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MONITORING SYSTEMIC RISK

A SURVEY OF THE AVAILABLE MACROPRUDENTIAL TOOLKIT

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A SURVEY OF THE AVAILABLE MACROPRUDENTIAL TOOLKIT

by

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Abstract

Understanding the nature of systemic risk and identifying the channels of diffusion of the shocks are the necessary prerequisite to anticipate and manage successfully the insurgence of financial crises. In order to prevent financial distress and manage instability, the macroprudential regulator needs to track and measure systemic risks ex-ante.

The aim of the paper is twofold: on one side, it reviews the theoretical frameworks which allow to assess the different dimensions of systemic risk and, on the other, it classifies accordingly and analyzes the methodologies available to assess in advance the occurrence of systemic distress.

The paper classifies the different definitions of systemic risk and discusses their significance during the 2007-08 crisis. It presents the tools available to extract real time information on market perception of risk from market prices of securities and derivatives (i.e. CDS and equity options). The analysis is extended to the methods focused on the measurement of the financial fragility due to the networks linkages within the financial system. On the basis of the available empirical research, the paper also reviews the capacity of the different methods to spot in advance the insurgence of the crisis prior to 2007-08 and draws some preliminary conclusions on the completeness and consistency of the toolkit available to policy makers.

Key words: systemic risk, financial crisis, prudential regulation, financial institutions.
Jel classification: G01, G18, G 21, G28.

Introduction

The 2007-08 financial collapse has catalyzed 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 analyze them.

The paper is divided into 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. In the fourth part, the paper reviews, on the basis of the empirical research carried forward mostly by the IMF, the capacity of the different methods to spot in advance the insurgence of the crisis prior to 2007-08. The fifth briefly suggest how to organize operationally the informational content of different tools. 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[1]. 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[2].

[1] Minsky [1982]; Kindleberger, Aliber [2005]

[2] 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[3], 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 macroprudential supervisors to identify *critical thresholds* beyond which the probability of a crisis is assumed to be increasing[4].

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. By estimating a probit model where probability of distress is a function of multiple risk factors and their interactions(Credit/GDP gap and growth; equity and house prices growth; banking sector leverage etc.) and calibrating a time-varying threshold for each risk indicator, Lund-Jensen [2012] shows that the joint assessment of the probability of systemic distress improves significantly, reducing the costs associated with false signaling. The methodology makes the observation of time-varying/slow-moving indicators more efficient and reliable, allowing the monitoring of the build-up of potential systemic instability several years in advance.

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 (the so called *near-coincident indicators*).

2. Market assessment of default risk

2.1 Single institution i-PoD

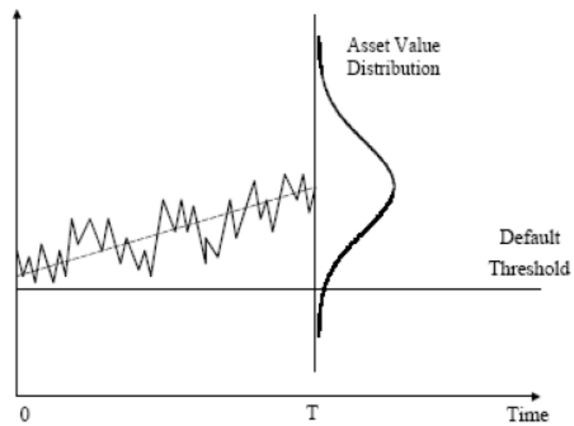
Market sentiment indicators can be extracted directly from market prices (equity, bonds and credit default swaps) in the form of implied probabilities associated by the market to the event of distress (either related to individual institutions or to the system as a whole). The intuition behind this approach is that market pricing of

[3] 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].

[4] *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].

either CDS or equity options embeds the expectations about the probability that market values of the firm's assets fall short of liabilities (default threshold) (Figure 1).

Fig.1 - Equity volatility and implicit probability of default



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[5] can be extracted. Since *i-PoDs* try to capture the risk assessed by market 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.

[5] 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].

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)[6]. 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[7]; *(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.

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].

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* (*Va*R) [Adrian, Brunnermeier 2009], CDS *spreads* (or bond risk premia) or measures of entropy[8]. 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-Va*R approach proposed by Adrian and Brunnermeier [2009] measures the *Value-at-Risk* (*Va*R) 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-Va*R and the total *Va*R of the whole system. Correlations between single *Co-VaRs* and the total *Va*R identify the extent of contagion effects within the system, even though correlation analysis is unable to identify the causal structure

[6] 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].

[7] 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].

[8] Chan Lau [2009]; Tarashev, Zhou [2006;2008]; Capuano [2008]; Segoviano, Goodhart [2009].

of systemic risk and is technically inadequate to capture the non-linearities which distort the significance of correlation coefficients during financial crises[9]. In order to fully account for such non-linearities, other studies have adopted either alternative approaches of risk measurement[10] or different techniques of parameter estimation[11].

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 analyzed and appropriate measurement criteria (such as the length of the connecting paths or the distribution degree) (Figure 2) 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].

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

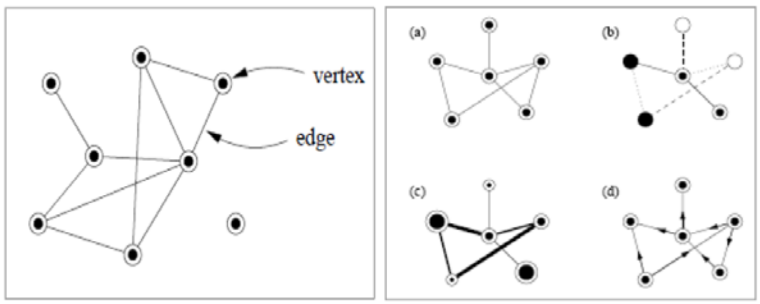
[9] Risk co-movements are not linear and non-linearity becomes more pronounced during periods of financial distress: systemic risk increases more than proportionally with respect to the traditional risk measures based on (log)normal distributions.

[10] 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].

[11] 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].

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 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.

Figure 2 – Network Topology



Source: Newman [2003].

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[12]. 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 in their connectedness (the newly discovered *too-connected-to-fail* issue).

4. Could the 2007-08 financial crisis have been overseen in advance?

As we have seen, the systemic risk shows up in multiple dimensions: exposure to the same risk factors, procyclicality and network interlinkages. After the crisis most of the research efforts have been aimed at identifying and measuring both the time varying and the cross-section faces of systemic risk. Most of the tools now available have been applied ex-post to the 2007-08 financial crisis, in order to check their explanatory power. Even though is goes beyond the scope of his paper to test empirically the alternative approaches, it is

[12] 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.

interesting to review also the evidences that could have been available to the authorities in the eve of the crisis, if –at the time-they had been endowed with the proper toolkit[13].

4.1 Balance-sheet indicators

According to IMF, the indicators based on balance-sheet data (which are backward looking/low frequency indicators), would have not supplied signals useful to prevent the crisis. Indicators of capital adequacy were not reliable at identifying ex-ante the institutions requiring intervention by the MAP. Though the working assumption is that low capitalized institutions are the most vulnerable, the degree of capitalization of the banks that actually required public intervention during the crisis was not *ex-ante* significantly lower than the capitalization of the banks that did not required any intervention[14].

The poor signalling power of capital/asset ratios could be attributed, to some extent, to the difficulties of measuring the actual riskiness of financial assets[15], to the imperfections of mark-to-market accounting[16], to the elusive nature of the shadow banking system[17] and to regulatory arbitrage[18].

For the same reasons, retrospective analysis shows that also common indicators of asset quality (as the percentage of non-performing loans or NPL) were not good predictors of the crisis: also in this case the incidence of NPL of banks that suffered severe financial stress was lower than the one of banks which required public financial support during the crisis[19]. To the same token, also liquidity indexes did not show any significant predictive power, since they were not able to capture the increasing importance of banks' liability management techniques in the interbank and repo markets[20]. .

More informative to detect in advance potential balance-sheet vulnerabilities would have been instead other indicators as the degree of leverage, the return on assets (RoA) and most of the common stock market multiples (as the P/E; P/BV and EPS ratios). In the eve of the crisis all these indicators showed up significantly higher in the banks that subsequently required support[21]. These indicators are analytically consistent, since high levels of RoA and leverage can be interpreted as indirect measures of the bank's propensity to risk, aimed at maximizing the shareholder value (return on equity), which in turn influences stock valuations.

A good warning signal would have been offered also by the percentage of banks' short-term indebtedness (interbank and repos):this evidence suggests that the degree of leverage, which represents the dominant incubator of financial stress, must be coupled with indicators of maturity mismatch[22].

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[13] Further insight into the empirical results reviewed here are in IMF[2009; 2011b] to which this paragraph mostly refers.

[14] This evidence applies to US banks but does not extends to European and Asian banks, where capital/asset ratios were, before the crisis, higher for those institutions that did not required any intervention IMF [2009].

[15] Le Lesle, Avramova [2012].

[16] There are significant differences between US accounting standards (GAAP) and Europeans' (IAS-IFRS).

[17]. Feder, .Mitchell [2009].

[18] Cannata, Castellina, Guidi [2012].

[19] IMF [2009].

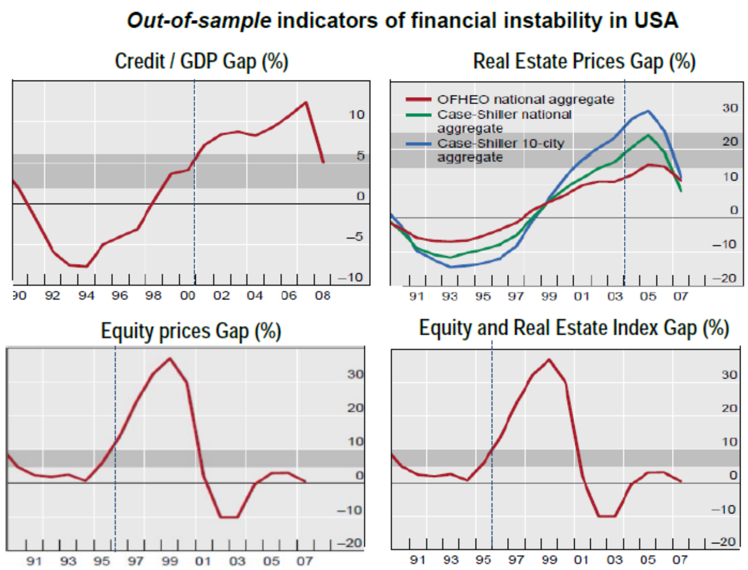
[20] Morris, Shin [2008].

[21] IMF [2009].

[22] BCBS [2010]; A. Haldane [2012]; Liikanen Report [2012].

Balance-sheet indicators at micro level have a natural counterpart, at macro level, in the financial cycle indicators (i.e. credit growth; credit/output or debt/output ratios; asset prices etc.)[23]. Applied to the US pre-crisis situation, some of these indicators were releasing signals of imbalances which were growing unsustainable since early 2000s (Figure 3)[24].

Fig. 3 – Financial cycle macroindicators



Source: Borio-Drehmann (2009)

The same indicators, applied to other countries, failed because they are unable to detect the stress originated by external imbalances (i.e. foreign debt of the banking system) which were the main channels of international contagion (Germany, Netherland, Switzerland; Canada). In this case, the indicators should have taken into account the weighted exposure of each bank towards each other country. Such an exercise requires a very granular database of banks' cross-exposures[25].

Since the 2007-08 crisis originated in the US and then spread around the world, the analysis of the interlinkages across different banking systems is crucial to assess the potential chain-effects of the shocks originated outside any single country. The IMF has extended the analysis of network effects, looking at the transmission of financial contagion across countries[26]. Given the matrix of cross- exposures (where, on the asset side of each bank's balance-sheet, appears any single exposure towards any other bank and, on the liability side, any single

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[23] Borio, Lowe [2002a; 2002b]; Borio, Drehmann [2009a]; CGFS [2012].

[24] Borio and Drehmann [2009a] adopt three indicators simultaneously (credit growth to the private sector; stock market prices and real estate prices) and define an early signal of potential distress when at least two out of three variables go beyond their *threshold* (see footnote for a definition). When calibrated over the period 1980-2003 and tested *out-of-sample* over the period of financial crisis (2004-2008), both the credit growth indicator and the real estate indicator have been able to jointly predict the crisis starting several years in advance (2000-2001). Significantly less efficient appeared the stock market indicator, probably influenced (during the calibrating period) by he burst of the dot.com bubble. Given the relevant weight of the stock market, also the composite index of stock and real estate prices do not perform well, while in previous work of the same authors the stock market index (calibrated before 2000) approximated the threshold (even though failing to release unambiguous signal of financial instability). Borio-Lowe (2002b).

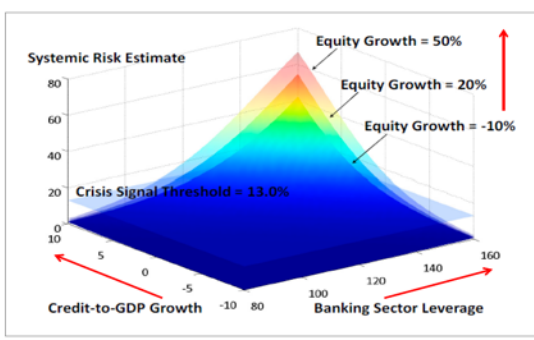
[25] Borio, Drehmann [2009]

[26] Chan-Lau [2010]; IMF [2009].

debt position), the IMF has studied the impact across the system of the default of either one or several banks, simulating the chain effect through the transmission channel of the network of reciprocal exposures. Corresponding to the initial shock, several rounds of potential defaults have been identified and measured (banks can be affected in the second round by banks affected in the first, and in turn, they become vehicles of higher order contagion effects). The domino effect is strengthened by the assumption of a liquidity constraint (i.e. interbank draught) and forced fire sales of assets. Applying this approach to the structure of cross-country interconnections among banking systems at March 2008 (i.e. at the time of the distress of Bear Stearns and six months before Lehman Brothers' default), the IMF exercise confirms, on one side, the centrality of US and UK banking systems as critical epicenters of financial shocks and, on the other, allows an ordering of countries according to their relative financial vulnerability to different types of contagion. The IMF analysis shows, for example, that Belgium. Netherland, Sweden and Switzerland appeared the most vulnerable countries to credit shocks (shocks transmitted through direct and indirect credit exposures); adding a liquidity shock (the drought of 45% of both interbank and repo markets and a 50% fall in asset prices) France appeared instead the most fragile country outside US and UK [IMF 2009].

The monitoring of *time-varying* indicators of systemic risk have been tested by the IMF[2011b] on a broader base of countries[27] applying the methodologies explained in Lund-Jensen [2012][28]. The tests show an encouraging evidence that slow moving indicators bring precious operative information to policy makers about systemic risk: (a) credit/GDP growth and credit/GDP gap have positive significant effect on systemic risk up to three years in advance (for example 1 std deviation increase in credit/GDP gap increases the systemic risk for the median country by 3.3%, 2.6% and 1.3% in the 3 following years respectively); (b) banking sector leverage appears to have a significant effect on systemic risk two years in advance (for example: 1 std deviation increase in leverage increases systemic risk within one year by 2.5% for the median country) [29]. Asset price inflation and real exchange rate appreciation are also found to have positive and significant effect on systemic risk up to three years in advance. As far as the efficiency of signal extraction is concerned, joint observation of multiple factors could release a more precise assessment of the danger embedded in the building up of financial imbalances: for example a crisis signal could be extracted for the median country when credit/GDP growth is above 4.9%, however the reliability of the signal can be controlled observing the joint impact on systemic risk also of banking leverage (indicating financial vulnerability) and of the rate of growth in equity prices (detecting potential bubbles)(Figure 4).

Fig. 4 – Systemic Risk and Crises Signals



Source: Lund-Jensen (2012)

[27] The model was estimated on an annual panel of 68 advanced and emerging countries over the period 1970-2010.

[28] See par.1.2 supra.

[29] The results reported here are based on the logit specification of the model of Lund-Jensen [2012].

4.3 Market based i-PoD

Estimating the implied probability of default (*i-PoD*) embedded either in option premia or CDS spreads[30] allows to detect in real time the sentiment prevailing in the market. It allows also to track the evolution of market sentiment over time, through the analysis of the shape of the probability distribution (i.e. its higher order moments: skewness, kurtosis and gamma[31]).

During financial distress, the implied probability distribution associated to equity prices deviates from "normality", reflecting non linearities linked to the systemic dimension of risk. It has been shown that, during periods of distress, even very small changes in the perception of default risk generate disproportionate volatility on equity prices. It follows that if the distribution is skewed towards the left (i.e. a negative skeweness), also the distribution of firm's asset values estimated by the market must be similarly skewed towards lower values. It implies, in turn, that the perceived probability of the firm's asset values falling short of its liabilities is higher (a similar attitude could be read in CDS spreads[32]).

The analysis of higher moments of *i-PoD* referred to institutions distressed during the financial crisis[33](Figure 5) shows that in August 2007, shortly after that the major central banks had jointly injected massive liquidity into the system[34], the distributions overshooted with respect their normal shape, getting taller (higher positive kurtosis), bending toward the right (higher positive skewness) and with a fatter right tail (higher gamma positive): it was reflecting the jump reassessment of the probability of default following the government intervention. Afterward (between September 2007 and the collapse of Lehman Brothers in September 2008) skewness and kurtosis started to decrease towards zero (distribution was shifting towards the left and flattening), while the fatness of tail risk (gamma) was initially deflating (the bulk of default risk probability was no longer extreme but central) and then getting thicker on the left in the eve of the Lehman default. After the Lehman collapse a new jump reassessment toward a normal shape occurred, following the renewed willingness of the government to save the day (AIG bailout, TARP etc).

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[30] Under the assumptions of market efficiency and risk neutrality.

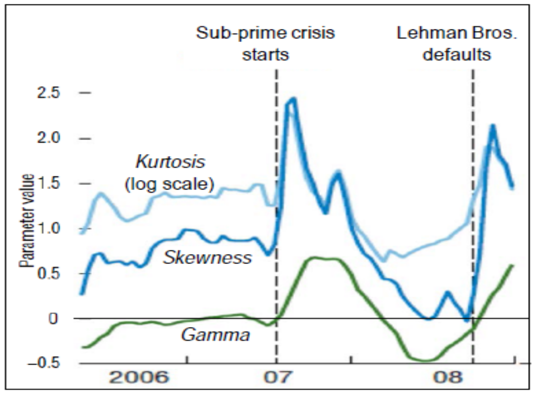
[31] *Skewness* is equal to 0 when there is perfect symmetry; it is >0 when the distribution in skewed to the right and, vice versa, it is <0 when the distribution is skewed to the left. When *kurtosis* is >0, the distribution is taller than he "normal" (*leptokurtic*); when *kurtosis* is <0 the distribution is flatter than the "normal" (*platkurtic*). *Gamma* measures the *fat tail risk*: the higher its value, the fatter the univariate *tail risk*.

[32] Capuano [2008].

[33] IMF estimates are based on implied volatility derived from at-the-money put options, whose expiration was the closest to the day of the distress.. The institutions involved in the i-PoD monitoring are (distress date in parenthesis): Bear Stearns (14/3/2008), Lehman Brothers (15/9/2008), Merrill Lynch (15/9/2008), Wachovia (29/9/2008) and Citigroup (24/11/2008). Ex-post the warning signals appear very informative for Bear Stearns, Merrill Lynch and Wachovia, while appear weaker for Lehman Brothers and Citigroup, IMF [2009].

[34] On August 9-10 2007, reacting to the crisis of three BNP mutual funds highly involved in ABS/CDO investments and the freezing of interbank markets, Federal reserve, BCE and Bank of Japan jointly injected 330 billion US dollar of extra liquidity in order to soften the liquidity crisis, signaling the determination of monetary authorities worldwide to stop the crisis.

Fig.5 i-PoD Higher Moments Analysis during 2007-08 crisis



Source: IMF (2009)

4.3 Market based J-PoD, BSI and PAO

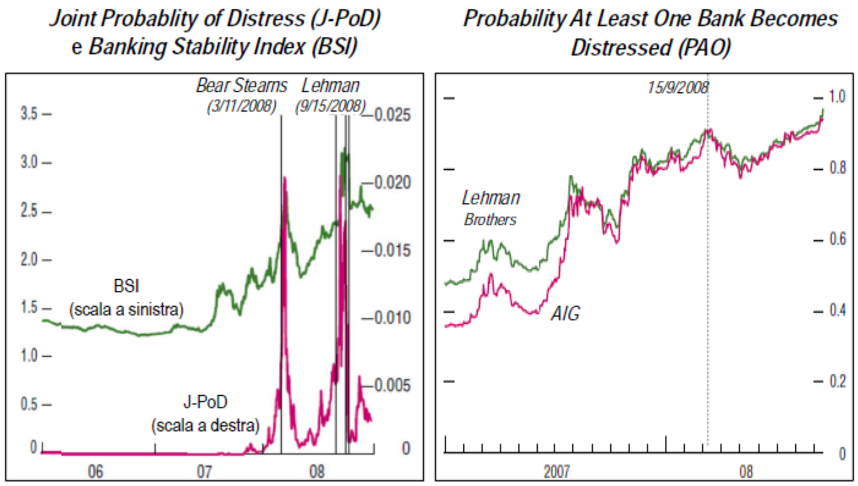
The estimation of a multivariate probability of default allows to take into account of systemic risk in both its cross-section and time-varying dimensions.

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 observable on a daily basis (option premiums and CDS spreads), they can also be traced in their (high frequency) time-varying dimension (Figure 6).

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*), showing peaks in connection with the two major episodes of distress (Bearn Stearns and Lehman Brothers) and starting to react 5-6 weeks in advance of the actual default.

The evidence confirms that, during crises, not only the probability of default of each bank is amplified significantly, but also that the financial equilibrium of each institution becomes highly dependent on the health of the others. It is also worth noting that the Banking Stability Index (BSI) –that measures the number of banks defaulting if one defaults- starts increasing steadily at the beginning of 2007, adjusting temporarily only after major public interventions. On the other hand, the Probability-of-at-least-one-default (PAO), which identify the relative systemic importance of each institutions to produce cascade effects on the others applied to two of the major hubs of the crisis (Lehman Brothers and AIG) shows an upward monotonic trend since the beginning of 2007, reaching the probability of 1 in September 2008 (certainty of a cascade effect approaching Lehman collapse).

Fig. 6 Multivariate probability indicators of systemic risk during 2007-08



Source: Segoviano-Goodhart (2009); IMF (2009)

4.4 Co-Risk based on CDS spreads

Research at the International Monetary Fund[35] has also applied quantile regression techniques to the linkages across the CDS spreads of financial institutions in order to obtain estimates of the co-movements of their default risk in the period July 1 2003-September 12 2008. The parameter estimates have been used to simulate out-of-sample the CDS spread of each institutions conditional to the probability of default of each other institution. The regression technique adopted (quantile regression) implies that only data falling in the extremes tails of their distribution are taken into account: therefore, differently from OLS, this approach enables to capture the non-linearities which characterize situations of acute financial stress.

The output of the exercise are double-entry matrices of a sort of *augmented i-PoDs,* that show the percentage increase of the probability of default (*i-PoD*) of each single bank that stems from its linkages to any other. From the same matrix it is also possible to build a vulnerability index of each bank, as a weighted average of the sensitivity of its PoD conditional to the probability of default of all the others[36].

For example, the evidence shows that, measured before the Lehman collapse, the average probability of default for any other bank correlated to the case of a Lehman default was 22% higher at the beginning of the subprime crisis (July 2007) and was almost twice as much (41% higher) one year later (August 2008), i.e. immediately before the Lehman event. Therefore the MAP authorities could have spotted one year in advance the destabilizing potential of the Lehman default (as of any other major institution).

[35] Chan Lau [2009]; IMF [2009]

[36] The CDS spreads analyzed covered the following institutions: in USA: AIG, Bank of America, Bear Stearns, Citigroup, Goldman Sachs, JP Morgan, Lehman Brothers, Merrill Lynch, Morgan Stanley, Wachovia, and Wells Fargo; in Europe: Fortis, Paribas, SoGen, Deutsche Bank , Commerzbank, BBVA, B. Santander, Credit Suisse, UBS, Barclays, HSBC; in Japan: Mitsubishi, Mizuho and Sumitomo.

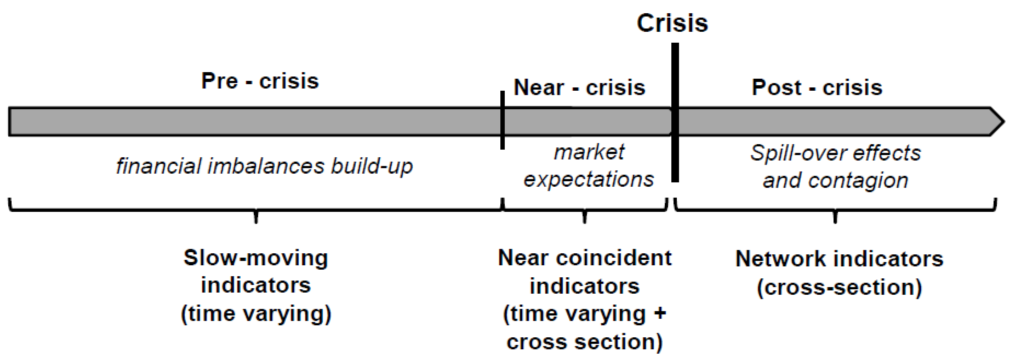
5. Organizing the toolkit

The availability of operative tools aimed at quantifying systemic risk proliferated epidemically in the last few years, giving MAP a much improved oversight on potential systemic events and a deeper capability to anticipate distress. This paper has just selected the most significant indicators, but more are at hand [Bisis et al. 2012]. However only by putting the pieces in the correct position the puzzle delivers a coherent picture.

Some effort was already devoted to organize the information in an order that could turn out operationally useful [FSB-IMF 2010; IMF 2011a; Blancher et al. 2013]. Properly managing systemic risk is a complex task that must be based on solid knowledge and clear-cut decision processes. On this ground further work has still to be done to link all the pieces of information available in an organic *tableau de bord* .

Despite such effort is beyond the scope of the paper, a preliminary ordering criteria of the tools reviewed has been implicitly traced and it is worth making it explicit here (Figure 7). Phasing the crisis process (pre-crisis; near-crisis; post-crisis), most of the indicators reviewed in the paper find their proper informational position: the long term, slow-moving build-up of financial imbalances (that beyond some threshold turn out unsustainable); the near-coincident dominance of a negative self-fulfilling market sentiment (which announces the actual occurrence of the crisis); the post-crisis transmission of domino effects to the rest of the system (depending on the network structure). As we have seen, for each phase, a different set of tools may be available, with different technical features and different time horizons.

Fig. 7 Informational content of systemic risk indicators



6. 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[37]. 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].

[37] Brunnermeier [2008]; Gorton [2010]; Borio, Lowe [2002a]; Cifuentes et al. [2005]; Adrian, Shin [2010]; Brunnermeier, Pedersen [2008].

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.

References

Adrian, T. and Brunnermeier, M. [2009], *Co-Var,* in "Federal Reserve Bank of New York Staff Reports", August 2009, n.348.

Adrian, T. and Shin, H. S. [2010], *Liquidity and Leverage*, in "Journal of Financial Intermediation", vol.19(3).

Agur, I. and Sharma, S. [2013], *Rules, Discretion, and Macro-Prudential Policy*, IMF Working Paper, 13/65, March.

Aharony, J. and Swary, I. [1996], *Additional Evidence of the Information Based Contagion Effects of Bank Failures*, in "Journal of Banking and Finance", January pp. 57-69.

Allen, F. and Babus, A. [2008], *Networks in Finance,* Wharton Financial Institution Center, Working Paper n.08-07, August.

Arinaminpathy, N., Kapadia, S. and May, R. [2012], *Size and Complexity in Model Financial Systems,* Bank of England, Working Paper n.465, October.

Arsov, I., Canetti, E., Kodres, L. and Mitra, S., [2013], *Near-Coincident Indicators of Systemic Stress,* IMF Working Paper 13/115, May.

Basel Committee on Banking Supervision (BCBS) [2010], *Calibrating Regulatory Minimum Capital Requirements and Capital Buffers: A Top Down Approach*.

Bisis, D., Flood, M., Lo A.W. and Valvanis. S. [2012], *A Survey of Systemic Risk Analytics*, US Department of the Treasury, Office of Financial Research, January.

Blancher, N., Mitra, S., Morsy H., Otani, A., Severo, T. and Verderrama L. [2013], *Systemic Risk Monitoring (SysMo) Toolkit. A User Guide*, IMF Working Paper 13/168, July.

Borio, C. [2013], *Macroprudential policy and the financial cycle: Some stylized facts and policy suggestions*, IMF Rethinking Macro Policy II Conference, First Steps and Early Lessons, April, 16-17.

Borio, C. and Drehmann, M. [2009a], *Assessing the Risk of Banking Crises-Revisited*, BIS Quarterly Review, March.

Borio, C. and Drehmann, M. [2009b] *Towards an Operational Framework for Financial Stability: Fuzzy Measurement and Its Consequences*, BIS Working Papers n. 284, June.

Borio C. and Lowe, P. [2002a], *Asset Prices Financial and Monetary Stability: Exploring the Nexus*, BIS Working Papers, n. 114, July.

Borio C. and Lowe, P. [2002b], *Assessing the Risk of Banking Crises*, BIS Quarterly Review, December.

Brunnermeier, M. [2001], *Asset Pricing Under Asymmetric Information: Bubbles, Crashes, Technical Analysis and Herding,* Oxford University Press.

Brunnermeier, M. [2008], *Deciphering the 2007-2008 Liquidity and Credit Crunch*, NBER Working Paper, December.

Brunnermeier, M. and Pedersen, L. H. [2008], *Market Liquidity and Funding Liquidity*, in "Review of Financial Studies", November.

Cannata, F., Castellina, S. and Guidi, G. [2012*], Inside the Labyrinth of RWA: How Not to Get Lost*, Banca d'Italia, Occasional Papers n. 132.

Capuano, C. [2008], *The Option i-PoD. The probability of Default implied in Option Prices Based on Entropy*, IMF Working Papers n. 194, August.

Chan Lau, J. [2009], *Default Risk Codependence in a Global Financial System: Was the Bear Stearns Bail-out Justified?,* in G.Gregoriou (ed.), *The Banking Crisis Handbook*, CRC Press, Boca Raton USA.

Chan Lau, J. [2010], *Balance-Sheet Network Analysis of Too-Connected-to-Fail Risk in Global and Domestic Banking Systems,* IMF Working Papers n. 107, April.

Cifuentes, R., Ferrucci, G. and Shin, H. [2005], *Liquidity Risk and Contagion*, in "Journal of European Economic Association", 3, pp.556-66, April-May.

Committee on the Global Financial System (CGFS), BIS, [2012], *Operationalising the Selection and Application of MacroprudentialInstruments*, Report submitted by a Working Group established by the Committee on the Global Financial System The Group was chaired by José Manuel González-Páramo, then European Central Bank, December, CGFS Papers No 38.

de Bandt, O., Hartmann, P. and Peydro, J. [2009], *Systemic Risk in Banking: An Update*, in Berger, Moliyneux, Wilson (eds.), *Oxford Handbook in Banking,* Oxford University Press.

De Nicolò, G., Favara, G. and Ratnovsky, L. [2012], *Externalities and Macroprudential Policy*, IMF Discussion Note SDN 12/05, June.

European Systemic Risk Board (ESRB) [2013], *Recommendation of April 4, 2013, on Intermediate objectives and instruments of macroprudential policy* (ESRB/20/2013/1), (2013/C 170/01), June 20.

Feder, I. and Mitchell, J., [2009], *The Future of Securitization. How to Align Incentives*, BIS Quarterly Review, September.

Financial Stability Board, International Monetary Fund, Bank of International Settlements (FRB-IMF-BIS) [2009], *Guidance to Assess the Systemic Importance of Financial Institutions, Markets and Instruments: Initial considerations,* Report to G-20 Finance Ministers and Central Bank Governors, October.

Financial Stability Board, International Monetary Fund (FSB-IMF) [2010], *Early Warning Exercise. Design and Methodological Toolkit*, September.

Gai, P. and Kapadia, S. [2010], *Contagion in Financial Networks,* Bank of England Working Paper n.383, March.

Gai, P., Haldane, A. and Kapadia, S. [2011], *Complexity, Concentration and Contagion,* in "Journal of Monetary Economics", 58, pp.453-70.

Goodhart C. and E. Perotti [2013], *Preventive Macroprudential Policy*, in "Journal ADEIMF".

Gorton, G. [2010], *Slapped by the Invisible Hand. The Panic of 2007,* Oxford University Press.

Gualandri, E. and Noera, M. [2014a], *Rischi sistemici e regolamentazione macroprudenziale*, in Bisoni C., Gualandri E., Landi A., Lusignani G.(editors), *Lo stato della finanza*, Il Mulino, Bologna.

Gualandri, E. and Noera, M. [2014b], *Towards a Macroprudential Policy in EU: Main Issues*, CEFIN WP n. 49.

Haldane, A. [2009], *Rethinking the Financial Network*, Bank of England, Speech delivered at the Financial Student Association, Amsterdam, April.

Haldane, A. [2012], *The Dog and the Frisby*, Bank of England, paper given at the Federal Reserve Bank of Kansas City's 36th economic policy symposium in Jackson Hole, Wyoming, August.

International Monetary Fund (IMF) [2006], *Financial Soundness Indicators: Compilation Guide.* Washington.

International Monetary Fund (IMF) [2009], *Global Financial Stability Report*, ch. 2, *Assessing the Systemic Implications of Financial Linkages*; ch.3 *Detecting Systemic Risk,* April.

International Monetary Fund (IMF) [2011a], *Macroprudential Policy: an Organizing Framework*, Washington.

International Monetary Fund (IMF) [2011b] *Global Financial Stability Report*, ch. 3, *Towards Operationalizing Macroprudential Policies: When to Act?,* Washington, September.

International Monetary Fund (IMF) [2013a], *The Interaction of Monetary and Macroprudential Policies*, Washington, January.

International Monetary Fund (IMF) [2013b], *Key Aspects of Macroprudential Policy*, Washington, June.

Kindleberger, C. and Aliber, R. [2005], *Manias, Panics and Crashes*, 5th ed., Wiley&Sons.

Koenker, R. and Hallock, [K. 2001] *Quantile Regression,* in "Journal of Economic Perspectives", 15, n. 4.

Kyotaki, N. and Moore, J. [1997], *Credit Cycles,* in "Journal of Political Economy", 105, n.2, April, pp. 211-248.

Le Lesle, V. and Avramova, S. [2012], *Revisiting Risk Weighted Assets*, IMF working papers 12/90.

Liikanen Report [2012], *High Level Group on Reforming the Structure of the Banking Sector*, European Commission, October.

Lund-Jensen, K. [2012], *Monitoring Systemic Risk Based on Dynamic Thresholds,* IMF Working Papers 12/159, June.

Merton, R.C. [1974], *On the Pricing of Corporate Debt: The Risk Structure of Interest Rates*, Journal of Finance, 29(2) pp.449-70.

Minsky, H. P. [1982], *Can It Happen Again? Essays on Instability and Finance*, M.E. Sharpe, Armonk, N.Y.; trad.it. *Potrebbe ripetersi?Instabilità e finanza dopo la crisi del'29*, Torino, Giulio Einaudi, 1984.

Morris, S. and Shin, H. [2008], *Financial Regulation in a System Context*, Brooking Papers of Economic Activity, Fall.

Newman, M. E. J. [2003], *The Structure and Function of Complex Networks*, SIAM Review, 45, pp. 167-256 , March

Nier, E., Yang, J., Yorulmazer, J. and Alentorn, A. [2008], *Network Models and Financial Stability,* Bank of England Working Paper n.346, April.

Noera, M. [2013] *Il rischio sistemico,* mimeo. [2013].

Onado, M. [2009] *I nodi al pettine,* Laterza, Bari.

Poon, S., Rockinger, M. and Tawn, J. [2004], *Extreme Value Dependence in Financial Markets: Diagnostics, Models and Financial Implications,* in "Review of Financial Studies", 17, n. 2.pp. 581-610.

Revell, J. [1975], *Solvency and Regulations of Banks*, Bangor Occasional Papers in Economics, 5, Cardiff, University of Wales Press.

Rocco, M. [2011], *Extreme Value Theory for Finance: A Survey,* Banca d'Italia, Questioni di Economia e Finanza, n.99, July.

Segoviano, M. [2006], *Consistent Information Multivariate Density Optimizing Methodology*, London School of Economics, Financial Markets Group Discussion Paper n.557, March.

Segoviano, M. and Goodhart, C. [2009], *Banking Stability Measures,* IMF Working Paper 09/04, January.

Tarashev, N. and Zhou, H. [2006], *The Pricing of Portfolio Credit Risk*, BIS Working Paper n.214.

Tarashev, N. and Zhou, H. [2008], *Market Perceptions of Systemic Risk in the Banking Industry*, BIS Quarterly Review pp.6-8, March.

Zhou, C. [2010] *Are Banks Too-Big-to-Fail? Measuring Systemic Importance of Financial Institutions*, in "International Journal of Central Banking", December.

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