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Measuring Systemic Risk in a Post-Crisis World

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Abstract

In response to the very large number of quantitative indicators that have been put forward to measure the level of systemic risk since the start of the subprime crisis, the paper surveys the different indicators available in the economic and financial literature. It distinguishes between *(i)* indicators related to institutions, based either on market data or regulatory/accounting data; *(ii)* indicators addressing risks in financial markets and infrastructures; *(iii)* indicators measuring interconnections and network effects - where research is currently very active-; and *(iv)* comprehensive indicators. All these indicators are critically assessed and ways forward for a better understanding of systemic risk are suggested**.**

Key words: systemic risk, market data, balance sheet data, regulatory data, financial network, funding liquidity
JEL Classification : G2, G3, E44

La Mesure du Risque Systémique suite à la crise financière

Résumé

Face au très grand nombre d'indicateurs quantitatifs qui ont été proposés pour mesurer le risque systémique suite à la crise des *subprimes*, le papier fait un bilan des indicateurs disponibles dans la littérature économique et financière. Il distingue entre (i) les indicateurs portant sur des institutions, à la fois sur la base de données de marché et de données comptables ou réglementaires ; (ii) les indicateurs portant sur les marchés financiers et les infrastructures ; (iii) les indicateurs mesurant les interconnexions et les effets de réseau, domaine où la recherche est très active, et (iv) les indicateurs synthétiques. Tous ces indicateurs sont évalués de façon critique et des voies d'amélioration sont proposées en vue d'une meilleure compréhension du risque systémique.

Mots clés : risque systémique, données de marché, données bilancielles, données réglementaires, réseaux financiers, liquidité
Classification JEL : G2, G3, E44

Summary

1. Introduction

Research on systemic risk measures has exploded since 2008. National supervisory authorities and central banks along with academia have developed a large number of approaches to assess systemic risk that took center stage during the last financial crisis. These advancements are not harmonized and a consensus is yet not possible. It seems now important to provide a critical assessment of these different methodologies in order to choose adequately which subsets of indicators appear to be the most relevant, to understand their limits and continue building new indicators.

A systemic event takes place when the financial sector amplifies a shock – either external or internal – affecting financial institutions, with serious negative consequences for the financial system and the real economy. Systemic risk quantifies the likelihood of a systemic event, also taking into account its impact.

Several kinds of shocks may cause a systemic disruption. It can be the failure of an institution, an operational dysfunctioning or a downswing in the macroeconomic cycle. An important distinction is between (i) the time-cyclical and (ii) the cross/section-structural dimension of systemic risk. Shocks are then not only transmitted but contagiously communicated either through the network of balance sheet exposures or through the channels of expectations. Transmission mechanisms that operate in 'normal times' are no longer valid often causing inefficient adjustments that are often of larger magnitude.

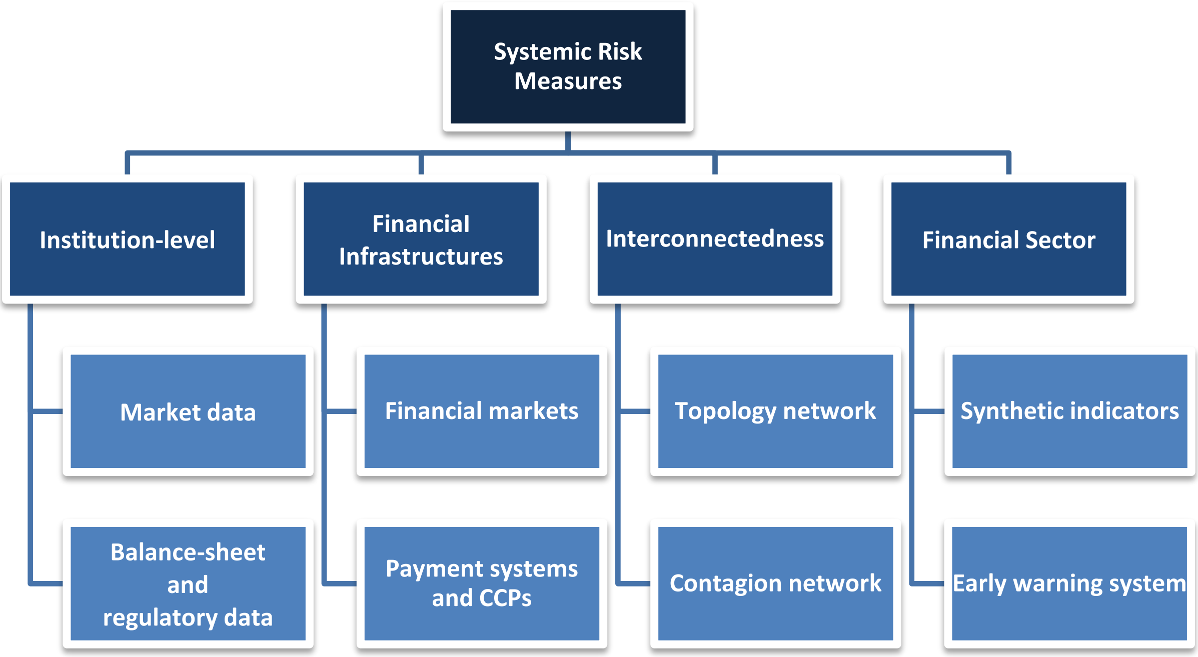
The objective of indicators of systemic risk is to assess the probability of occurrence of these shocks, to model the contagion mechanism and their adverse impacts. Measuring systemic risk helps design the relevant regulatory interventions that can be accounted for and challenged within an economic model (Hansen, 2012). Quantification is the necessary condition for objectivity, rigor and impartiality. Since quantification requires defining systemic risk, *then* measuring it, purely statistical indicators may also be useful: in the absence of a canonical model of systemic risk, one cannot avoid being eclectic and has to rely on a large set of indicators. Since the last crisis, the number of indicators has literally exploded in the empirical literature: Bisias *et al. (*2012), report 31 different quantitative measures. Therefore, the current challenge is no longer to look for evidence of systemic risk, but rather to find out the most appropriate measure of systemic risk.

In order to inform potential users of systemic risk indicators, we provide a taxonomy of systemic risk measures according to their level of analysis – institution-level, market-level or system-level. We then suggest a comprehensive list of characteristics that have to be assessed depending on users' final objectives: information content, data sources, forward-looking properties, ability to effectively detect contagion. The remainder of the paper is organized as follows. Section 2 develops the taxonomy of systemic risk indicators. Section 3 presents the associated user's guide. Section 4 concludes.

2. New indicators and methods[1]

Here, we survey time series or cross-sectional indicators of systemic risk and new methods providing evidence of systemic risk. We distinguish between (i) indicators focusing on institutions –banks and insurance companies, (ii) indicators measuring systemic risk in financial markets and infrastructures, (iii) indicators of interconnectedness and networks; (iv) comprehensive or system-wide indicators (see Table 1). To sum up the discussion in this section, Table 2 summarizes the various systemic risk measures from the above classification.

Table 1: Systemic risk measures taxonomy



2.1 Indicators based on institutions: Banks and Insurance Companies

Financial institutions are mutually linked. In a non-negligible amount, an institution's assets are another one's liabilities. As regards banks, the most blatant manifestation of these connections is the interbank money market. In the insurance sector, even though traditional activities are vulnerable to systemic disruptions rather than causes of them, reinsurers form a network of exposures that can propagate systemic risk (Frey *et al*., 2013; van Lelyveld *et al.*, 2009).

Since financial institutions may be vulnerable to systemic risk, they cannot assess their risk independently from the rest of the system they are a part of. To account for systemic risk, many measures have been proposed since the recent financial crisis. Many of these indicators measure the contribution of a given institution to overall systemic risk. They are based either on market data or balance-sheet and regulatory data.

[1] An exhaustive description of each and every measure of systemic risk is beyond the scope of this paper. See Bisias et al. (2012) and ECB (October 2012).

2.1.1. Market data

A large subset of the literature relies on the information included in market prices to assess systemic risk, using probabilistic concepts: tail risk or quantiles, default probability and statistical causality. Since economic theory considers that financial market participants have forward-looking expectations, most measures based on market data are presented as potential predictors of systemic disruptions.

For a long time, systemic risk was considered as a tail risk, hence the idea to implement extreme value theory on banks' stock prices. See notably the reduced form models by Hartmann *et al.* (2005). More recently a number of indicators have been introduced based on bank's sensitiveness to extreme events ("systemic fragility") or their capacity to trigger extreme events ("systemic importance"[2]). For that purpose, the usual risk measure VaR – Value at Risk – has been adapted to measure systemic risk by Adrian and Brunnermeier (2011) through the so-called Contagion Value-at-Risk (CoVaR). The contribution of an institution is measured as the 5%-quantile of loss of the system, that is the usual VaR, conditional on the fact that the specific institution is already at its 5%-VaR. The CoVaR gauges therefore the impact of the situation of a specific institution to the whole financial system, hence measures the "systemic importance" of the bank To build a measure of systemic risk generated by one institution, the authors propose the DCoVaR computed as the difference between the CoVaR corresponding to a situation for distress of the institution (defined as being at its own 5%-VaR) and the CoVaR corresponding to a normal situation for the institution. Therefore, the DCoVaR captures the marginal contribution of institutions to systemic risk.[3]

Acharya *et al.* (2011) have extended the concept of Expected Shortfall[4] to define the Marginal Expected Shortfall (MES). Here the indicator measures the "systemic fragility" of an institution. The systemic risk generated by one institution (its marginal contribution) is measured as the average net equity return on the 5% lowest daily market returns. Conditioning on these returns restricts the analysis to a situation of general distress. The risk measure aims at capturing the need for capital of an institution in the case of a crisis. Taking a simplified view of banks' balance sheet, the MES, combined with the leverage ratio, constitutes a leading indicator to predict an institution's SES (Systemic Expected Shortfall) that captures the propensity to be undercapitalized when the system as a whole is in that case. Controlling for balance sheet composition, the MES is turned into SRISK by Brownlees and Engle (2011) who also include a very refined dynamic model on returns. The SRISK is the expected capital shortage of a financial institution, conditional on a substantial market decline (a 40% fall over 6 months) and taking leverage and size into account. All these systemic risk measures are provided at V-LAB (2012): see Figures 1 to 3 in Appendix.

Shifting from stock to debt markets, IMF (2009) introduces an indicator similar to the CoVaR, but using CDS spreads rather than banks' equity returns.

Another important set of contributions in the literature relies on default probability. Instead of measuring the financial institutions' under an extreme event it focuses here on quantifying the likelihood of the failure of a financial institution.

[2] These two concepts of systemic fragility and importance are discussed more fully in section 3.1.

[3] The DCoVaR captures the contribution of one institution to systemic risk. However, it is possible to reverse the conditioning to analyze the exposition of one institution to systemic risk (called "exposure CoVaR" by the authors although it is not developed in the paper).

[4] The Expected Shortfall is the expected loss conditional on a distress situation.

In particular, Segoviano and Goodhart (2009) develop a Banking Stability Measure, for inclusion in the IMF's toolkit, that relies on the multivariate distribution of returns. They define the banking system as a portfolio of banks and infer the system's multivariate density from which the proposed measures are estimated. They compute joint failure probabilities for each pair of banks. They capture linear and non-linear distress dependencies among the banks in the system and their changes over the economic cycle (see Figure 9 in Appendix).[5] Huang *et al.* (2009) compute the Distress Insurance Premium, i.e. the insurance price against large default losses in the banking sector in the coming 12 weeks (see Figure 4 in Appendix).[6] This systemic risk indicator reflects market participants' perception of failure risk as well as their expected probability of common default. They provide an estimated risk-neutral probability of default using CDS spread data and default correlations using the underlying assets return correlation. Gray and Jobst (2011) develop a Contingent Claims Analysis based on Merton (1973) and using Black-Scholes option pricing techniques. They compute the price of a put option on the firm's assets (without accounting for the government's implicit guarantee). They compare it to CDS spreads, which captures the expected loss of the firm accounting for the government's implicit guarantee. The difference between the two indicators is the market-implied government guarantee. The measure of systemic risk is the sum of the guarantees over all the institutions in the system, aggregating sector indicators.

A final strand of the literature relies on the time series Granger-causality which is interpreted as a spill-over effect. In particular, Billio *et al.* (2010) evaluate systemic risk through the degree of possible contagion to other institutions in the banking, insurance and hedge-fund sectors. To do so, the authors test for Granger-causality between institutions' returns. Hence, they build a measure of financial links' prominence.

2.1.2. Balance-sheet and regulatory data

Balance-sheet data allow interesting descriptive statistics to assess systemic risk (see table 1 for a list proposal of generic indicators). We present comprehensive indicators, indicators on leverage, on liquidity and funding.

First, bank and insurance supervisors compile detailed confidential accounting and regulatory data to assess the overall level of systemic risk and the contributions of Systemically Important Financial Institutions (SIFIs). The G-SIBs (Global Systemically Important Banks) framework characterizes systemic banks through 5 classes of indicators[7] (see Figure 5 in Appendix) proposed by the Basel Committee (BCBS, 2011). The values of the individual indicators are then transformed into scores, dividing by the aggregate value of the indicator for the population of large banks, representing the contribution of each bank to the whole systemic risk. It seems therefore quite clear that large banks will have high systemic scores.[8] However, the failure of a G-SIB is an extremely rare event. On the contrary, we have observed defaults of non G-SIBs. The G-SIBs framework is probably too much focused on Loss-Given Default[9] without considering Probability of Default levels, or other indicators of vulnerabilities, to measure systemic risk. It is therefore legitimate to wonder whether it makes sense to focus on banks that are probably the most dangerous if, and only if, they default

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[5] This approach is notably applied by the ECB in its Financial Stability Reviews.

[6] Chen *et al.*(2012) replicates this method for the insurance sector.

[7] Cross-jurisdictional activity, size, interconnectedness, substitutability/financial institution infrastructure and complexity.

[8] The rankings of the systemic institutions are published annually by the Financial Stability Board and may differ significantly from those provided by statistical model based on market data and reviewed in 2.1.1

[9] Loss Given Default - percentage of loss over the total exposure when a counterparty defaults.

while their distance to default remains substantial. A similar method has been developed for insurance companies. IAIS (2012) proposes a methodology to assess the Global Systemically Important Insurers (G-SIIs). It suggests to create an index thanks to the weighted aggregation of selected indicators that can be grouped into 5 categories (IAIS, 2012).[10] The major difference is that systemicity stems largely from “non traditional” activities, based on the assumption that “traditional” insurance activities are not systemic.

On the other hand, many models are estimated based on available accounting data and focus on specific risks such as high leverage or liquidity and source of funding shortages.

Greenwood *et al.*(2012) model a banking sector subject to fire sales, hence to contagion effects on the basis of data published by EBA on banks’ exposure to EU sovereigns. They are able to derive bank exposures to system-wide deleveraging and the spillover of a single bank’s deleveraging onto other banks. They also distinguish between a bank’s contribution to financial sector fragility and a bank’s vulnerability to systemic risk.[11] Their approach originally uses granular regulatory data as input.

Brunnermeier *et al.* (2011) propose a risk topography of the financial system based on the Liquidity Mismatch Index (LMI). This indicator is expressed as the difference between the cash equivalent values of assets and liabilities in the worst case scenarios, leading to a computation of a ‘Value at Liquidity Risk’. They propose setting up a regular survey that would elicit from financial firms their LMI and capital position sensitivities to various shocks. They suggest this panel should be publicly available, forming a sound basis for systemic risk measurement in its two dimensions, namely liquidity and solvency. Jobst (2012) develops a measure of systemic liquidity risk, quantifying how the size and the interconnectedness of individual institutions can create short-term liquidity risk on a system-wide level and under distress conditions. This is the institution’s contribution to systemic liquidity risk. It is computed in three steps: (i) generating a time-varying measure of funding risk by valuing the components of the Basel III Net Stable Funding Ratio at market prices, (ii) estimating the expected losses arising from insufficient stable funding and (iii) aggregating them so as to determine the probabilistic measure of joint liquidity shortfalls at the system-wide level.

From a general point of view, it is possible to derive, from balance sheet and regulatory information, indicators of risk taking that matter for the occurrence of systemic risk. Some examples of relevant indicators that could be considered for banking institutions are presented in Table 2.

[10] Size, global activity, interconnectedness, non-traditional and non-insurance activities, substitutability.

[11] In order to distinguish between the contribution and the vulnerability to systemic risk, the BIS proposes a way to attribute to each institution its contribution to system-wide risk using the game theory concept of Shapley value (Tarashev *et al.*, 2009). The Shapley axioms enable attributing pay-offs in a game (here, systemic risk) to each participant with desirable properties. The systemic level of an institution is the weighted average of its marginal contribution to systemic risk (the game total pay-off) over each possible financial system (coalition). It assumes that when two institutions enter a financial system, the increase of risk is equally split between them.

Table 2: Systemic risk Balance sheet indicators

1/ Indicators on capital
Buffer to CET1 ratio regulatory requirements
Large exposures to capital
2/ Indicators on credit distribution
Bank credit growth over total credit growth
Interest rate of bank new loans minus interest rate of all banks new loans
Nonperforming loans over total loans
Bad loans over total bad loans
3/ Indicators on concentration
Number of counterparties (based on large exposures)
Sum of Large Exposures over own funds
SME loans over total loans
4/ Indicators on liquidity and funding
Loans to deposits ratio
Structure of total liabilities :
Total customer deposits over total liabilities
Wholesale funding over total liabilities
Stable funding over total required stable funding
Maturity distribution mismatches between asset and liabilities
Currency mismatch
Liquid assets over total assets
Total unencumbered asset over total liquid assets
5/ Indicators on market activity
Fair Value over total assets
Total off balance sheet derivatives over total assets
6/ Indicators on leverage
Buffer to leverage ratio regulatory requirements
Total off balance sheet over total asset
8/ Indicators on profitability
Returns On Assets over the average Return On Assets on an exhaustive sample
Returns On Equity over the average Return On Equity on an exhaustive sample
Net Profit over Risk Weighted Assets
Income on retail activities over total income
Provision variation over a period
9/ Indicators on interconnectedness
Total Interbank exposures over total assets
Total Interbank liabilities over total liabilities
Bank Number of counterparties (asset and liability side)

2.2. Systemic risk in financial markets and infrastructures

Beyond financial institutions, the cross-sectional dimension of systemic risk investigates the resilience of financial markets and infrastructures to shocks.

2.2.1. Financial markets

The existence of systemic risk in financial markets has long been a challenging issue, given the non contingent nature of financial instruments traded on exchanges (see, however, de Bandt and Hartmann, 2000, for evidence of contagion at the international level).

The subprime crisis has changed the perspective, with explicit cases of market breakdowns. It is now admitted that runs are possible on Money Market Mutual Funds, especially those that are priced at Constant Net Asset Value, which are deposit-like investments, as opposed to Variable Net Asset Value Funds (see also Krainer, 2012). Schmidt *et al.* (2012) study daily investor flows to and from each money market mutual fund during the period surrounding the September 2008 crisis. They determine who initiated runs and the timing of withdrawals. They weight against each other the self-fulfilling and the informationally-efficient theories of bank runs. They propose an econometric methodology to disentangle both effects. The former can be envisaged as a measure of systemic risk.

In addition, Gorton and Metrick (2010) describe the runs on the repo markets, as well as asset-backed commercial paper programs and structured investment vehicles. In the case of the repo market, some banks suffered unprecedented high haircuts and even the stop of repo lending on many forms of collateral. They construct an indicator of systemic risk as the spread between the Libor and the Overnight-Indexed-Swap (see Figure 6 in Appendix).

2.2.2. Payment systems, financial infrastructures and Over-the-Counter transactions

It is well known that systemic risk may occur in payment systems (de Bandt and Hartmann, 2000). However it is difficult to monitor and quantify such a risk. Based on TARGET2[12] data transactions, Heijmans and Heuver (2012) propose a set of informal indicators to monitor money market risk over time through 5 major dimensions: overall liquidity position, demand and supply liquidity, timing of payment, use of collateral and signs of a bank run.

A prominent component of contagion is counterparty risk. Payment systems' structure influences how shocks may propagate through the financial system. It also determines how severe banks contagion can be. On the one hand, central counterparty clearing houses (CCPs) promote the resilience of the financial system since it handles counterparty risk by becoming "the seller to every buyer, and buyer to every seller". On the other hand, CCPs real-time risk management can be strongly pro-cyclical: margin calls may rise with the risk of the underlying assets or the risk of counterparties. Obviously, if CCPs are not properly supervised and risk-proof, they may themselves create a systemic risk since all the risks are concentrated in one institution (Chande *et al.* 2010, Idier and Fourel, 2011). There is a trade-off between the reduction of counterparty risk and the development of concentration risk. CCPs decrease the probability of system failure; yet they can be costly if the risk does materialize. To monitor the role of CCPs in systemic risk, the work of Galbiati and Soramaki (2012) suggests describing the topology of clearing systems along two dimensions: concentration and tiering. Concentration increases with the variability of each CCP's market share, while tiering decreases with the number of CCPs. They find that the best topology depends on the objectives. CCPs are always better-off in topologies with higher concentration and higher tiering (i. e. where all the banks are linked to a small number of CCPs) since it enhances their netting capacities. From the network perspective, there is a trade-off between efficiency in

[12] TARGET2 is an interbank payment system for the real-time processing of cross-border transfers throughout the European Union (Trans-European Automated Real-time Gross Settlement Express Transfer System).

normal times (higher netting level, increasing in both concentration and tiering) and resilience to tail risks.[13]

Besides, over-the-counter (OTC) derivatives markets, suffering from a lack of transparency of exposures and risk management, are a significant source of systemic risk. A loss of confidence between counterparties can exacerbate a market crunch in some key markets such as Interest Rate Swaps (see G20, 2009). The design of the clearing system can impact financial institutions risk-taking (see Biais *et al.*, 2011). Nonetheless, in this field, we cannot easily expect a specific measure able to capture systemic risk mainly due to information deficiency.

2.3. Indicators of interconnectedness

In order to assess the resilience of the financial system from a cross-sectional perspective, many indicators investigate interconnectedness and network effects. There are two different directions: on the one hand, a descriptive approach of the structure of the network; on the other hand, an analysis of contagion mechanisms.

Insofar as the network structure of the financial network determines propagation channels that can quickly generate systemic risk, describing the topology and identify the salient links are simple ways to uncover possible risks.

One strand of the network literature describes the network topology without modeling economic behavior or financial features. The objective is to provide a few indicators that grasp the main stylized characteristics of the network structure with most of the time specific network metrics. The literature in this field mainly analyzes national interbank markets. A tired structure is displayed. A few big banks are interconnected and many small banks are linked only with these big banks, as reviewed in Upper (2011). However, Alves *et al.* (2013) analyze a European network of 53 large EU banks. They show that big European banks are highly connected to one another, invalidating the idea of a fractal pattern of interbank networks since the tiered structure is not found at the international level. Different network dimensions can be analyzed related to the links (type, size) and the nodes (centrality measures).[14] Intensive work for deriving systemic risk indicators from these measures is currently undertaken (see for instance van den Brink and Gilles 2000 ; De Castro Miranda *et al.*,2012 ; Battiston *et al.*,2012 ; Leon and Perez, 2013). An important caveat for the use of these metrics is that most of them are directly transferred from other sciences, social networks studies and graph theory. Thus, applying usual interpretation of these measures, which are perfectly established in sociology and socio-economic for instance, may lead to severe misunderstanding in a financial framework. In an attempt to try to improve network descriptions, Karas and Schoors (2012) introduce the K-coreness, defined by a recursive algorithm borrowed from physics that sequentially weights nodes with respect to their

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[13] Assuming a high concentration and a high tiering network structure, in case of an extreme shock, if a CCP did not manage correctly counterparty risks, the network will be affected by the failure of a central infrastructure.

[14] Usual network statistics include: number of links, density (ratio of the number of links to the total number of possible links), average path length (average of shortest length between two nodes), cluster coefficient (probability of two nodes being connected to a third knowing they are connected), weighted cluster coefficient (weighted by the links size), excentricity of a node (the longest of the shortest path to this node), diameter (maximum of excentricity).

connectivity.[15] It is presented as a robust and reliable predictor of an individual bank's potential to spread contagion. This indicator indeed clearly outperforms others when tested on the Russian interbank market leading to a promising way to identify too-interconnected-to-fail banks. Squartini *et al.* (2013) compute high order topologic measures summing up dyadic and tryadic properties of the network of interbank measures. Having controlled for the size and the density of the network, they display patterns which can be used as early warning indicators for systemic crisis. They interpret these network characteristics as measures of banks confidence. Interestingly, they show these signals cannot be detected from bank-specific data.

The second major strand in the network approach is to model contagion mechanisms in order to understand how losses are diffused through the system.[16] One can identify two sub-strands: on the one hand, some authors focus on refining contagion mechanisms (including solvency aspect, liquidity features…); on the other hand, other papers use sophisticated calibration of shocks to derive some systemic risk measures in a stress-test perspective. In the first sub-strand, following the seminal paper of Eisenberg and Noe (2001), Gouriéroux et *al.* (2012) develop a model of solvency contagion through interbank lending and cross-holding. The way a banking system responds to a given shock is the outcome of a simultaneous equilibrium that respects both limited liability of shareholders and the seniority of debtors over shareholders. The authors explain that interbank relationships are only the medium of contagion but that they do not create this phenomenon on its own. Contagion is due to a shock on assets, common to all banks or specific to one bank, external to the banking system. Even if the authors do not build a realistic shock on external assets, they provide a methodology to disentangle the direct effects of the shock and the effects of contagion. This methodology can be useful to identify the most sensitive links, or the most sensitive institutions to a given shock. This identification methodology underlines that the contagion risk is not a one-dimensional issue: a type of network can be very resilient to one type of shock and fragile to another.[17] Latest research supplements solvency contagion models with source of funding liquidity contagion[18] following research by Cifuentes *et al.* (2005), Gai and Kapadia (2011) or Arinaminpathy *et al.* (2012). For instance, Alves *et al.* (2013) add to an Eisenberg and Noe (2001) algorithm a mechanism of liquidity propagation. Fourel *et al.* (2013) simulate the Furfine (2003) algorithm,[19] with liquidity contagion on French interbank exposures data. Such a source of interconnection increases contagion, but its magnitude is still limited compared to the impact of the common exogenous shock. In addition, the endogenous creation of networks in response to shocks (e.g. exposure limits to the weakest banks in the system, hence the existence of multiple equilibria) is still an area of investigation. In the second sub-strand, authors focus on deriving systemic risk measure from contagion model. For instance, Bastos Santos *et al.* (2012) define indicators of default contagion and systemic impact, the Default

[15] The algorithm removes all nodes with degree 1 (i. e. banks that are only connected with another bank) and all nodes that may be left with one link by the procedure, until there is no node left. Institutions so spotted out are attributed a K-coreness of value 1. The value is incremented at each iteration for the remaining banks and so on.

[16] Allen and Gale (2000) is the seminal paper of a theoretical strand that analyses networks of banks. See Allen and Carletti (2006) or Allen *et al.* (2008).

[17] Yet, in this paper, only two types of stakeholders -debtors and shareholders- are identified. However, the resolution of a bank hinges on the concept of seniority: senior debtors get more than junior ones. Therefore, the previous model is extended in order to take into account several levels of seniority of debtors in Gouriéroux *et al.* (2013). Generally speaking, the senior level can be interpreted as a proxy for collateralized loans while junior level can be interpreted as a proxy of uncollateralized debt.

[18] For a discussion on liquidity concepts, see Brunnermeier and Perdersen (2008).

[19] The Furfine's algorithm, as known Iterative Default Cascade, is composed of two rules. First, a bank defaults when its capital falls below an exogenously fixed threshold. Second, when a bank defaults, all its counterparties suffer a loss expressed as a fraction of their exposures; the recovery rate is exogenous. For the Furfine's algorithm, the two exogenous parameters clearly affect results (see Upper 2010). On the contrary, the Eisenberg and Noe's algorithm generates endogenously the recovery rates on interbank exposures. Eisenberg and Noe's model is based on the Merton's value-of-the-firm model.

Impact and the Contagion Index. Using data on interbank exposures, they quantify the impact of a given institution default in terms of capital losses taking into account balance sheet contagion and common shocks. The Default Impact is the total loss in capital in the cascade[20] triggered by the default of an institution. The Contagion Index of an institution is its expected default impact in a market stress scenario.

2.4. Financial sector

To assess systemic risk for the whole economy, a few comprehensive indicators summarize information from different sectors. In parallel, early warning system of financial crisis may be useful indicators of pending systemic risks.

On the one hand, different types of synthetic indicators are available. Hollo *et al.* (2012), construct the ECB's CISS (Composite Indicator of Systemic Stress, see Figure 8 in Appendix) to assess contemporaneous stress. Using mostly market-data, they first compute a financial stress sub-index for 5 sub-markets: financial intermediaries sector, money markets, equity markets, bond markets and foreign exchange markets. These sub-indicators are then aggregated using basic portfolio theory. The index takes a higher value in situations when stress prevails in several market segments at the same time, a standard feature of a systemic event.[21] Kritzman and Li, (2010) use the Mahalanobis Distance[22] to detect and quantify "financial turbulences", i.e. periods in which asset prices, given their historical patterns of behavior, behave in a non standard fashion (extreme price moves, decoupling of correlated assets or convergence of uncorrelated assets). Kritzman *et al.* (2010) compute the Absorption Ratio (see Figure 7 in Appendix). It is the fraction of the total variance of a set of assets returns explained or 'absorbed' by a fixed number of eigenvectors in a principal component analysis. The ratio measures the extent to which markets are tightly correlated. In addition, other interesting approaches were implemented to model the whole system impacting financial institutions. Aikman *et al.* (2009) develop an ambitious and comprehensive financial stability model. The RAMSI framework aims at assessing how balance sheets dynamically adjust to macroeconomic and financial shocks. It allows for macro-credit risk, interest and non-interest income risk, network interactions, and feedback effects arising on both the asset and liability side. From a more macroeconomic perspective, Niccolo and Lucchetta, (2011) propose general equilibrium models accounting for connections between the financial and the real economies, the transmission of shocks and their "tail" realizations. They distinguish between systemic real risk (entailing welfare consequences) and systemic financial risk. The systemic real risk indicator is GDP-at-Risk, the worst predicted realization of quarterly growth in real GDP at 5 percent probability over a predetermined forecast horizon. The indicator of systemic financial risk (FSaR) is an analogue for a system-wide financial risk indicator.

On the other hand, as underlined in Gramlich *et al.*, (2010) handling macro-prudential risk calls for a reassessment of existing systemic risk early warning systems. Detecting variables associated with past crises is necessary to alert policy makers of potential future crises.[23]

[20] The definition of the cascade is the output of a solvency contagion algorithm following Furfine (2003).

[21] There also exists a variant focused on financial markets only, the ESMA (European Securities and Markets Authority) CISS.

[22] The Mahalanobis Distance is the generalization of the Euclidean distance to assess the difference from equilibrium.

[23] Generally, variables that need to be monitored are high real interest rates, low output growth, rapid domestic credit growth and falls in the terms of trade/ real exchange rate.

Schwaab *et al.* (2011) use the decoupling of credit risk conditions from macro-financial fundamentals as an early warning signal for the simultaneous failure of a large number of financial intermediaries, on the basis of latent macro-financial and credit risk components. Jahn and Kick, (2012) build a stability indicator for the banking system based on information on all financial institutions (institutions' individual standardized probabilities of defaults, a credit spread, a stock market index for the banking sector) in Germany between 1995 and 2010. They identify asset price indicators, leading indicators for the business cycle and monetary indicators as significant macro-prudential early warning indicators. Babecky, *et al.* (2012) build early warning indicators for developed countries using Bayesian model averaging. They find that the growth of domestic private credit, increasing FDI inflows, rising money market rates as well as increasing world GDP and inflation were common leading indicators of banking crises for the period 1970-2010. Barone-Adesi *et al.* (2011) argue that changes in 'sentiment' in financial markets can give rise to systemic risk. They measure sentiment as a component of the pricing kernel using behavioral asset pricing theory. According to them, variations in 'sentiment', correlated with changes in fundamentals, should be closely monitored to anticipate systemic risk.

<table>
<tr><th colspan="2">Institution-Level Measure</th></tr>
<tr><th>Market Data</th><th>Balance Sheet and Regulatory Data</th></tr>
<tr><td>Tail Risk
• Hartmann, et al. (2005)
• Forbes (2012)

Quantile Approach
• Acharya et al. (2011) – MES, SES
• Adrian and Brunnermeier (2011) – CoVaR
• Brownless and Engle (2011) – SRISK

Default Probability
• Gray and Jobst (2011)
• Huange et al. (2009) – Distress Insurance Premium
• Segoviano and Goodhart (2009) - Banking Stability Measures

Statistical causality
• Billio et al. (2010)</td><td>• BCBS (2010) - G-SIBs
• Brunnermeiere et al. (2012) – Liquidity Mismatch Index
• Greenwood et al. (2012)
• IAIS (2012) – G-SIIs
• Jobst (2012)</td></tr>
<tr><th colspan="2">Financial Markets and Infrastructures</th></tr>
<tr><th>Non-banks & Financial markets</th><th>Payment, clearing and settlement systems</th></tr>
<tr><td>• Gorton and Metrick (2010) – LIB-OIS spread
• Schmidt et al. (2012)</td><td>• Galbiati and Soromaki (2012)</td></tr>
<tr><th colspan="2">Synthetic and interconnection indicators</th></tr>
<tr><th>Synthetic indicators</th><th>Interconnection indicators</th></tr>
<tr><td>Synthetic Indicators
• Hollo et al. (2012) – CISS
• Kritzman and Li (2010) – Mahalanobis Distance

Macroeconomic Indicators
• Aikman et al. (2009) – RAMSI
• Niccolo and Luccheta (2011) – GDP-at-Risk, FSaR

Early-Warning Systems
• Babecky et al. (2012)
• Barone-Adesi et al. (2011)
• Jahn and Kick (2012)
• Schwaab et al. (2011)</td><td>• Alves et al. (2013)
• Fourel et al. (2013)
• Gouriéroux et al. (2012)
• Karas and Schoors (2012) – K-shell
• Squartini et al. (2013)
• Upper (2011)
• Bastos Santos et al. (2012) – Default Impact, Contagion Index</td></tr>
</table>

Table 3: Summary table of systemic risk measures

3. A user's guide of systemic risk measures

As underlined in the introduction, systemic measures are numerous, as an echo to the still blurred definition of systemic risk. Thus, it is necessary to take a step back to check their relevance. In order to inform policy-makers and financial institutions regarding the most appropriate indicators, we suggest assessing them along four different dimensions – information content (what information is brought by the measure?), data sources (on what class of data is the measure based?), forward looking properties (has the measure anticipatory features?), ability to detect contagion (is the measure able to able to capture non linear features?). It is intended as a guide to classify measures according to criteria the importance of which may depend on the final objective of the indicator.

3.1 Information content

The indicators and measures of systemic risk are numerous. However, very few do effectively meet the initial objective (the probability of occurrence of these shocks and their adverse impacts). Comparing the informational content of prominent systemic risk indicators - ΔCoVaR, SRISK and MES (see for instance Figure 10 in Appendix), Benoit, *et al.* (2012) - conclude that the MES helps little to rank systemically important financial institutions. Castro and Ferrari (2012) show that banks in higher buckets of ΔCoVaR cannot be said to have a larger systemic risk contribution than lower banks, by performing pairwise dominance tests. The reason is that the measure is not precise enough (confidence bands are large) to derive consistent rankings from it. Consequently, considering one of these measures is probably not the most adequate in a supervisory perspective, since none is a reliable guide for setting individual systemic capital requirements. However, one may argue that each of these measures captures indeed a part of systemic risk. One should therefore acknowledge that the concept is too large to be tackled by a unique ready-to-use indicator. In addition, it is important to keep in mind that some of these indicators fail to meet standard criteria of consistency (e. g. additivity, see Gouriéroux and Monfort, 2011 generalizing Artzner et al. 1998).

More importantly, indicators target different objectives. We can distinguish between two different concepts: "systemic fragility" and "systemic importance" (Alves, *et al.*, 2013). Systemic importance refers to the impact of a bank's default on the system, while systemic fragility is related to the bank's vulnerability to a systemic event. The notion of systemic importance is implicit for most indicators (for instance, DCoVaR). Of course, one can approximate the systemic fragility of an institution by the magnitude of its exposure to systemic shocks. But it would be misleading to base decisions on private costs estimates to limit the social costs of the phenomenon. From a microprudential point of view, it is useful to assess individual institutions' exposures to systemic risk by computing their systemic fragility. However, from a macroprudential perspective, it is more relevant to measure each institution's systemic importance in a way to prevent systemic spill over.

3.2 Data Sources

Systemic risk indicators rely either on market or on balance-sheet data, which matters for assessing the indicators' performance. Market data are publicly and readily available. Balance sheet data are more comprehensive and detailed but are backward-looking, available at a lower frequency and hard to compare over time and across countries due to accounting standards discrepancies. It seems natural for financial institutions to rely on market data, especially since market-based measures are intuitive and easily computable.

However, the use of market data by supervisors is questionable. While very informative, they might be difficult to incorporate in the toolbox of a supervisor. First, one has to keep in mind that there are some non-listed banks; for instance, France has significant cooperative banks. The same is true for savings banks in many European countries. Second, these measures rely on correlation rather than on causality, thus a pre-emptive policy may be challenged on the basis of the Lucas critique. Then, they reproduce market perception – which is important as systemic risk is an endogenous phenomenon, leading to multiple equilibria based on market participants' perception– whereas a supervisor is concerned by fundamentals (underlying risk as opposed to speculation or panics). Besides, their predictive power is very low. Finally, most of them are unable to disentangle the several factors of risk (contagion, liquidity, solvency, fire-sales…).

The use of market data by supervisory authorities has been studied to test whether supplementing the supervisor's information set with market signals helps having a better assessment of the financial situation. Gropp, *et al.* (2004) and Curry, *et al.*, (2008) present market data as useful complements to supervisory assessments. On the contrary, Idier *et al.* (2012) find that the MES can be roughly rationalized in terms of standard balance sheet indicators of bank financial soundness and systemic importance. Furlong and Williams (2006) point to the fact that both sets of information (namely regulatory and market data) are consistent, but the performance of market signals to assess banks' situation is not blatant. Berger *et al.* (1998) compare government and market assessments of Bank Holding Companies' conditions in terms of both timeliness and accuracy. They underline that both sets of information are complementary but do not reflect the same dimensions due to the different incentives of the supervisor and market participants. They argue that supervisory assessments are much more accurate when there has been an on-site inspection the past quarter, warning against mistaking high frequency for informational content.

Indeed, while supervisors have access to private information during on-site inspections, there is no reason to consider that market data are fully informative regarding systemic risk, which is a consequence of externalities. A pre-condition for using market data to assess systemic risk is that market participants are able to price it and are not deterred from doing so by regulatory intervention. Nonetheless, Balasubramian and Cyree (2011) and Balasubramnian and Cyree (2012), show that it may not be the case, analyzing the lack of default risk sensitivity in yield spreads on bank-issued subordinated notes and debentures. Indeed, the Too-Big-To-Fail policy disrupts market discipline because large banks have an artificially low cost of debt that is not strongly connected to bank risks. Market prices are plagued with regulatory second-order effects and have to be used with caution in order to derive signals on externalities they are not supposed to account for.

Cerutti *et al.* (2012) even argue that currently available supervisory data are not precise enough. According to them, a better data collection is required to properly assess systemic risk, even across borders, in spite of the national perspective of regulators. Group-level data can be misleading since implicitly assuming resources can be immediately and at no cost transferred from an entity to the other. According to the authors, only additional data could shed light on systemic risk and enhance market discipline.

3.3 Forward looking properties

A third crucial dimension for systemic risk measures is their forward looking properties. We distinguish three different time dimensions: leading, coincident or lagging indicators. First, leading indicators allow supervisors and financial institutions to react before a systemic event appears. Coincident indicators help deal with a systemic event in a systematic and orderly way. Lagging indicators are only able to explain past crises, hence may not help detect the next one, but they include useful information to avoid the resurgence of specific past events. Financial institutions and supervisors' risk management practices would obviously prefer leading – at least coincident – measures which consistently balance type I and type II errors.[24] For example, to be relevant, the countercyclical capital buffer proposed in Basel III regulation needs a consistent measure of systemic risk build-up.

Using the recent crisis as a natural experiment, Idier *et al.* (2012) find that the cross section of the bank MES as computed before the crisis is a poor indicator to detect which institutions are the more likely to suffer the most severe losses during a true systemic event. As a matter of fact, their results suggest that some standard balance-sheet metrics like the Tier one solvency ratio are more apt to predict the cross section of equity losses.

The early warning system literature has recently tackled the issue of systemic crises predictions. They benefit from the experience of leading indicators accumulated in this field. Rodriguez-Moreno and Pena (2013) rank high frequency systemic indicators, distinguishing between macroeconomic (for the whole market) and microeconomic (using data for individual institutions) ones. After a comprehensive review of many indicators, they conclude that the first principal component on a portfolio of CDS spreads and the multivariate densities computed from CDS spreads outperform measures based on interbank or stock market prices.[25] But predicting financial distress may not be enough. Bell (2000) stress that results are not robust and with *a posteriori* hindsight, are not good forecasters. He makes the important distinction between detecting a crisis and detecting fragility. It is indeed even more important to detect latent crises than crises themselves.[26] This is even more difficult when selecting systemic events.

3.4 Ability to detect contagion

Shocks are naturally transmitted from economic agents to others. To characterize an event as systemic, transmission channels have to turn into contagion mechanisms. Causes of potential efficient defaults would lead to inefficient ones as well, in particular through domino effects from exposures due to interconnectedness. As highlighted by the literature on contagion, systemic risk goes beyond the simple transmission of macroeconomic shocks or defaults (see de Bandt and Hartmann, 2000).

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[24] Type I error is failing to detect a crisis while Type II error is wrongly predicting a crisis.

[25] However the authors warn about possible market manipulations on CDS dealt outside organized exchanges.

The literature on country spillovers raises the question whether any spillover measure is an indicator of systemic risk. Ongena *et al.* (2012) assess how multinational banks can be the support for contagion. Degryse *et al.* (2012) quantify the relative contribution of determinants of cross-country financial contagion. Forbes (2012)[27] detects extreme-negative return (in the bottom 5% of the US return distribution). The paper underlines that the coincidence of extreme negative returns is a rough proxy for contagion across countries. Simultaneity can only be the result of a global shock. Their analysis is crucial to design financial regulation coordination across countries.

Indicators are available in the literature that provides evidence of faster or more significant transmission of shocks in crisis periods. The CISS indicator (see Figure 8 in Appendix) as shown by Hollo *et al.* (2012) displays non linearity during crisis periods. Typically, in a VAR model, Impulse response function (IRF) exhibit a more significant impact of shocks during "crisis" periods than in "normal" times. This is the case for the housing market in de Bandt and Malik (2010), using Markov Switching FAVAR models (see Figure 11 in Appendix). In order to identify periods of systemic risk, the analyst needs to provide evidence that the impact of the shocks, as measured by IRFs, are, from the statistical point of view (ie for standard confidence levels) significantly more pronounced in crisis periods than in normal times.

The objective of uncovering a different behavior in crisis period is also shared by papers that derive "financial stress" indicators. These indicators are seen to be different from indicators of "financial conditions", the latter being associated with periods when the financial system is able to perform its usual functions, which is typically not the case during "stress periods" (see for example Carlson *et al.* 2012).

4 Conclusion

Systemic risk measures appear to be rather plethoric. Academics and policy makers have proposed indicators making use of various data sources. Measures can capture systemic risk at the institution level, through the financial network infrastructure or in the wider financial system. As a consequence, systemic risk stakeholders cannot expect to rely on a unique ready-to-use indicator. Classifying the measures along their information content, data sources, forward looking properties and ability to detect contagion should help them to choose the set of indicators that best suits their needs.

However, one needs to acknowledge that these diagnoses still face serious drawbacks: systemic risk is a general equilibrium concept while usual indicators fail to take this necessary condition into account and are generally subject to the Lucas critique; many measures do not distinguish between "systemic importance" and "systemic fragility". In addition indicators very often rely on assumptions most likely to hold in normal times: crisis times, when they should be the most useful, deeply challenge these assumptions. Further, the exercise is made even more complex by the low number of events over which the statistical apparatus must be calibrated. Producing financial system diagnosis remains therefore a complex task and analysts need to be aware of these tools' limits. Addressing these issues are new challenges for future research.

[27] The measure of contagion it proposes is a by-product of this exercise, but not the primary goal of the author's work.

References

Acharya V., Pedersen L., Philippon T. & Richardson M. (2011). *Measuring Systemic Risk*, AFA 2011 Denver Meetings Paper.

Adrian T. & Brunnermeier M. (2011). "CoVaR", *FRB of New York Staff Report*, 348.

Aikman D., Alessandri P., Eklund B., Gai P., Kapadia S., Martin E., Mora N., Sterne G. Willison M. (2009). "Funding liquidity risk in a quantitative model of systemic stability", *Bank of England WP*, 372.

Allen F. & Carletti E. (2006). "Mark-to-market Accounting and Liquidity Pricing". *Journal of Accounting and Economics*, 45, 2-3, 358-378.

Allen F. & Gale D. (2000). "Financial Contagion". *Journal of Political Economy* , 108, 1, 1-33.

Allen F., Carletti E. & Gale D. (2008). "Interbank Market Liquidity and Central Bank Intervention", *European University Institute WP*, 2009/09.

Alves I., Ferrari S., Franchini P., Héam J-C., Jurca P., Langfield S., Laviola S., Liedorp F., Sanchez A., Tavolaro S. & Vuillemey, G. (2013). "Structure and Resilience of the European Interbank Market", *ESRB Occasional Paper Series*, 3.

Artzner P., Delbaen F., Eber J.M. & Heath D. (1999). "Coherent Measures of Risk", *Mathematical Finance*, 9, 3, 203-228.

Arinaminpathy N., Kapadia S. & May R. (2012). "Size and complexity in model financial systems", *Bank of England WP*, 465.

Babecky J., Havranek T., Mateju J., Rusnak M., Smidkova K. & Vasicek B. (2012). "Banking, Debt, and Currency Crises. Early Warning Indicators for Developed Countries", *ECB WP*, 1485.

Balasubramian B., & Cyree K. (2011). "Market discipline of banks: Why are yield spreads on bank-issued subordinated notes and debentures not sensitive to bank risks?", *Journal of Banking and Finance*, 35, 21-35.

Balasubramnian B., & Cyree K. (2012). *Has market discipline improved after the Dodd-Frank Act?* mimeo.

de Bandt O., & Malik S. (2010). "Is There Evidence of Shift-Contagion in International Housing Markets", *Banque de France WP*, 295.

de Bandt O. & Hartmann P. (2000). "Systemic Risk: A Survey", *ECB WP*, 35.

de Bandt O., Hartmann P. & Peydro J.L. (2010). "Systemic Risk in Banking; An Update" in *Oxford Handbook of Banking*, ed. by Berger, Molyneux, Wilson, Oxford University Press, 633-672.

Battiston S., Puliga M., Kaushik R., Tasca P. & G. Caldarelli (2012) "DebtRank: Too Central to Fail? Financial Networks, the FED and Systemic Risk", S*cientific Reports*, 2, 541.

Barone-Adesi G., Mancini L. & Shefrin H. (2011). "Systemic Risk and Sentiment", to be published in *Handbook on Systemic Risk* edited by Fouque, J. P. and Langsam, J..

Bastos Santos E., Cont R. & Moussa M. (2012) *Network structure and systemic risk in banking systems*, mimeo.

Basel committee on Banking Supervision (BCBS) (2011). *Global Systemic Important Banks: Assessment Methodology and the Additional Loss Absorbency Requirement*, Consultative Document of the Bank of International Settlement, July 2011.

Bell J. (2000). "Leading indicator models of banking crises - a critical review", *Bank of England Financial Stability Review*.

Benoit S., Colletaz G., Hurlin C. & Perignon C. (2012). *A Theoretical and Empirical Comparison of Systemic Risk Measures*. mimeo.

Berger A., Davies A. & Flannery, M. (1998). "Comparing Market and Supervisory Assessments of Bank Performance: Who Knows What When?", *Journal of Money, Credit and Banking, 32, 3, 2, 641-667.*

Biais B., Heider F. & Hoerova M. (2011). "Clearing, counterparty risk and aggregate risk", *IMF Economic Review*, 60, 2, 193-222.

Bisias D., Flood M., Lo A. & Valavanis S. (2012). "A Survey of Systemic Risk Analytics", *U.S. Department of Treasury, Office of Financial Research*, 1

Billio M., Getmansky M., Lo A. & Pelizzon L. (2010). "Measuring Systemic Risk in the Finance and Insurance Sectors", *NBER Working Paper*, 16223.

van den Brink R. & Gilles R.P. (2010). "Measuring Domination in Directed Networks", *Social Networks*, 22, 1141-157.

Brunnermeier M., Gorton G. & Krishnamurthy A., 2011. "Risk Topography"NBER Chapters, in *NBER Macroeconomics Annual* 2011, Volume 26, pages 149-176 National Bureau of Economic Research, Inc.

Brunnermeier M., & Pedersen L. (2008). "Market Liquidity and Funding Liquidity", *Review of Financial Studies*, *NBER Working Paper*, 12939.

Brownlees C. T., Engle R. (2011). *Volatility, Correlation and Tails for systemic Risk Measurement*, mimeo.

Carlson M., Lewis K. & Nelson W. (2012). *Using Policy Intervention to Identify Financial Stress*, Federal Reserve Board mimeo.

Castro C. & Ferrari S. (2012). "Measuring and testing for the systemically important financial institutions", *National Bank of Belgium WP*, 228.

Cerutti E., Claessens S. & McGuire P. (2012). "Systemic Risks in Global Banking: What Available Data can tell us and what more data are needed?", *NBER WP*, 18531.

Chande N., Labelle N. & Tuer E. (2010). "Central counterparties and systemic risk", *Bank of Canada, Financial Stability Review*, December 2010.

Chen H., Cummins J., Viswanathan K. & Weiss M. (2012)."Systemic Risk and the Inter-Connectedness between Banks and Insurers: An Econometric Analysis", *Journal of Risk and Insurance*, forthcoming.

Cifuentes R., Ferrucci G. & Shin H. (2005). "Liquidity Risk and Contagion", *Journal of the European Economic Association*, *3*, 2, 556-566.

Curry T., Fissel G. & Hanweck G. (2008). "Equity Market Information, Bank Holding Company Risk and Market Discipline", *Journal of Banking and Finance*, 32, 5, 807-819.

De Castro Miranda R. C., Stancato de Souza S.R. & Miranda Tabak B. (2012). *Connectivity and Systemic Risk in the Brazilian National Payments System*, Bank of Brasil, mimeo

Degryse H., Ather Elahi M., & Penas M. (2012). "Determinants of Banking System Fragility: A Regional Perspective", *Tilburg University DP*, 2012-015.

ECB, European Central Bank (2012). *Report on the First Two Years of the Macro-Prudential Research Network.*

Eisenberg L. & Noe T., (2001) . "Systemic risk in financial systems", *Management Science*. 47, 2, 236–249.

Frey L., Tavolaro S. & Viol S.(2013) "Analyse du risque de contrepartie de la réassurance pour les assureurs français", Autorité de Contrôle Prudentiel, *Débats Économiques et Financiers*, 4.

Forbes K. (2012), “The "Big C": Identifying Contagion”, *NBER WP*, 18465.

Fourel V., Héam J.C., Salakhova D. & Tavolaro S. (2013), "Domino Effects when Banks Hoard Liquidity: the French Network", *Banque de France WP*, 432.

Furfine C. (2003). "Interbank Exposures: Quantifying the Risk of Contagion", *Journal of Money, Credit, and Banking*, 35, 1, 111-128

Furlong F. & Williams R. (2006). "Financial Market Signals and Banking Supervision:Are Current Practices Consistent with Research Findings?" *FRBSF Economic Review*, 17, 29.

Gai P. & Kapadia S. (2011) *Liquidity Hoarding, Network Externalities, and Interbank market Collapse*, mimeo.

Galbiati K. & Soramaki M. (2012). "Clearing Networks" *Journal of Economic Behavior & Organization*, 83, 3, 609-626.

Gorton G. & Metrick A. (2010). "Securitized Banking and the Run on Repo", Yale ICF *WP*, 09-14.

Gouriéroux C. & Monfort A. (2011). "Allocating Systematic and Unsystematic Risks in a Regulatory Perspective", *CREST WP*, 2011-04.

Gouriéroux C., Héam J.-C. & Monfort A. (2012). "Bilateral Exposures and Systemic Solvency Risk", *Canadian Journal of Economics*, 45, 4, 1273-1309.

Gouriéroux C., Héam J.-C. & Monfort. A. (2013). "Liquidation Equilibrium with Seniority and Hidden CDO. *Journal of Banking and Finance*, forthcomming.

Gramlich D., Miller G., Oeat M. & Ong S. (2010). "Early Warning systems for systemic banking risk: critical review and modeling implications", *Banks and Bank Systems*, 5.2, 199-211.

Gray F. & Jobst A. (2011). "Modelling Systemic Financial Sector and Sovereign Risk", *Sveriges Riksbank Economic Review*, 2, 68-106.

Greenwood R., Landier A. & Thesmar D. (2012). *Vulnerable banks*, mimeo.

Gropp R., Vesala J. & Vulpes G. (2004). "Market Indicators, Bank Fragility and Indirect Market Discipline", *FRNBY Economic Policy Review*, 53-62.

Hartmann P., Straetmans S. & de Vries C. (2005). "Banking System Stability: a cross-Atlantic perspective", *ECB WP*, 527.

Heijmans R. & Heuver R. (2012) Is this bank ill? The diagnosis of doctor TARGET2. Mimeo.

Hollo D., Kremer M. & Lo Duca M. (2012). "CISS - A Composite Indicator of Systemic Stress in the Financial System", *ECB WP*, 1426.

IAIS, International Association of Insurance Supervisors (2012). "Global Systemically Important Insurers: Proposed Assessment Methodology". 31 May 2012, available at www.iaisweb.org

IMF, International Monetary Funds (2009). "Global Financial Stability Report".

Huang X., Zhou H. and Zhu H. (2009). "A framework for assessing the systemic risk of major financial institutions", *Journal of Banking and Finance*, 33, 11, 2036–2049.

Idier J, Lamé G. & Mésonnier J.S.. (2012). "How useful is the Marginal Expected Shortfall for the Measurement of Systemic Exposure ? A Practical Assessment", *Banque de France WP*, 348.

Idier J. & Fourel V. (2011). "Des effets théoriques de l'introduction d'une contrepartie centrale pour l'organisation des marchés OTC", *Revue d'Economie Financière*, 101.

Jahn N. & Kick T. (2012). *Early Warning Indicators for the German Banking System: A Macroprudential Analysis*, mimeo.

Jobst A. (2012), "Measuring Systemic Risk-Adjusted Liquidity (SRL) - A Model Approach", *IMF WP*, 12/209

Karas A. & Schoors K. (2012). *Bank networks, interbank liquidity runs and the identification of banks that are Too Interconnected to Fail*, mimeo.

Krainer R. (2012). "Regulating Wall Street: The Dodd–Frank Act and the New Architecture of Global Finance, a review", *Journal of Financial Stability*, 8, 2, 121-133.

Kritzman M. & Li Y. (2010). "Skulls, Financial Turbulence, and Risk Management", *Financial Analysts Journal*, 66, 5.

Kritzman M. & Li Y., Page, S., & Rigobon, R. (2010). "Principal Components as a Measure of Systemic Risk", *MIT Sloan Research Paper*, 4785-10.

Merton R. (1973). "An Intertemporal Capital Asset Pricing Model", *Econometrica*, 41, 5 867-887.

Leon C. & Pérez J. (2013). *Authority Centrality and Hub Centrality as metrics of systemic importance of financial market infrastructures*, Central Bank of Colombia mimeo.

van Lelyveld I., Liedorp F. & Kampman M. (2009). "An empirical assessment of reinsurance risk", *Journal of Financial Stability*, 2011, 7, 4, 191-203.

Niccolo G. & Lucchetta M. (2011). "Systemic Risks and the Macroeconomy", *NBER WP*, 16998.

Ongena S., Peydro J. & Horen N. (2012). *Shocks Abroad, Pain at Home ? Bank-Firm Level Evidence on Financial Contagion during the Recent Financial Crisis,* mimeo.

Rodriguez-Moreno M. & Pena J.I. (2013). "Systemic Risk Measures: the simpler, the better", *Journal of Banking and Finance*, 37, 1817-1831.

Schmidt L., Timmerman A. & Werners R. (2012). *Runs on Money Market Mutual Funds*, mimeo.

Schwaab B., Koopman S. & Lucas A. (2011). "Systemic Risk Diagnostics. Coincident Indicators and Early Warning Signals", *ECB WP*, 1327.

Segoviano M., & Goodhart C. (2009). "Banking Stability Measures", *IMF WP*, 09/4.

Squartini T., van Lelyveld I., Garlaschelli D. (2013). *Early-Warning signals of topological collapse in interbank networks*, mimeo

Tarashev N., Borio C. & Tsatsaronis K. (2009). "Attributing Systemic Risk to Individual Institutions", *BIS Working Paper*, 308.

Upper C. (2010). "Simulating methods to assess the danger of contation in interbank markets", *Journal of Financial Stability*, 7, 3, 111-125.

V-LAB, S. N.-Y. (2012). *The Volatility Lab*. available at http://vlab.stern.nyu.edu/ (05/14/2013).

Appendix

Figure 1: JP Morgan Chase MES - MES is equity loss for a 2% daily market decline

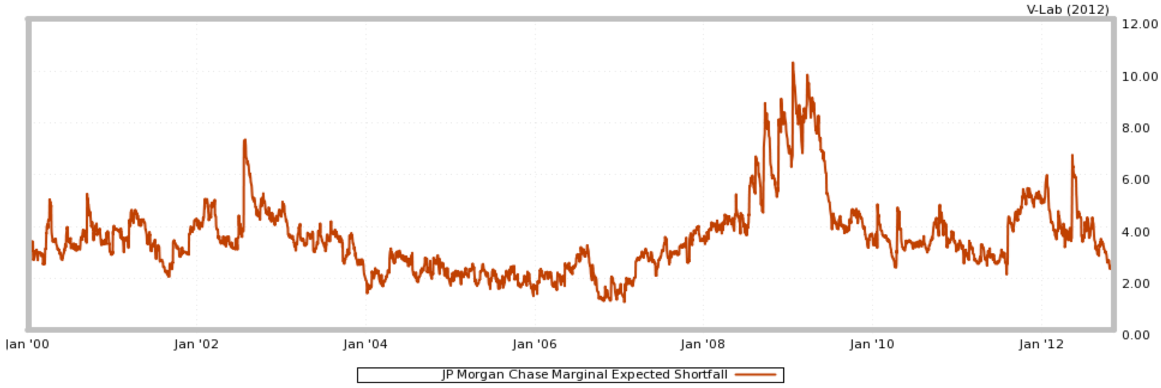


Figure 2: Risk Analysis Overview - World Financials Total SRISK (US$ billion) – Accessed on November, 12th, 2012 http://vlab.stern.nyu.edu/welcome/risk/

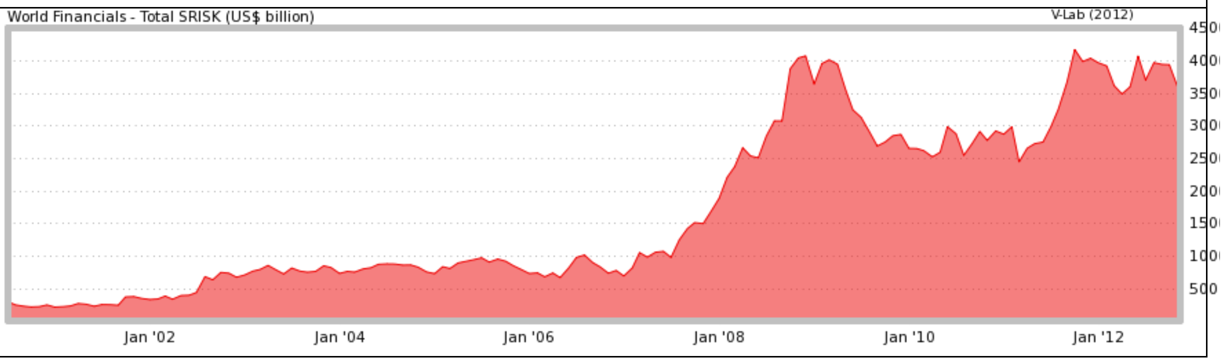


Figure 3: ECB, Financial Stability Review, June 2012

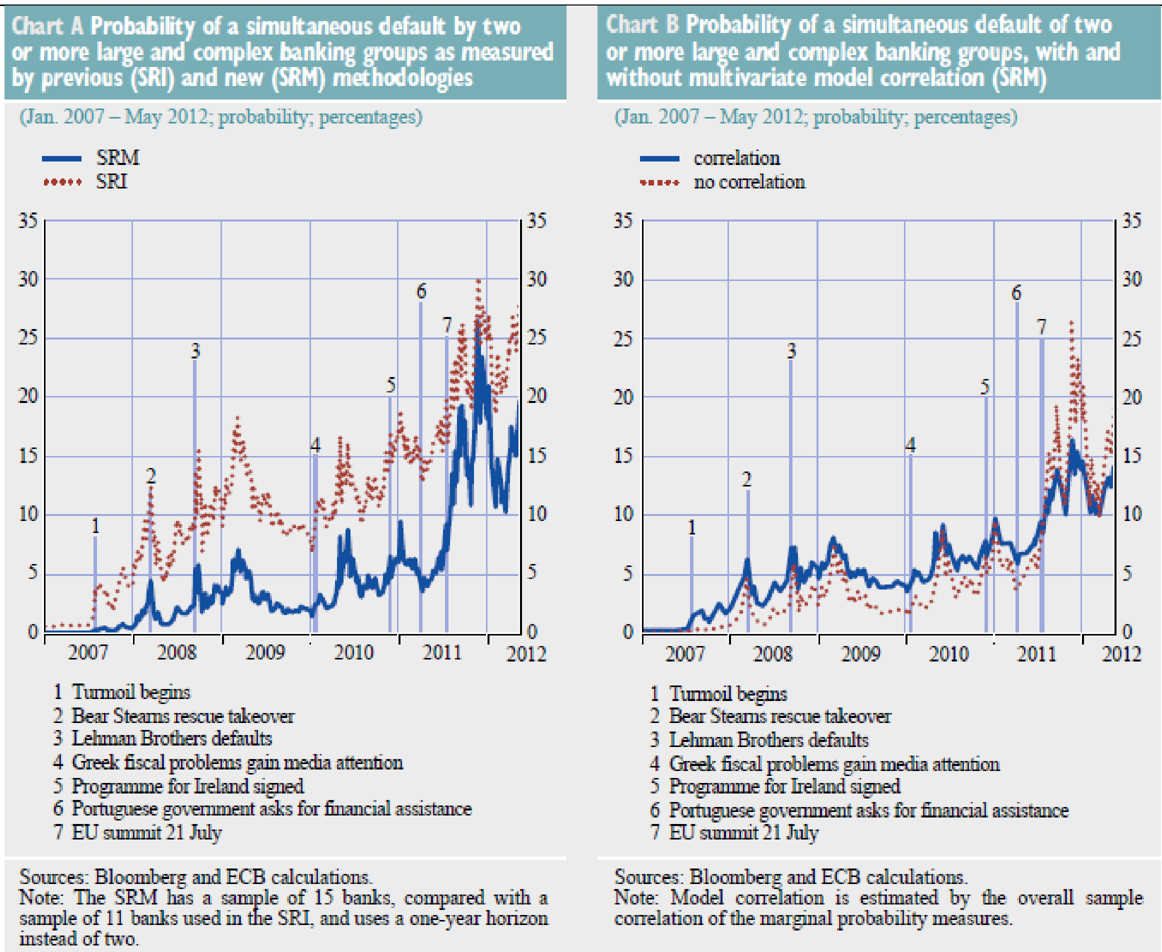
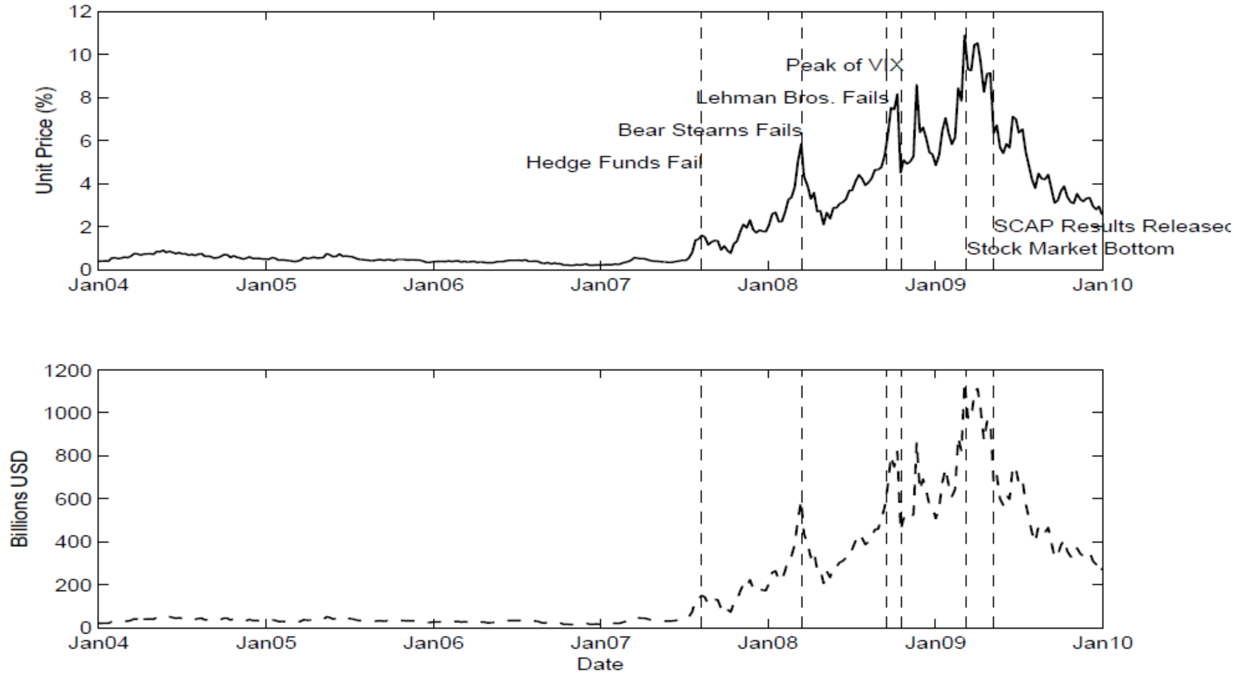


Figure 4: Distress Insurance Premium - Huang *et al.* 2011



Notes: The graph plots the systemic risk indicator for the SCAP banks, defined as the price for insuring against financial distresses (at least 10% of total liabilities in the banking system are in default). The price is shown as the cost per unit of exposure to these liabilities in the upper panel and is shown in dollar term in the lower panel.

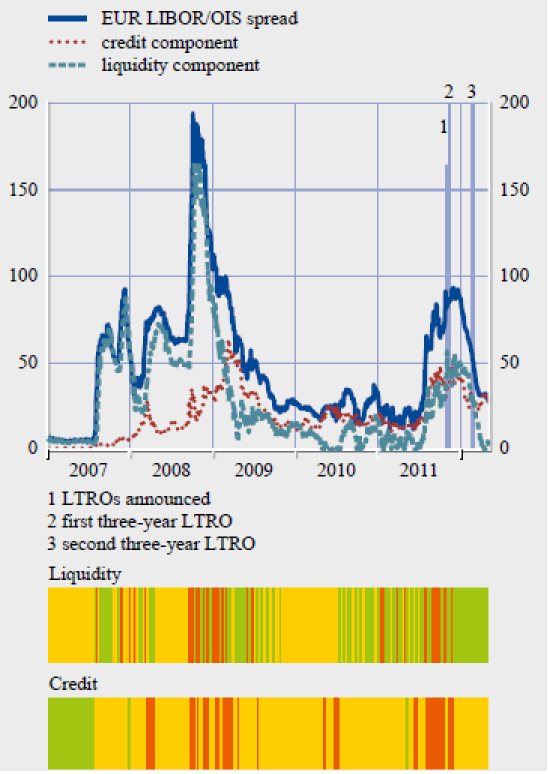
Figure 5: G-SIBs indicators - Global Systemically Important Banks: Assessment methodology and the additional loss absorbency requirement, November 2011

Category (and weighting)	Individual Indicator	Indicator Weighting
Cross-jurisdictional activity (20%)	Cross-jurisdictional claims	10%
	Cross-jurisdictional liabilities	10%
Size (20%)	Total exposures as defined for use in the Basel III leverage ratio	20%
Interconnectedness (20%)	Intra-financial system assets	6.67%
	Intra-financial system liabilities	6.67%
	Wholesale funding ratio	6.67%
Substitutability/financial institution infrastructure (20%)	Assets under custody	6.67%
	Payments cleared and settled through payment systems	6.67%
	Values of underwritten transactions in debt and equity markets	6.67%
Complexity (20%)	OTC derivatives notional value	6.67%
	Level 3 assets	6.67%
	Held for trading and available for sale value	6.67%

Figure 6: LIBOR-OIS spread & decomposition - ECB Financial Stability Review, june 2012

Chart C Decomposition of the three-month euro LIBOR/OIS spread and related heat maps

(Jan. 2007 – May 2012; basis points)



Sources: Bloomberg and ECB calculations.
Note: Red indicator points to rising, yellow to moderating and green to falling pressure on the respective spreads.

Figure 7: Absorption Ratio – Kritzman *et al.*2010

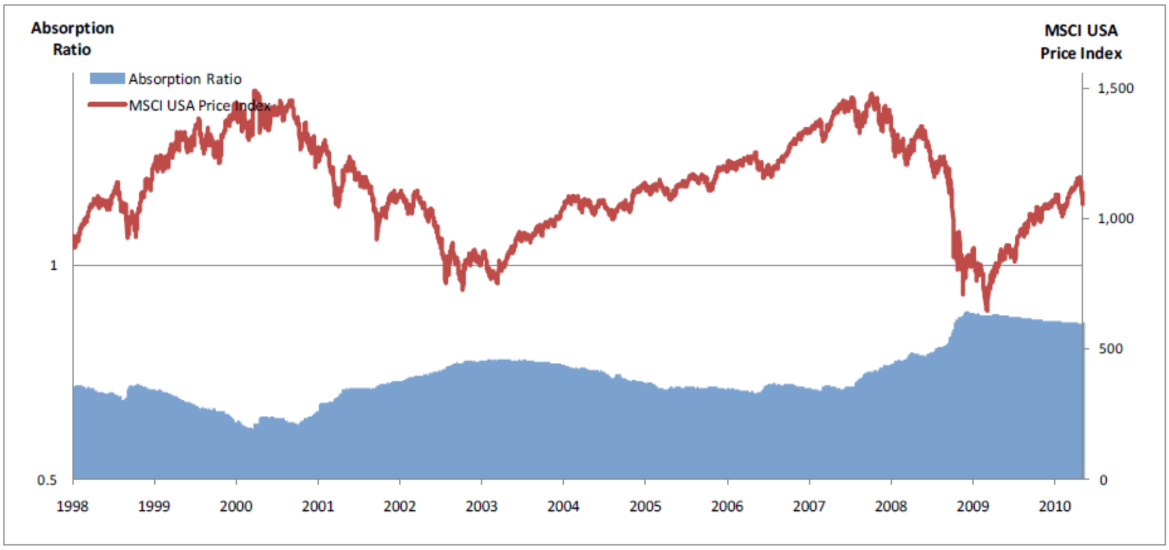


Figure 8: Composite indicator of systemic stress in the financial system – Hollo *et al.* 2012

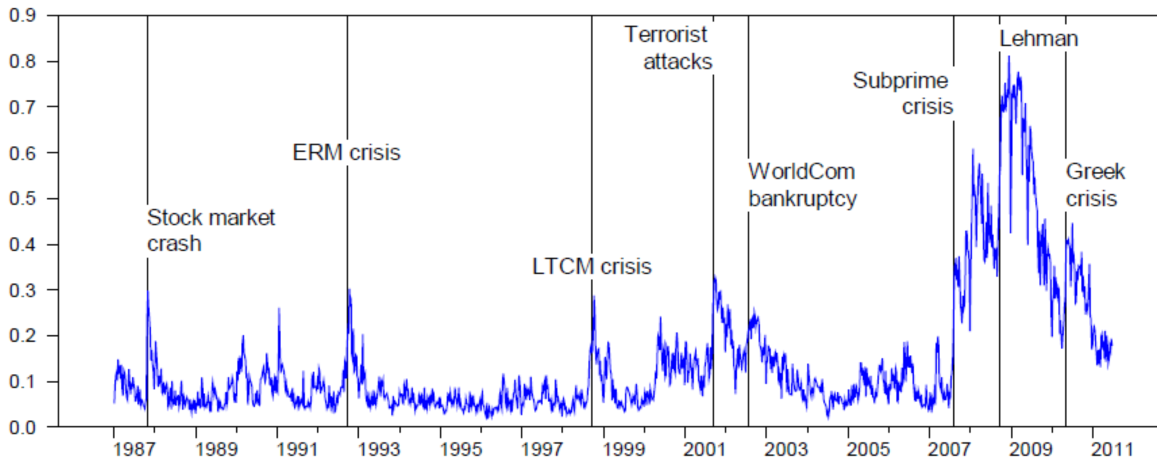


Figure 9: Banking Stability Measures - Segoviano and Goodhart 2009

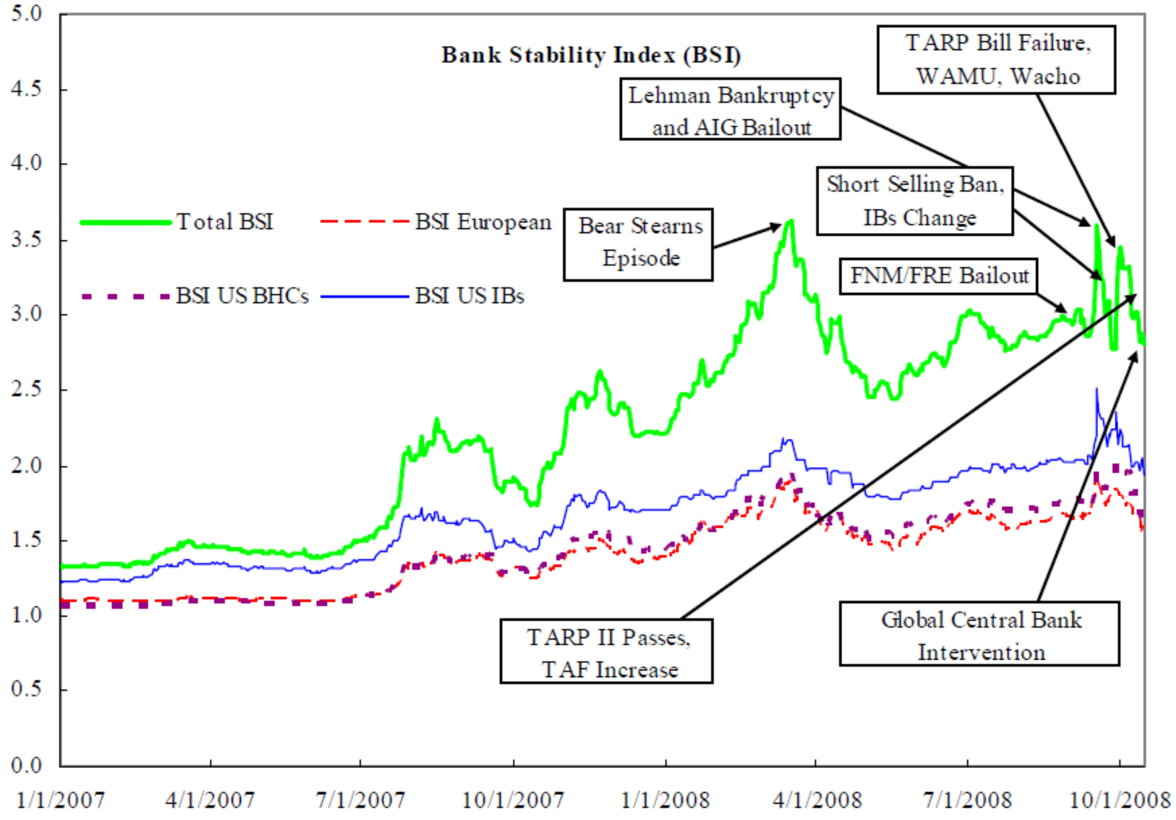


Figure 10: Bank of America VaR and DCoVaR - Benoit *et al.*, 2012

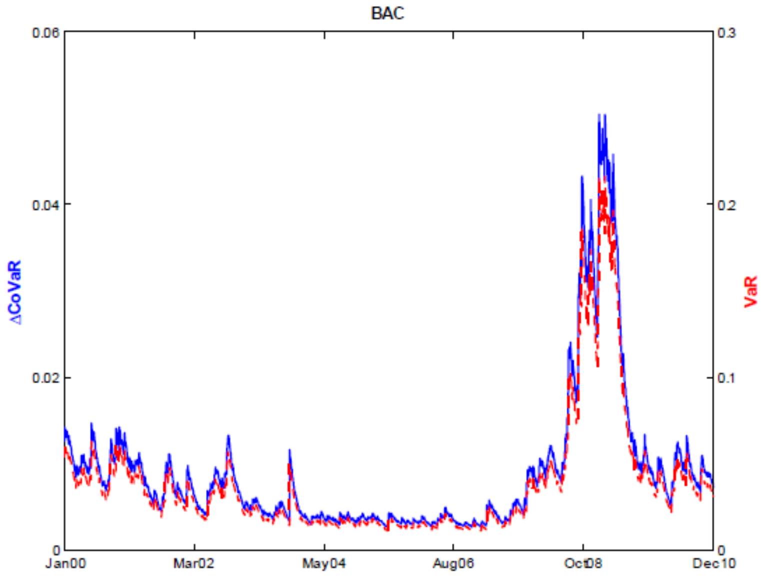
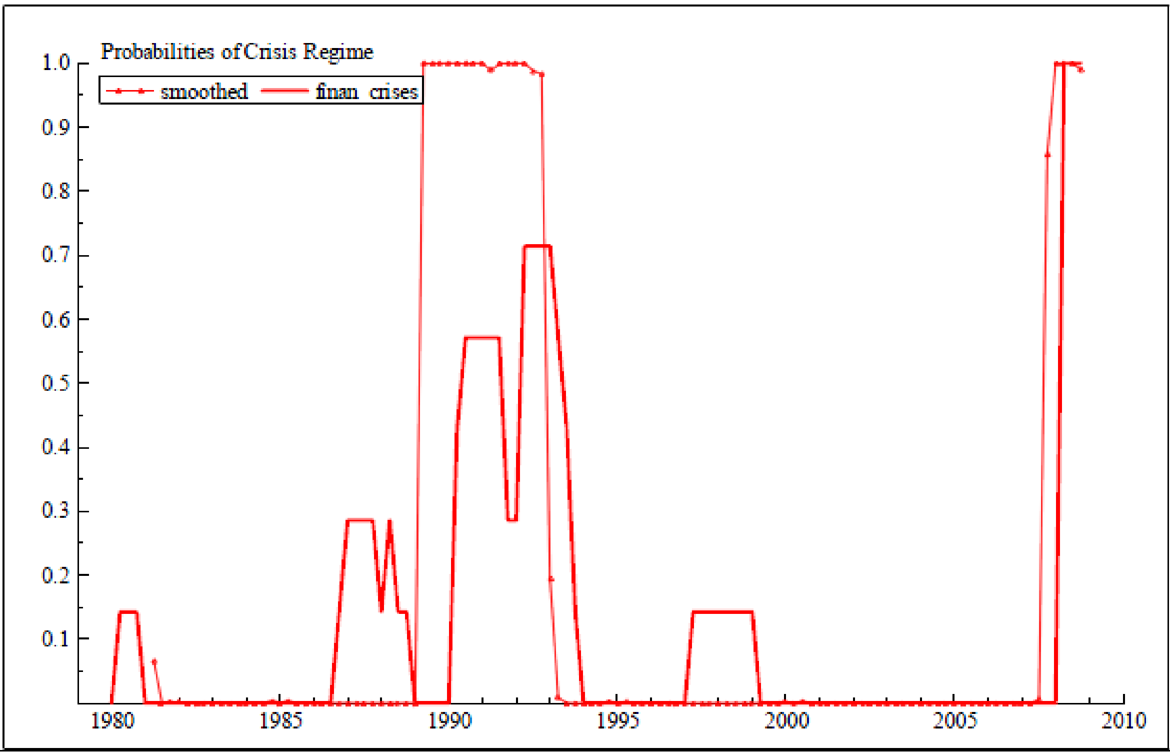


Figure 6: **ΔCoVaR is Equivalent to VaR in Time Series:** The figure displays the ΔCoVaR (solid line, left y-axis) and the 5%-VaR (dashed line, right y-axis) of Bank of America (BAC). The estimation period is from 01/03/2000 to 12/31/2010.

Figure 11: Probabilities of crisis regime - de Bandt and Malik, 2010



Débats Économiques et Financiers

1. M. Dietsch and H. Fraisse, « De combien le capital réglementaire diffère-t-il du capital économique : le cas des prêts aux entreprises par les grands groupes en France », Février 2013.

2. O. de Bandt, N. Dumontaux, V. Martin et D. Médée, « Mise en œuvre de stress tests sur les crédits aux entreprises» Mars 2013

3. D. Nouy, « Les risques du shadow banking en Europe : le point de vue du superviseur bancaire », Avril 2013.

4. L. Frey, S. Tavolaro, S. Viol, « Analyse du risque de contrepartie de la réassurance pour les assureurs français », Avril 2013

5. D. Nouy, « La réglementation et la supervision bancaire dans les 10 prochaines années et leurs effets inattendus », Mai 2013.

6. O. de Bandt, J.-C. Héam, C. Labonne et S.Tavolaro « Mesurer le risque systémique suite à la crise financière » Juin 2013.

Economic and Financial Discussion Notes

1. M. Dietsch and H. Fraisse, “How Different is the Regulatory Capital from the Economic Capital: the Case of Business Loans Portfolios held by Major Banking Groups in France”, February 2013

2. O. de Bandt, N. Dumontaux, V. Martin and D. Médée, “Stress-testing Banks’ Corporate Credit Portfolio”, March 2013

3. D. Nouy, “The Risks of the Shadow Banking System in Europe: the Perspective of the Banking Supervisor”, April 2013.

4. L. Frey, S. Tavolaro, S. Viol, “Counterparty Risk from Re-Insurance for the French Insurance Companies”, April 2013

5. D. Nouy, “Banking Regulation and Supervision in the Next 10 Years and their Unintended Consequences”, May 2013.

6. O. de Bandt, J.-C. Héam, C. Labonne and S. Tavolaro “Measuring Systemic Risk in a Post-Crisis World”, June 2013.

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