. The red line is the same indicator for other medium/large banking groups.[9]

The impact of capital on systemic risk decreases substantially in the midst of the sovereign debt crisis, with the dry-up of unsecured interlinkages. This result has a straightforward implication in terms of capital regulation: authorities should be encouraged to actively adjust capital regulation across the cycle as even small increases of the requirement (the

[9]The corresponding figures for the difference between DR- and the DR are almost perfectly identical, suggesting a symmetric effect of the imposition and the release of the buffer, at each date.

accumulation of a counter-cyclical capital buffer) in good times generate significant effects in terms of reduction of the systemic risk. At the same time, the buffer may be released in bad times, with an almost negligible increase of the systemic risk.

4.4. Size, interconnectedness and DR

The regulatory approach to systemic risk is changing. Several regulatory reforms are currently underway in all major jurisdictions worldwide and at the international level. These reforms aim not only at increasing the capital and liquidity requirements for financial institutions but, in some cases, at transforming the architecture of the financial system by imposing constraints on activities and types of exposures. At the international level, the Basel III proposal envisages an additional capital buffer for global systemically important banks (G-SIBs) and, more broadly, for systemically important financial institutions (SIFIs).[10] The G-SIB surcharges will cope with the potential impact of an institution failure on the global financial system and the wider economy. Interestingly, the focus of the Basel Committee goes beyond the size of the financial institution and encompasses some measure of interconnectedness. In the proposal, the latter is captured using three indicators, intra-financial system assets and liabilities[11], intra-financial system liabilities[12] and the wholesale funding ratio. The proposal surely represents a step forward. However, for each institution, the scores for the first two indicators are calculated on the basis of the aggregate claims and obligations towards the rest of the financial network. Our analysis emphasis the limits of measures based on aggregate exposures and that neglect the topology of the network.

Result 4. *The DR captures features of the systemic importance of a bank that go beyond leverage, capital, size and interconnectedness.*

As one would expect, the DR and the size of the bank are positively related. This is mostly due to economies of scale in market making activity. In general, one important caveat in the interpretation of the relationship between size and systemic risk is that we confine the analysis to the domestic interbank market. Large institutions are more able to capture

[10]Consultation material can be found at http://www.bis.org/publ/bcbs207.htm.

[11]Lending to financial institutions (including undrawn committed lines), holdings of securities issued by other financial institutions, net mark to market reverse repurchase agreements with other financial institutions, net mark to market securities lending to financial institutions and net mark to market OTC derivatives with financial institutions.

[12]Deposits by financial institutions (including undrawn committed lines), all marketable securities issued by the bank, net mark to market repurchase agreements with other financial institutions, net mark to market securities borrowing from financial institutions and net mark to market OTC derivatives with financial institutions.

funds in the cross-border interbank market thanks to higher visibility. Therefore, the whole picture that includes foreign linkages would be different, especially in the first months of our sample period, due to the intense cross-border interbank activity. For this reason, in an extension of the exercise to the whole Euro area network, we would expect an increase of the systemic risk posed by large banking groups. However, the relationship between size and DR is absolutely non linear and banks with similar size may show very different DR values. Interconnectedness plays a key role in determining the systemic risk of a bank. Institutional features and banks' business models may help explain the relatively high DR of some medium-size institutions. They operate as a liquidity hub of regional networks of very small, mostly co-operative banks.[13]

The systemic relevance of these banks is tied to the significant number of institutions that would be involved in the distress-cascade, despite the relatively low size of their trades. In particular, the increase of their DR is due to larger unsecured borrowing by co-operative banks from ICCREA, their liquidity pool, that had access to ECB funding through the first Long Term Refinancing Operation (LTRO).

5. Conclusions

In this work we try to put forward a new class of stress-testing techniques that (i) accounts for non-linearities in contagion propagation that are typical of network-based models and (ii) allows to identify systemically relevant institutions beyond default–cascade models. We applied the methodology to a unique dataset of bilateral exposures in the Italian interbank market.

Our results show that traditional indicators underestimate contagion risk. Our measure, DR, captures features of a bank's systemic relevance that would not be apparent under standard default cascades models. DR estimates for the Italian banking system show that systemic risk in the interbank network has decreased significantly since 2008. However, the decline is mainly due to the fact that a crisis has indeed happened somewhere else in the financial system, namely in the sovereign bond market, as opposed to increased capitalization of the banking system. Such evidence strongly supports policy options in line with Basel III such as counter-cyclical capital buffers for banks: the effect of a bank's capital on its systemic risk is much higher when the financial network is tightly interconnected, which is

[13] Figure 10 reports interbank exposures and Tier1 capital for Italian banking groups, classified with respect to their size.

most likely to happen in good times, its impact decreases with leverage in “bad” times.

Extensions of the current setting to liquidity-run contagion could complement policy-makers discussion on countercyclical liquidity insurance fees.

List of Figures

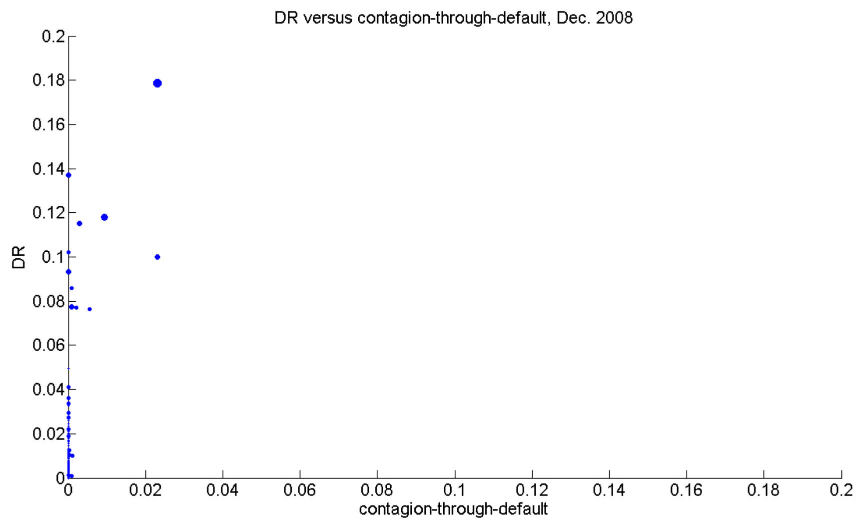


Figure 1: DR versus contagion-through-default. Each dot is an Italian banking group. Vertical axis: DR; horizontal axis: impact on the network measured with the equity loss, considering exclusively contagion-through-default. Dot size: interbank lending and borrowing relative to total assets. December 2008.

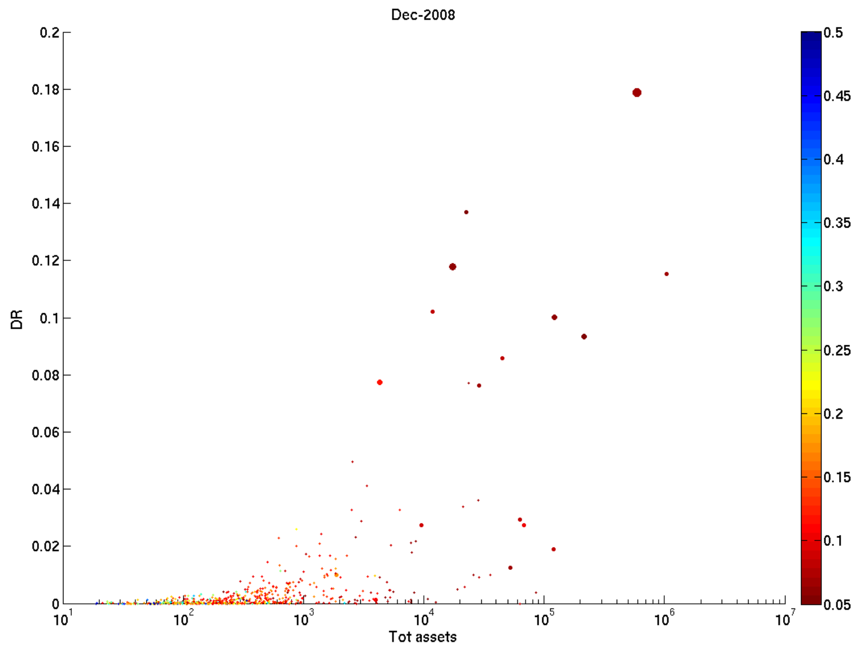


Figure 2: The DR of Italian Banking Groups at December 2008. Vertical axis: DR; horizontal axis: total assets; dot size: interbank lending and borrowing; dot color: Tier1 ratio.

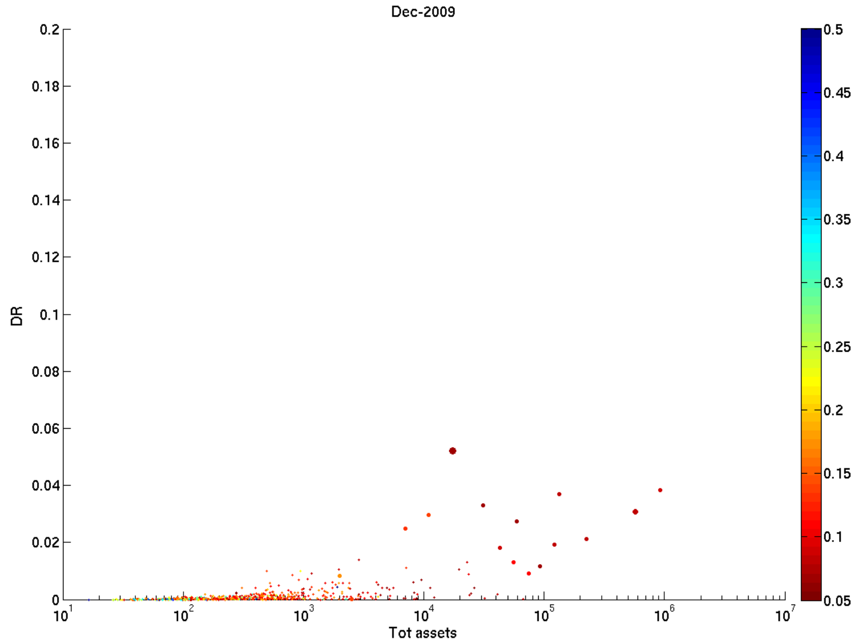


Figure 3: The DR of Italian Banking Groups at December 2009. Vertical axis: DR; horizontal axis: total assets; dot size: interbank lending and borrowing; dot color: Tier1 ratio.

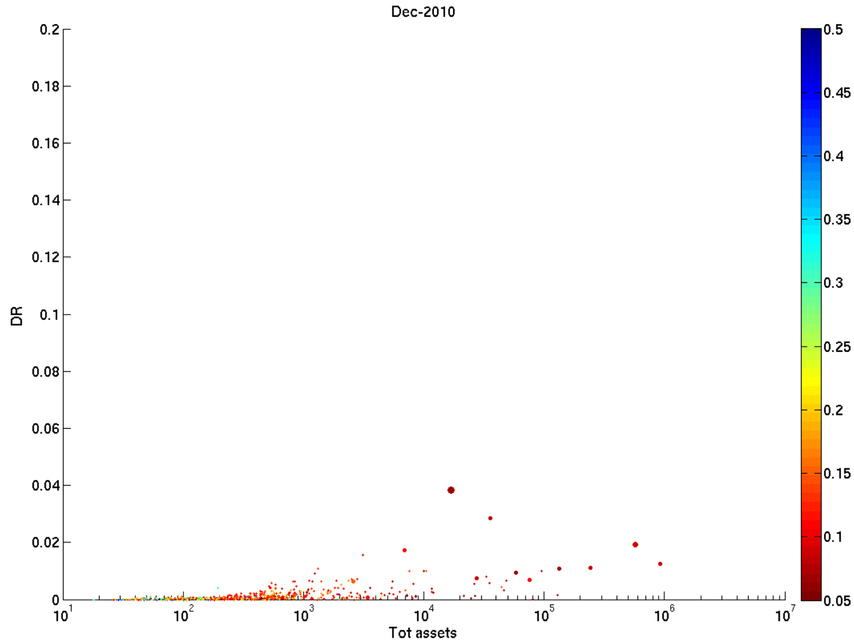


Figure 4: The DR of Italian Banking Groups at December 2010. Vertical axis: DR; horizontal axis: total assets; dot size: interbank lending and borrowing; dot color: Tier1 ratio.

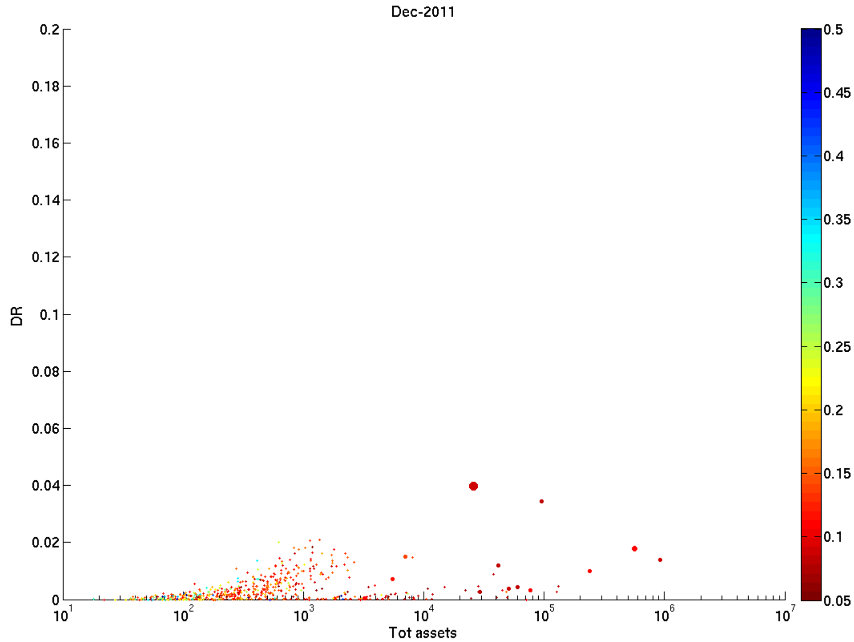


Figure 5: The DR of Italian Banking Groups at December 2011. Vertical axis: DR; horizontal axis: total assets; dot size: interbank lending and borrowing; dot color: Tier1 ratio.

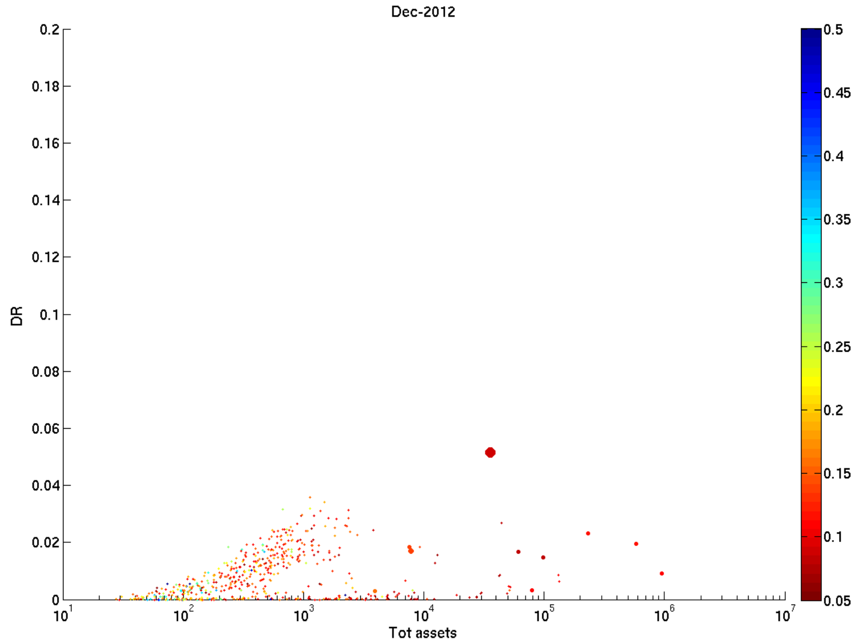


Figure 6: The DR of Italian Banking Groups at December 2012. Vertical axis: DR; horizontal axis: total assets; dot size: interbank lending and borrowing; dot color: Tier1 ratio.

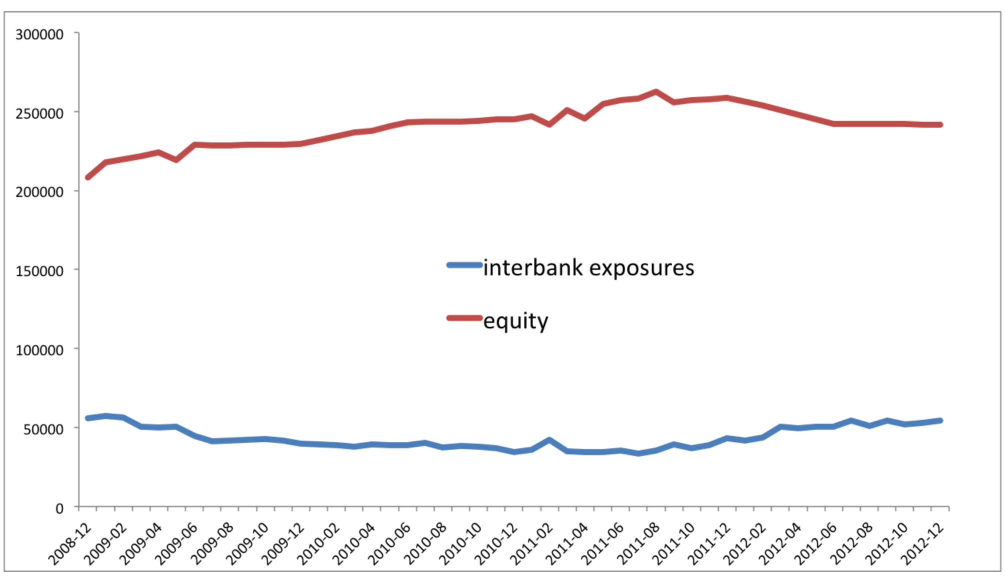


Figure 7: Interbank exposures and Tier1 capital of Italian banking groups (millions of euros).

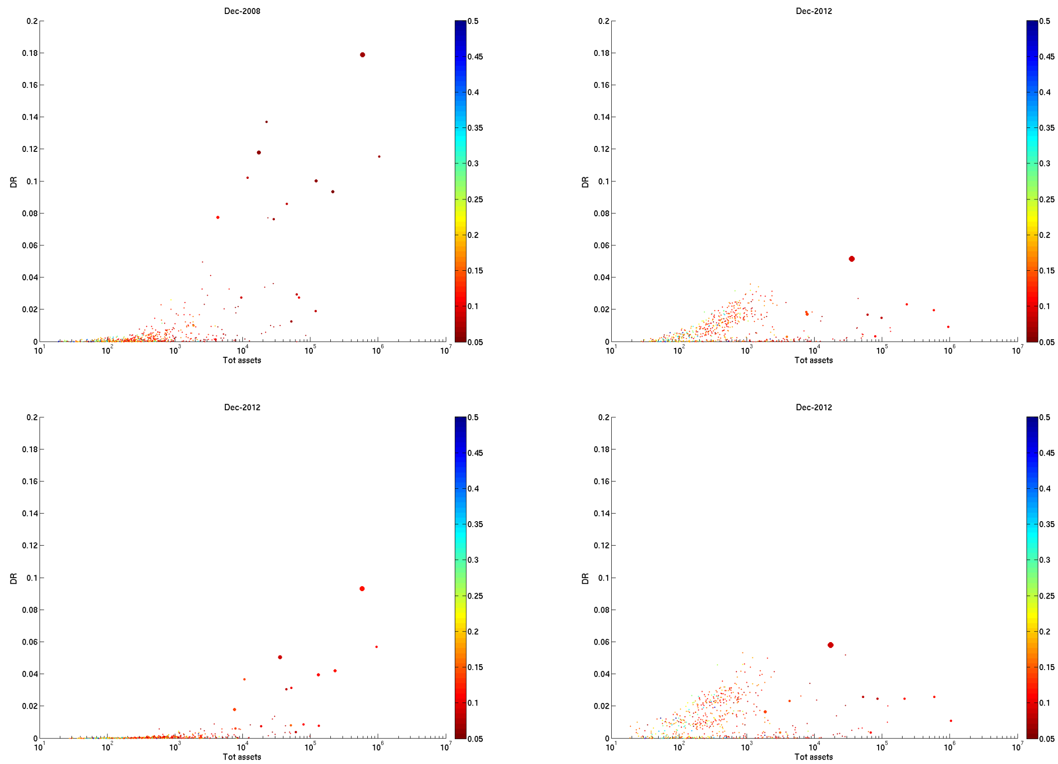


Figure 8: Lower volumes and higher capital. Top/left: DR at Dec. 2008. Top/right: DR at Dec. 2011. Bottom/left: DR with Tier1 of Dec. 2012 and exposures of Dec. 2008. Bottom/right: DR with exposures of Dec. 2012 and Tier1 of Dec. 2008. Vertical axis: DR; horizontal axis: total assets; dot size: interbank exposures; dot color: Tier1 ratio.

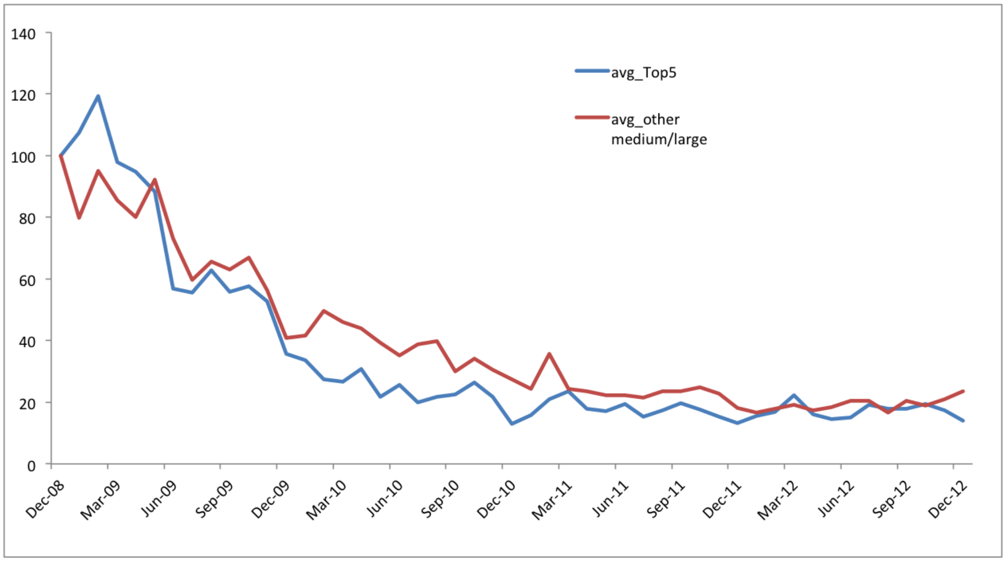


Figure 9: The impact of capital on the DR of top 5 and other medium/large Italian banking groups. Dec 2008=100. Shock range =[1% - 15%] of total assets, interval between two successive shocks = 1%. Probabilities of the shocks are taken from a Normal distribution, with mean= 5% and std deviation = 0.1.

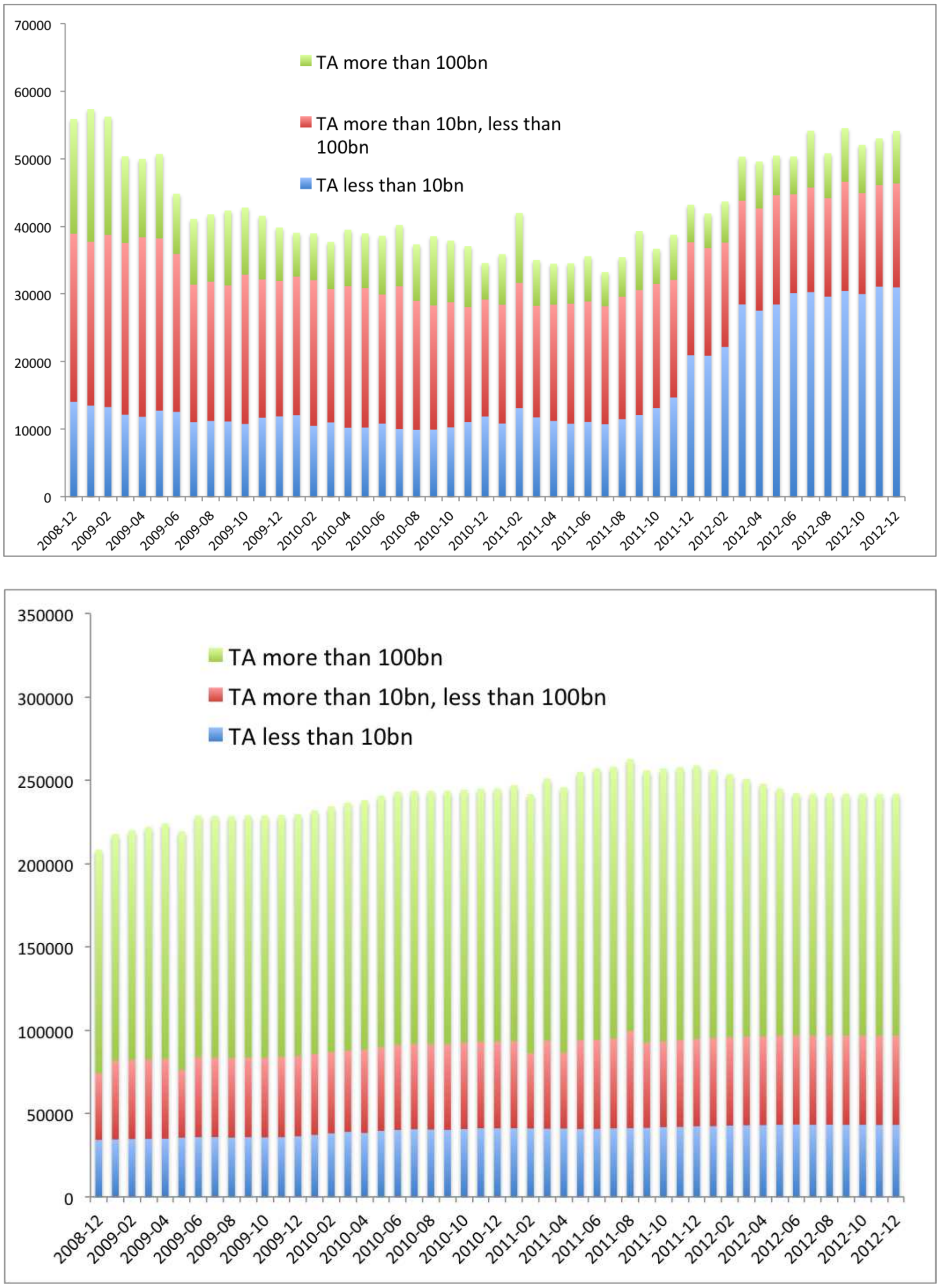
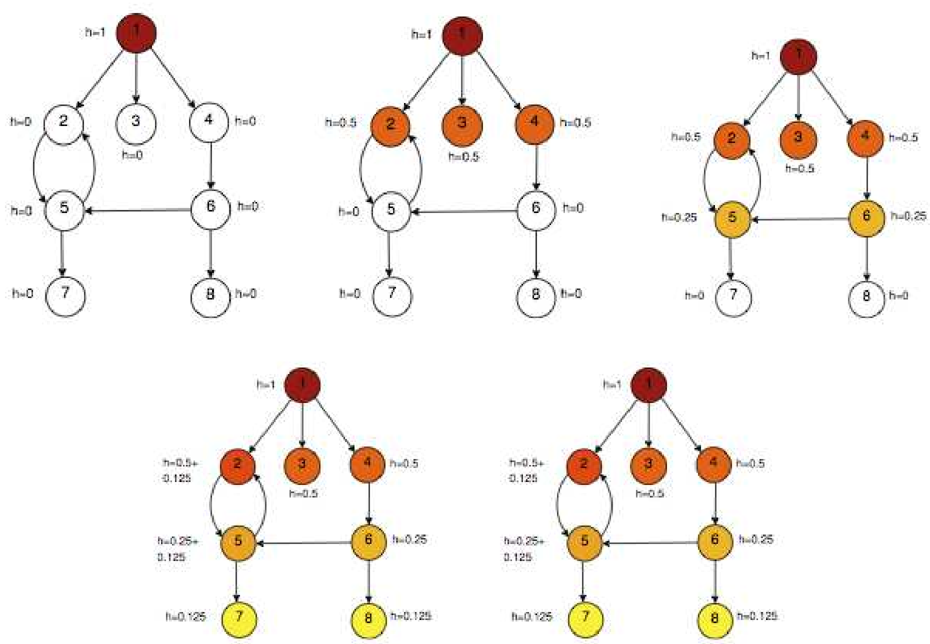


Figure 10: Interbank exposures (top panel) and Tier1 capital (bottom panel) by bank size measured with total assets (TA, in millions of euros).

6. Reverberations

In this paper we follow the DR methodology (Battiston et al. (2012)) and exclude second order reverberation in loops. To clarify the issue, consider Figure (11), with a simplified financial network, with 8 banks that interact through mutual exposures. Assume bank1 defaults following some exogenous event. For sake of simplicity, the contagion is taken to be $h = 0.5$ for all exposures. What is key as regards reverberations, is the contagion between bank 2 and bank 5, for instance. These two banks form a loop, as bank 2 is exposed to bank 5 and vice versa. In the cascade, the contagion may potentially reverberate ad infinitum or, at least, until one or both banks default. In the present version of the paper, we consider only one reverberation, excluding from the computation of the DR all the paths that have been already visited.

Figure 11: Reverberations (read clockwise from the top-left).



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