MONITORING SYSTEMIC RISK:

A SURVEY OF THE AVAILABLE MACROPRUDENTIAL TOOLKIT

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by

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Introduction

The 2007-08 financial collapse has catalysed the attention of scholars and policy-makers on the very nature of financial crises, stimulating a new, fresh wave of research on the topic, aimed at defining and measuring systemic risks. Understanding the nature of systemic risk and identifying the channels by which shocks spread are the necessary prerequisite for anticipating and successfully managing the onset of financial crises. In order to prevent financial distress and manage instability, the macroprudential regulator needs to track and measure systemic risks ex-ante. Has the massive wave of research prompted by the crisis produced new tools able to anticipate financial distress? How do these innovative tools work?

Conceptually, systemic risk has multiple dimensions. Systemic risk shows a time-varying pattern (which follows the build-up of financial imbalances over time) and a cross-sectional structure (which determines the degree of fragility of the system and governs its resilience to shocks). Financial shocks are endogenously fueled (stemming from the co-dependent behaviors and chain-reactions of the financial institutions themselves). The time-varying and cross-sectional dimensions of risk are compounded during the run up to a crisis. The disruptive impact of the crisis transcends the resilience of each of the institutions involved. Individual soundness does not add up to aggregate stability. The non-linear properties of financial networks represent a major challenge to the microprudential approach to bank regulation.

The aim of the paper is twofold: on the one hand, it reviews the theoretical frameworks which allow the assessment of the different dimensions of systemic risk, while on the other it classifies the methodologies available for the advance assessment of the potential for systemic distress accordingly and moves on to analyse them

The paper is divided int four sections. In the first section, the paper classifies the different definitions of systemic risk and discusses their significance during the 2007-08 crisis. In the second section, it presents the tools available for the extraction of real-time information on market perception of risk from market prices of securities and derivatives (i.e. CDS and equity options). In the third section, the analysis extends to the methods focused on the measurement of financial fragility arising from the linkages between networks within the financial system. Some concluding remarks are put forward in the final section.

1. *What is systemic risk?*

1.1 Definitions of systemic risk

The notion of systemic risk usually refers to the probability of a collapse of the financial system prompted by unidirectional and simultaneous downside co-movements of asset prices and/or by a generalized draught of liquidity. Systemic risk is the risk of a banking crisis when the defaults of one or more banks appear to be chain-connected.

Understanding the genoma of systemic risk and identifying the channels through which it spreads are the conceptual and empirical prerequisites needed to anticipate the occurrence of financial and banking crises. However, even the concept of systemic risk is not uniquely defined [de Bandt et al. 2009]. Sometimes it is referred to as an exogenous and unexpected macro-shock affecting many banks at once (as in the case either of a deep recession which feeds back into bad loans for most banks or of a fall in asset prices triggering a generalized process of deleveraging); on other occasions, the notion of systemic risk relates to the chain reaction prompted by the default of one debtor which translates into the default of its creditors and then, with further *cascade* effects, into the default of the creditors of the latter. In this case, it is neither the original source of shock nor its size that matters, but the nature of the endogenous self-fulfilling process of diffusion which makes the crisis implode.

By nature, banking is highly exposed to both risks: banks are vulnerable to exogenous shocks because their activity involves maturity mismatch between assets and liabilities. At the same time, banks are directly linked through the network of interbank deposits. Furthermore, banks operate mostly on the same segments of the financial market, often share the same business model and adopt the same risk management procedures: all these features make them exposed to the same risk factors and make them prone to adopt similar behavior in case of crisis.

In addition, there may also be indirect channels of distress transmission (i.e. channels not implying direct connection between the subjects involved). For example, due to information asymmetries, even solvent banks may be affected by the uncertainty generated by a bank default. The more similar their risk profile to that of the defaulted bank, the higher the probability attached by market participants to the event that they may be heading the same way (irrespective to their actual solvency) . It follows that fund withdrawals and liquidity shortages could affect, at the same time, not just insolvent banks, but also banks which are perfectly sound, pushing them, too, towards undeserved distress. [Aharony, Swary 1996, Revell1975]. Of course, faster the rate of contagion, the higher the vulnerability of each single bank involved (i.e. lower capital ratio, higher leverage, higher maturity mismatch etc.).

In order to define the perimeter of macroprudential control and identify adequate monitoring tools and policy instruments, it is useful to dig into two complementary features of systemic risks: (i) the endogenous nature of financial fragility; (ii) the structural complexity of financial systems.

i. *Exogenous shocks vs. endogenous cycles.* Before the 2007-08 financial crisis, most of the empirical literature on financial distress focused on modeling exogenous shocks and their quantitative impacts over time. Stress tests, and econometric simulations (such as vector auto-regression impulse-response analyses) belong to this tradition, which is based on the assumption that the structure of the financial system is given and does not modify over time. However there is also an alternative approach which focuses on the internal dynamic of the financial system itself as a major engine of financial fragility and instability [Minsky 1982; Kindleberger, Aliber 2005]. This approach (often neglected because of the dominant paradigm of market efficiency) postulates that the genesis of financial imbalances is rooted in the financial behavior prevailing during periods of economic expansion. Those imbalances compound over time, increasing the fragility of the system, up to the point where they turn out to be unsustainable. When the breaking point is reached the financial implosion is sharp and huge. The extension of the crisis has no apparent relationship to the size of the first shock triggering it (which is sometimes even undetectable), but depends rather on the size and diffusion of the financial imbalances accumulated in the past. In this dimension, systemic risk is correlated to the pro-cyclicality of agents' behavior, it is dynamic in nature and it can be detected only through observation over long time spans. The focus on the endogenous cycle of financial fragility implies that in order to anticipate systemic financial distress, authorities must control the accumulation of financial imbalances over time, by monitoring key indicators such as excessive credit expansion, excessive leverage or asset bubble inflation. This dimension is labelled as the *time-varying* dimension of systemic risk [Kyotaki, Moore 1997; Borio, Lowe 2002a; 2002b; Borio, Drehmann 2009a; 2009b; Brunnermeier 2001; Borio 2013].

ii. *Structure of the financial system.* The common feature of any systemic crisis is the velocity of diffusion, which depends on the nature and strength of direct and indirect linkages among agents. As we have already seen, the working of any banking system requires a wide network of direct financial connections, through both the payment system (*clearings*) and interbank deposits. Being exposed to the same risk factors, banks are also vulnerable through indirect channels (such as runs on deposits and/or assets sales). Given their cross-country/cross-currency operations, banks are also the vehicle of international diffusion of shocks. Microprudential tools (such as capital ratios and caps on leverage) may moderate banks' vulnerability, since the speed of contagion is higher when the banks involved along the transmission chain are weaker. However, stronger defensive lines at the micro level may prove an insufficient antidote against systemic crises: the overall structure of inter-linkages within the system could overwhelm individual balance sheet equilibria, generating an explosive pattern of feed-backs. This aspect of systemic risk is not adequately captured by the dynamic over time of financial aggregates (*time-varying dimension*), but also requires a specific assessment of the structure of the banking/financial network and the measurement of its internal interconnections at each point of time. This is called the *cross-section* dimension of systemic risk [Allen, Babus 2008; Gai et al. 2011].

1.2 Systemic risk indicators and measurement metrics

For the combating of financial distress to be viable, systemic risk must be traceable and measurable. Both the accountability of macroprudential authorities and their ability to prevent financial distress depend on the proper measurement of systemic risk. In the first case (accountability) authorities can rely on *ex-post* indicators, which signal the build-up of imbalances able to trigger a financial crisis. Whenever such imbalances reach a critical limit (identified by looking back at past experiences of financial distress), action is within the domain of macroprudential supervisors. However, ex-post evidence of unsustainable imbalances, albeit necessary, is not a sufficient condition for triggering macroprudential action. Waiting for financial distress to show up (either at micro or at macro level) could substantially weaken the effectiveness of prudential policy. In order to prevent the occurrence of distress, macroprudential authorities need also to assess its probability in advance. In other words, prevention requires *ex-ante* or forward-looking indicators of distress, able to measure both the potential vulnerability of the system and the proximity of financial disruption. As a matter of fact, the financial system could function and grow for very long periods even in the presence of major imbalances. As stated by *Financial Instability Hypotesis* [Minsky 1982], it is actually during the good phases of the cycle that financial imbalances build-up, because economic agents do not perceive the dangers of moral hazard and high leverage ratios are generally considered a positive fuel for growth and profitability. Systemic risk is exposed to a paradox: it tends to accumulate when liquidity is abundant, volatility is low and risk premiums are thin. In a nutshell, systemic risk behaves like an asymtomatic pathology that works undetected, weakening the immune defences while the patient is apparently sane, but exposes the body to major threats when the pathology manifests itself.

In order to act in time and monitor the effectiveness of policies, macroprudential authorities need diagnostic tools that must be not only reliable but also available within a useful time span. This severely limits the universe of data which can be processed within the necessary time. In addition, since systemic risk is a latent factor, authorities must also rely on counterfactual approaches (such as, for example, stress tests and network simulations), which are by nature conditional on discretionary model representations and calibration choices.

As mentioned in the previous section, systemic risk has multiple dimensions. Systemic risk has a *time-varying* pattern (which follows the build-up of financial imbalances over time) and a *cross-sectional* structure (which determines the degree of fragility of the system and governs its resilience to shocks at any given point of time). It means that financial shocks are not only the effect of exogenous shocks, but are also fueled by endogenous factors (stemming from the co-dependent behaviors and chain-reactions of the financial institutions themselves). *Time-varying* and *cross-sectional* dimensions of risk compound during the run up of a crisis and the disruptive impact of the crisis transcends the resilience of each of the single institutions involved. Individual soundness does not sum up to aggregate stability. The non-linear properties of financial networks represent a major challenge to the microprudential approach to bank regulation.

Each of these dimensions of systemic risk appears to be measurable using different tools [Noera 2013]. Since the 2007-08 financial crisis a new wave of research has been trying to refine and test methods able to offer, on the one hand a forward-looking approach to the measurement of systemic risk (mainly by extracting market expectations from the pricing of securities and derivatives) and on the other hand able to highlight the assessment of systemic vulnerability (by looking at the properties of the financial networks and the strength of the inter-linkages among financial institutions). Table 1 offers a bird-eye view of the main indicators of systemic risk now available to macroprudential authorities. They are classified according to: (a) the nature of the data from which they are drawn (i.e. macro-statistics, accounting data; market data); (b) the methods of processing (ratios; statistical-econometric estimates; model simulations); (c) their focus (either on individual institutions or system-wide). However, the most important distinction among them is between *time-varying* and *cross-section* indicators.

The distinction according to the nature of the data is sometimes straightforward: on one side, there are the usual financial statistics referring to the financial system as a whole (mainly credit and/or debt aggregates) and/or accounting data (either referred to single institutions or consolidated). Most of these indicators are simple ratios or rates of growth of the quantities observed (financial soundness indicators, FSI; credit growth; debt-to-income, DTI etc.). On the other hand, there are methodologically more complex indicators based on market prices of both securities (bonds) and derivatives (equity options, CDS). Some of them are used to assess the implied probability of default of single institutions (*distance-to-default* or *DD*; implicit probability of default or *i-PoD*; higher moments analysis of the univariate probability of default). Other indicators apply to multiple institutions and take into account the structural interconnections within the system (*Co-Risk* indicators). Some of the latter can be observed also in their dynamics over time (time varying multivariate distress dependence) [Bisis et al. 2012].

Table 1 – A Taxonomy of Systemic Risk Indicators

Time-varying dimension		*Cross-section dimension*
Main indicators	***Statistical & simulative***	
Macro indicators • Broad credit aggregates • Measures of debt sustainability (DTI)	• Impulse-response analysis (VAR models) • Markov regime switching (VIX)	• GARCH Dynamic Conditional Correlation Analysis
Bank balance sheet indicators • Leverage /capital ratios • Maturity and currency mismatch • Indicators of funding vulnerabilities	• Micro Stress tests	• Conditional correlation matrices • Cluster analysis • Network simulations
Market-based indicators • Asset valuations in equity/property markets • CDS spreads and risk premia • Margins & haircuts • Lending spreads	• Option or CDS *i-PoD* • Tail risk & Distribution higher moments *(skewness; curtosis)*	• *Co-Risk* analysis • Time-varying multivariate distress dependence

In general, the basic indicators of financial stress, both macro and micro[1], are built on data available only at low frequency (monthly, quarterly and even annually) and are backward-looking (*ex-post* accounting measures). By nature, their predictive power is poor. The time patterns of these indicators is slow moving as they tend to signal the progressive accumulation of disequilibria that, once calibrated on past stress episodes, may help the

[1] Among the most common macroindicators are: credit/GDP ratio, debt/GDP ratio (both public and private); equity prices and real estate prices (all the variables may be observed both in terms of absolute level and in terms of rate of growth). The most common balance-sheet microindicators measure: (a) capital adequacy (capital/assets ratio; tier1 capital/assets ratio; tier1 capital over RWA; tier1+tier2 capital over RWA); (b) asset quality (non-performing loans; provisions); (c) leverage ratio (debt over capital; share of short term debt); (d) liquidity (loan/deposit ratio; loan/asset ratio); (e) profitability (RoA; RoE); equity valuation (PE ratio; EPS; P/B ratio). IMF [2006; 2011a].

macroprudential supervisors to identify *critical thresholds* beyond which the probability of a crisis is assumed to be increasing[2].

At the macro level, useful indicators of financial stress are the positive deviations both of the credit-to-output ratios and asset prices (mainly equity and real estate) with respect to their respective medium term trends [Borio, Lowe 2002a, 2002b; Borio, Drehmann 2009a]. The size of the deviation of asset prices from the trend signals the progressive inflation of bubbles, the increasing likelihood of a burst and the severity of the subsequent adjustment. The size of the deviation of the credit/GDP ratio from its trend captures the increasing vulnerability of the financial system, as at higher levels of aggregate credit dependence the financial system becomes less able to absorb losses. The predictive power of these indicators improves significantly if they are analyzed jointly [Lund-Jensen 2012].

Even though credit-to-output ratio and asset price imbalances are sometimes able to signal the risk of a financial crisis in advance, they are incapable of identifying the exact point in time when the disruption actually occurs. This means that additional information is needed on the prevailing mood of market participants. Indicators based on market prices try to fill this informational gap. The rest of the paper is dedicated to this family of forward-looking indicators.

2. Market assessment of default risk

2.1 Single institution i-PoD

Market sentiment indicators can be extracted directly from market prices (equity, bonds and credit default swaps) in the form of implied probabilities associated by the market to the event of distress (either related to individual institutions or to the system as a whole). The underlying assumption of this approach is that the market constantly monitors the soundness of banks and the capabilities of the management and that this assessment is directly reflected in equity prices and CDS spreads. Under the hypothesis that the market is efficient (i.e. that prices fully incorporate all the available information), the information deduced from market prices is inherently *forward-looking*, as it reflects expectations. In other words, equity option premiums and CDS spreads are the raw materials from which the implicit probability of default (or *i-PoD*) expected by the market for each listed financial institution[3] can be extracted. Since *i-PoDs* try to capture the risk assessed by market

[2] *Time varying indicators* are based on *"signal extraction"* techniques, which look at the deviation of the observed variable (for example: credit growth) with respect to its long term trend: when the deviation widens beyond a pre-definite threshold, the indicator assumes the signal 1 (while during normal times it is set to 0). Theoretically, when the indicator is 1, a crisis should follow. However, when tested in sample (i.e. on historical data), the indicator may give false signals. The errors are classified in two categories: *type 1 error* is when the indicators fails to signal a crisis which actually occurs; *type 2 error* is when it signals a crisis that fails to materialize. Therefore, calibration is needed in order to optimize the trade-off between the two types of errors and get reliable signals that financial distress is actually building up. Borio, Drehmann, [2009a].

[3] Following the Merton [1974] *contingent claims* approach, implicit volatility can be used to estimate the expected future value of the assets (A) of the bank (which is assumed to follow a stochastic path) and of its equity capital (E), which can be treated as a call option on assets, with strike price equal to the maturing debt (L). Given the value of collateral plus guarantees (H), the default risk for the creditors of the bank is equal to total liabilities net of collateral and/or guarantees. Given the two equations (budget constraint A=D+E and risky debt D=L-H), the system can be solved for two unknowns (assets valuation and implicit volatility of assets) which allow derivation of the implicit probability of default of the bank (*i-PoD*). Tarashev, Zhou [2006; 2008]; Capuano [2008].

participants at any point of time, they are very sensitive to the likelihood of default (either actual or just perceived). Unlike (*time varying) slow moving* indicators, this category of signals reacts with a very short lead-time (few months or weeks) as the critical point of disruption approaches: that is why they are also known as *near-coincident* [Arsov et al. 2013].

3. The cross-section dimension of systemic risk

3.1 Multivariate distress dependence

When applied to a single institution, the *i-PoD* indicators do not account for systemic risk arising from direct and indirect inter-linkages among financial bodies. One interesting research development of this approach is the extension of similar techniques to estimation of the cross-probability of default of each institution conditional to the probability of default of any other [Segoviano, Goodhart 2009]. Looking at the financial system as a portfolio of banks, this approach estimates the multivariate probability distribution of distress of the whole system and extracts a set of indicators of the joint probabilities of default of any pair of banks or groups of banks from the multivariate distribution, implicitly taking into account the structure of their cross-correlations.

There are several indicators elaborated using this approach which have different focus: *(a)* the *J-PoD* (or *joint probability of distress*) measures the probability that all the banks in the sample could default (this estimate is equivalent to the tail systemic risk of default)[4]. Further systemic risk indicators can be calculated from the *J-PoD* : *(b)* the *Banking Stability Index* (or *BSI*), which estimates the number of distressed banks associated to the case in which at least one of the others is distressed (the larger the number of banks exposed to contagion, the less stable the system); *(c)* the *PAO* or *Probability-that-at least-one-bank-becomes-distressed* as a consequence of the default of a specified bank in the sample (i.e. Lehman Brothers; AIG etc), which can be also considered a measure of the systemic relevance of each single institution[5]; *(d)* the *Distress Dependence Matrix (*or *DDM)*, i.e. the double-entry matrix of the cross-probabilities of distress of each bank, conditional on the probability of the distress of each of the others (Table 2).

The *DDM* shows the probability of distress of each bank indicated in any row, conditional on the probability of default of each bank listed in any column. Even though there is no causal direction in any bilateral linkage, the *DDM* maps the interconnectedness among institutions and accounts for the non-linearities which characterize the contagion effect during episodes of financial stress.

Applied to the 2007-08 period, *J-PoD* and *BSI* show that the default risk of each single institution is substantially higher when the linkages with other institutions are taken into account than when the single institution is analyzed in isolation. What is even more interesting is that, since *J-PoD*, *BSI* and *PAO* are extracted from values

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[4] This technique is based on the estimation of a multivariate density function of the banking system (BSMD). The BMSD function is estimated through the CIMDO-copula technique which captures both linear and non-linear correlations using single PoDs as inputs (derived either from equity option or CDS spreads). Segoviano [2006].

[5] An extension of the Segoviano and Goodhart [2009] methodology shows that the systemic importance of financial institutions (SIFI) does not correlate to their size, but just to the probability that each one of them could influence the stability of the others. Zhou [2010].

observable on a daily basis (option premiums and CDS spreads), they can also be traced in their (high frequency) time-varying dimension.

Table 2 – Distress Dependence Matrix

	Bank X	Bank Y	Bank R
Bank X	1	P(X/Y)	P(X/R)
Bank Y	P(Y/X)	1	P(Y/R)
Bank R	P(R/X)	P(R/Y)	1

Source: Segoviano, Goodhart [2009].

During 2007-08 cross-dependence among US financial institutions strengthened and the joint probability of distress (*J-PoD*) increased more rapidly than the probability associated to the same single-out institution (*i-PoD*). The evidence confirms that, during crises, not only is the probability of default of each bank amplified significantly, but also the financial equilibrium of each institution becomes highly dependent on the health of the others [IMF 2009].

3.2 Co-Risk Measures

A similar strategy for monitoring systemic risk consists of the direct tracking of the linkage between the risk exposure of several institutions. These *co-risk* indicators try to measure the variations of overall risk, conditional on the event that one institution could default.

Inputs can be either the single *Value-at-Risk* (*VaR*) [Adrian, Brunnermeier 2009], CDS *spreads* (or bond risk premia) or measures of entropy [Chan Lau 2009; N.Tarashev, H.Zhou 2006; 2008; C.Capuano 2008; M. Segoviano, C. Goodhart 2009].. Since these indicators are also based on market prices, they implicitly account for the market assessment of both direct (i.e. interbank) and indirect linkages (such as homogeneity of business models, similar asset structure and risk management methods) and could also capture endogenous risk-feeding factors.

The *Co-VaR* approach proposed by Adrian and Brunnermeier [2009] measures the *Value-at-Risk* (*VaR*) of any financial institution conditional on the probability that other institutions fall in distress. The marginal contribution to systemic risk of each financial institution is given by the difference between its own *Co-VaR* and the total *VaR* of the whole system. Correlations between single *Co-VaRs* and the total *VaR* identify the extent of contagion effects within the system, even though correlation analysis is unable to identify the causal structure of systemic risk and is technically inadequate to capture the non-linearities which distort the significance of correlation coefficients during financial crises[6]. In order to fully account for such non-linearities, other studies

[6] Risk co-movements are not linear and non-linearity becomes more pronounced during periods of financial distress: systemic risk increases more than proportionally with respect to the traditional risk measures based on (log)normal distributions.

have adopted either alternative approaches of risk measurement[7] or different techniques of parameter estimation[8].

3.3 Network model simulations

After the 2007-08 crisis, the theory of complex systems (or networks) has been rediscovered and applied to financial markets in order to obtain a better understanding of the role played by interconnectedness in financial markets [Allen and Babus, 2008].

Network topology is a tool widely applied in several fields of research (physics, biology, ecology and engineering), but it has been generally neglected in economic disciplines. Traditional economic and financial theories are not endowed for the understanding of complex ecosystems. Even if individuals were rational and markets were efficient, the aggregation of individual behaviors still does not sum-up linearly to the collective behavior of the system as a whole. Since the structure of internal feed-backs is neither linear nor homogeneous, complex systems are unstable. The more complex the system, the higher its potential fragility. Mainstream economic theory, based on the paradigm of the representative agent, does not even see the issue [Haldane 2009].

A *network* is a set of agents (called *vertices* or *nodes*) linked by multiple connections (*edges*) of which the statistical properties can be analysed and appropriate measurement criteria (such as the length of the connecting paths or the distribution degree) (Figure 1) can be defined. When dealing with very large networks (thousands of vertices), it is useful to build simulation models to understand the internal dynamics of the network (i.e. how the network assumes a particular shape and how the *vertices* interact). Based on the network structure and given behavioral rules of the *vertices,* the model allows the researcher to observe the aggregate behavior of the system [Newman 2003].

Applied to the banking system, network analysis allows empirical simulation of the final impacts of *domino effects* (or chain reactions) beyond the point where the initial shock originates. Empirically, this methodology requires the reconstruction of a double entry matrix of data, which collects the entire set of bilateral exposures of each bank with respect to each of the others. Given the data matrix, it is possible to simulate a shock initially hitting one or more institutions and to track the subsequent chain effects (direct and/or indirect) for a number of successive rounds [Chan Lau, 2010]. Several studies have adopted a similar research strategy, exploring the role played by payment systems, interbank markets or asset markets as channels for the spread of systemic shocks [Allen, Babus 2008].

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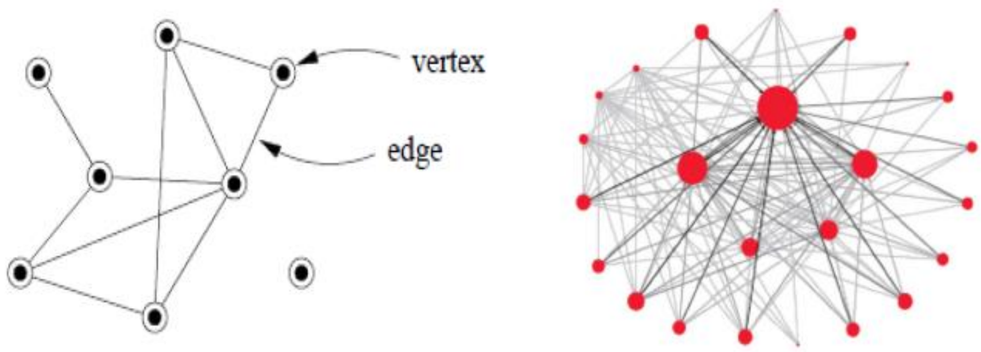
7 Application of the *Extreme Value Theory (EVT)* to multivariate distributions allows estimation of interdependencies among tail risks (*joint tail dependence*) capturing the probability of extreme shocks. However, the *ETV* approach misses a significant portion of data information, which makes it inapplicable when the time series available are too short. Poon et al. [2004]; Rocco [2011].

8 An alternative way to track non-linearities during financial crises is *quantile regression analysis*. While traditional regressions capture the average relationship among the variables, the *quantile regression* is estimated using only tail observations (i.e. the 95th quantile of data distribution), which represent just extreme states of financial stress. Koenker, Hallock [2001]; Chan Lau [2009]

Figure 1 – Network Topology



An alternative strategy in network analysis has been adopted by a group of economists at the Bank of England. In 2008, Nier et al. [2008] built a laboratory model where banks are linked through interbank deposits and where the behavior of the network is analyzed by setting alternative values for key-parameters (such as capital ratios, size of reciprocal exposures, degree of interconnectedness, concentration, etc.). The exercise generated findings of great importance on the aggregate behavior of the system. On the one hand, the simulation confirmed the common assumptions that the vulnerability of the system to shocks increases with the size of credit/debt exposures and that the banks most resilient to contagion are the best capitalized ones; on the other hand, the analysis also showed that immunization to shocks is not linearly proportional to banks' capital ratios: surprisingly, there is a level of aggregate capitalization below which minimum capital ratios are not sufficient to stabilize the system. In addition, the study has discovered that the effect of connectivity among banks does not behave monotonically: a small variation in connectivity may substantially increase the probability of contagion; however, if connectivity grows beyond a certain threshold, it significantly improves the system's capability to dilute shocks. In other words, dispersed networks are more stable than concentrated networks.

Using the same approach, further studies at the Bank of England [Gai, Kapadia 2010; Arinaminpathy et al. 2012] have shown that the probability of contagion does not fully capture the potential exposure to systemic risk: even when such probability is low, minor shocks may have a very large negative impact due to the internal structure of the network, where the degree of connectivity and the nature of the edges can compound the feed-back effects within the system. For the same reason, shocks that appear similar in nature and magnitude may have impacts which turn out to be very different, due to the relative importance of the institutions (*vertices*) first hit by the shock[9]. If the institutions impacted first are either those with the largest exposures or those with the highest degree of connection, the final effect tends to be stronger.

These results help to focus macroprudential policies on the structural characteristics of the system too, and highlight the importance of concentration both in the size of single institutions (the well-known *too-big-to-fail* issue) and their connectedness (the newly discovered *too-connected-to-fail* issue).

[9] It confirms that bank size is not a sufficient indicator of systemic importance. The contribution of banks to systemic fragility increases more than proportionally with respect to their size as a function of the connectivity and concentration of the system.

4. Concluding remarks

In 2007-08, the international financial system reacted to a minor shock which originated in the US subprime mortgage market with a self-fulfilling loss of confidence among banks, mainly due to the ubiquity of toxic assets and the similar structure of balance sheets. The increase in credit and counterparty risks perceived by agents led to illiquidity of securitized assets, drought of interbank deposits and forced deleveraging for most banks (which because inadequately capitalized). Up to the Lehman default, government support was able to anticipate any chain reaction, absorbing the losses and isolating the distressed institutions; however when the *too-big/too-connected* hub of the network was hit (Lehman), the system reacted like a wounded ecosystem, irradiating destabilizing waves through a tangled web of systemic inter-linkages (repos, interbank exposures, holdings of illiquid assets, credit derivatives etc.), shifting abruptly towards the total collapse of the financial system [Brunnermeier 2008; Gorton 2010; Borio, Lowe 2002a; Cifuentes et al. 2005; Adrian, Shin 2010; Brunnermeier, Pedersen 2008].

During the 2007-08 crisis, both dimensions of systemic risk (*time-varying* and *cross-section*) came into play, reinforcing each other. The long period of credit expansion had been inflating the real estate bubble, encouraging excessive leverage and maturity mismatch across the economy, while low interest rates and abundant liquidity had been encouraging risk tolerance and moral hazard. Financial innovation and deregulation had increased the complexity and interconnectedness of financial institutions, compounding financial fragility Onado [2009]

Macroprudential supervision has been identified as the appropriate answer to the 2007-08 financial crisis [FSB-IMF-BIS 2009] and during the last few years it has been assuming a clearer operative profile. A significant effort has been dedicated to defining the final objectives specific to macroprudential policies, starting from the identification of the market failures (or externalities) that could trigger systemic financial distress[De Nicolò et al. 2012; ESRB 2013]. It has been recognized that some externalities arise endogenously from the behavior of financial institutions themselves, amplifying the cross-correlations among the risk exposure of individual firms (high leverage, similar business models; same risk management procedures); other externalities depend on market and liquidity risks due to fire sales of assets, which could simultaneously damage the balance sheets of multiple banks; a further source of externalities is the complex network of financial interconnections which link institutions to each other. Appropriate policy instruments have been associated with each macroprudential objective [ESRB, 2013; CGFS, 2012; IMF, 2011a, 2011b, 2013a, 2013b; Gualandri, Noera 2014a].

However the monitoring of systemic risk is the necessary pre-requisite for timely and effective implementation of macroprudential policies. Macroprudential policies face a continuously changing financial environment, where several risk factors could combine unexpectedly. Since macroprudential action is mostly pre-emptive, it requires the *ex-ante* evaluation and measurement of systemic risks [Goodhart, Perotti 2013].

Under the pressure of the 2007-08 experience, a wide and diversified range of diagnostic tools have been developed and there seem to be grounds for concluding that now, should the conditions of a new financial crisis occur, they could be spotted in advance. Some of the available indicators rely on the backward observation of the build-up of imbalances over time (*time-varying* dimension) and would allow tracking of the probability of distress several years before its actual occurrence. Other tools focus on the extraction of risk perceptions from market prices, delivering forward-looking probabilities of distress, which may signal that a disruption is as close as few months or weeks ahead. More complex applications allow measurement (or simulation) of the non-linearities embedded in the system (*cross-section* dimension), helping supervisors to identify those institutions that are systemically important and deserve special attention.

A look at the set of tools available leads to the conclusion that decisive progress has been achieved in technical knowledge and in the capability for preventing systemic shocks. Maybe some further effort is needed to collect the plurality of indicators into a single, and operatively manageable *tableau de bord*. Each available indicator has its own properties and limits and their joint use would require them to be organized according to a consistent syntax [Arsov et al, 2013; Blancher et al. 2013; Lund-Jensen 2012].

However, for macroprudential policies to be effective, the major challenge left appears no longer to be theoretical or technical. By itself, the efficient monitoring of systemic risk is unable to deliver suggestions either in the dominion of policies (the issues of *when* and *how* macroprudential action must be put in place) or in that of institutions (the issue of *who* is in charge of taking decisions)[Gualandri-Noera 2014b].

Firstly, even though the activation of macroprudential policies requires some degree of freedom, it is doubtful that they could be totally discretionary. The need to act pre-emptively requires the macroprudential supervisor to take restrictive decisions when the cycle is still in its positive phase (or it is widely perceived to be so): it follows that macroprudential supervisors are exposed to considerable pressure (from government and market agents) to dilute, to delay or even to give up intervention. Such interference, in a fully discretionary decision process, could turn out to amplify the conservative attitude and the risk aversion of decision makers, lengthening the process and weakening its timeliness. Therefore the requirements of the institutional, organizational and functional independence of the macroprudential supervisor must be pinpointed in predefined and transparent policy rules, which trigger non-discretionary action. Secondly, the working of macroprudential regulation and policies may overlap (due to the selection of instruments) with the areas of competence of other authorities (microprudential and monetary policies, in particular), giving rise to the institutional issue either of centralizing competences or of coordinating different agencies [Agur, Sharma 2012]. .

The review of both policy and institutional aspects goes far beyond the scope of this paper, but it is worth keeping in mind that the ability to spot systemic risk is just the first link in a very long chain in the macroprudential supervision process.

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