SYSTEMIC RISK: AN OVERVIEW

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Abstract

In hindsight of the 2008 crisis, the conspicuous underestimation of systemic risk has turned into a strong incentive for authors to develop appropriate measurement techniques. Given the continuously changing nature of the financial system, measurement tools have developed quickly to address diverse and progressively more complex aspects, thereby adding to the issue of establishing a universal framework of measuring systemic risk. In this respect, we tried to devise a brief overview of extant systemic risk approaches, from definition to a selection of measurement instruments. Valuable steps have been made towards producing comprehensive models. However, systemic risk measurement and mitigation remain open issues.

Keywords: systemic risk measurement, systemic crises, prudential measures

JEL Classification: G15, G20, H12

1. Introduction

An extensive amount of literature has been dedicated to studying systemic risk. However, we have yet to reach a commonly, universally accepted definition. Systemic risk is frequently addressed in terms of financial markets, thus being a risk to financial stability so widespread to the point where it entails material effects on economic growth and welfare (European Central Bank, 2010). This risk may take various forms, but it generally occurs in the context of the propagation of economic distress from one economic agent to another (Rochet & Tirole, 1996). Since interdependencies and mutual claims are the very core of financial activities, it is only natural for risks as such to arise in the financial system. Consequently, the nexus between systemic risk and financial contagion is widely acknowledged. There are numerous studies dealing with this issue, of which we mention among many

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others: Allen & Gale (2000), Kaminsky & Reinhert (2000), Claessens & Forbes (2013).

Kaufman (1995) defines systemic risk as "a risk of a chain reaction of falling interconnected dominos". Therefore, risk arises from any disturbance that works itself through the system and is strong enough to threaten the public's confidence in the financial system and its stability as a whole (Sheldon & Maurer, 1998; Billio et al, 2012). Accordingly, market stability may be affected by the impossibility of an institution to fulfil its obligations, because this will impair, in turn, other institutions. According to Martinez-Jaramillo et al. (2010), systemic risk can be conceptualized from two basic principles: the existence of an initial shock that affects one or more financial institutions up to the point of bankruptcy, and the existence of a transmission mechanism of the negative effects of this shock in the system. As these two elements compose the so-called systemic event, systemic risk can also be defined, in a broad sense, as the risk of encountering systemic events (de Bandt & Hartmann, 2000).

There is also a widespread confusion as far as trigger events are concerned. Schwarcz (2008), points out the inconsistency of the existing definitions of systemic risk:

- "the probability that cumulative losses will occur from an event that ignites a series of successive losses along a chain of institutions or markets comprising a system" (Kaufman, 1995);
- "the potential for a modest economic shock to induce substantial volatility in asset prices, significant reductions in corporate liquidity, potential defaults and efficiency losses" (Kupiec & Nickerson, 2004);
- "the risk that a default by one market participant will have repercussions on other participants due to the interlocking nature of financial markets" (Chan et al., 2005)

He states that the singular common factor of these is that one trigger event causing a series of negative economic effects. Otherwise, both the definition of a systemic event and its consequences are inconsistently explained and differ among authors.

As far as the geographical reach is concerned, systemic risk may have regional, national or international character. Strong failures of several institutions, the crash of several markets or, shortly put, events that impact most of the financial system become a source of systemic crises (de Bandt & Hartmann, 2000). Therefore, the propagation of one bank's failure as a contagion that causes the failure of several banks represents a systemic financial crisis (Acharya, 2009).

A central issue of this debate is that any problem aimed at being solved needs to be clearly defined in the first place. The lack of a clear definition slackens the attempts of addressing and solving multifaceted problems like this.

The subsequent sections build on the following topics: Section 2 addresses several recurring issues debated in literature on systemic risk; in Section 3 we present, in brief, a number of measurement instruments frequently deployed in this field. We conclude in Section 4.

2. Challenges of systemic risk measurement

Systemic risks that are not mitigated properly in a timely manner may materialize, propagate and amplify further up to the point where a systemic crisis becomes impending. Systemic crises imply overwhelming social and economic costs, hence the rising concerns towards ensuring and maintaining the financial stability of the system, and reducing the probability of such events in the future. Ensuring financial stability is particularly dependent on understanding systemic risk. There are some major impediments that derive from the complexity of systemic risk: the actual difficulty of measurement (the multitude of risk measurement instruments) and the relative lack of data needed to perform this task. Brunnermeier & Oehmke (2013) state that systemic risk appears and develops just like an economic cycle, hence data requirements for detecting imbalances will differ depending on the targeted phase:

- the run-up phase, during which disequilibria builds up in the background of the financial system (can be analysed based on low frequency data according to the authors)
- the crisis phase, during which risk materializes and spills over across the financial system (requires more granular, higher frequency data to grasp the system's vulnerabilities).

Beyond the failure of financial institutions, systemic risk has an impact on investors, for it cannot be neutralized through portfolio diversification. That is because risks that are positively correlated with the market cannot be diversified away (Posner, 2003).

Maintaining financial stability can only be done through regulation of the financial system, or else, market participants would most likely not limit their risk-taking behaviour in order to reduce the contagion hazard for the good of others. This is why regulating systemic risk not only deems appropriate, but is actually necessary (Cifuentes et al., 2005). However, there are also downsides of regulation and safety measures. Such a non-targeted consequence could be fostering moral hazard. The more market participants are being protected from the consequences of risk prone behaviour, the more likely it is for them to engage in this kind of behaviour, as argued by Hallinan (1986). This holds especially for financial institutions that are commonly considered “too big to fail”, which means that irrespective of the risk they incur, they will be bailed out for certain.

Some other undesirable consequences would be the institutions performing fewer transactions, thus lowering economic welfare, or regulation acting like a barrier against financial innovation through the implied compliance costs (Gowland, 1990). This is exactly why financial innovation has often coincided with deregulation and new instruments developed the most among non-traditional, less regulated institutions, as stated by Bisias et al. (2012).

The need for systemic risk measurement has been widely discussed. Alexander (2010) highlighted different purposes of systemic risk measures: identifying institutions of systemic importance that pose high risks for the financial system; assessing particularly vulnerable structures of the financial system; identifying shocks that are threatening financial stability; providing early warning signals when financial instability is rising.

Thus, ex-ante systemic risk measures can help policymakers tighten macroprudential policies and supervisory standards, when and where it is necessary to temper instability-inducing pressures and even provide an incentive for building stress scenarios to test for the system’s resilience. Ex-post assessments may be just as important in helping identify ineffective policies, in order to mend what has gone wrong before in the system. Therefore, systemic risk measures are a key element in implementing crisis management systems, as well as safety nets for financial institutions.

The usefulness of early warning signals has also been discussed in the light of the Lucas critique (reiterated by Bisias et al., 2012). Simply put, signals as such presumably become ineffective because individuals adapt their behaviour in response to them. But is that necessarily bad in respect to systemic risk measurement? It clearly isn’t, if market participants undertake actions by themselves in order to limit their risk exposures, instead of relying on governmental intervention and saviours of last resort exclusively. However, from another point of view, financial institutions may react adversely, by manipulating disclosed data and therefore confirming the Lucas critique (Brunnermeier & Oehmke, 2013).

Given the continuously changing nature of the financial system, measurement tools have developed quickly to address diverse and progressively more complex aspects, thereby adding to the issue of establishing a universal framework of measuring systemic risk. It is clear that many risks stemming from different sources will provide for as many approaches and risk measurement tools built to emphasize various aspects.

The global financial crisis of 2008 has spurred even more interest towards measuring systemic risk, as it has revealed that systemic risk must have been underrated. It shifted the attention of policymakers and academia from traditional institutions (banks) to the less supervised ones such as private equity and hedge funds. The crisis reaffirmed the need for heightened prudential supervision[1] and for risk buffers on one hand, as well as for disclosing risk exposure of financial institutions of systemic importance on the other. In hindsight of the 2008 crisis, an impressive amount of studies acknowledged the failure of surveillance as a main contributor to proliferating systemic risk to unbearable levels. We mention Freixas (2010), Hanson et al. (2011), Masciandaro et al. (2011), Akerlof et al. (2014).

As discussed before, extant literature encompasses an extensive number of studies aiming at measuring systemic risk in various contexts. That being the case, surveying the methods has proven to be a correspondingly difficult task. Some issues arose: given the bewildering number of analyses, literature surveys cannot claim to be exhaustive, and secondly, complex methods become difficult to classify into broad categories.

3. Approaches to measuring systemic risk

Lehar (2005) based his systemic risk measurement on a Merton type model of default. He introduced the well-known Expected Shortfall (ES), which is the debt value that cannot be covered by the firm's assets if it defaults. In brief, summing the computed Expected Shortfalls accounts for an aggregated index of systemic risk. Huang,

[1] *Macroprudential and microprudential alike. Distinction between them has been discussed by Brunnermeier et al. (2009).*

Zhou, and Zhu (2012) develop a systemic risk indicator that measures the price of insurance against systemic financial distress. In order to be computed, this cost of insurance requires parameters such as probabilities of default, loss-given defaults, leverage and dynamic conditional correlations between equity returns. According to the authors, this metric is quite similar to expected shortfall (ES), but differs in the aspect that the probabilities in the tail event underlying the cost of insurance are not normalized.

Acharya (2009) models systemic risk as the choice of correlations of banks' returns on assets. He finds that banks are willing to undertake correlated investments in the event of a shock in the system, therefore, prudential measures may actually favour building-up systemic risk. Moreover, regulation is not able to capture risks arising from inter-banking contracts. Allen, Bali & Tang (2012) use both parametric and nonparametric VaR and ES methods to estimate CATFIN as a measure of systemic risk. According to their results, CATFIN is a useful predictive instrument, thus being able to signal economic declines six months in advance.

Kritzman et al. (2011) estimate the fraction of a number of assets' total variance explained by a limited number of factors, by applying a principal component analysis (PCA) and call this the absorption ratio (AR). They find that AR captures very well market fragility. Stock returns drop around spikes in the AR and while most of the global crises corresponded with its increases, the authors state that spikes in AR do not necessarily signal a market crash for certain. That being the case, the AR accounts better for an ex-post measure of systemic risk, rather than an ex-ante one. Billio et al. (2012) also employ principal component analysis (PCA) and Granger causality networks to measure the correlation of monthly returns on hedge funds, brokers and dealers, banks and insurance companies. Among their main conclusions we mention: banks distinguish from other institutions by their very important role in shock transmission; the increase in systemic risk was favoured by the growing interdependencies between the four sectors in the analysed period (1994 to 2008). Lupu et al. (2018) focus on the fragility of the Eastern European capital market through the PCA framework. They assess the contribution of each index to the aggregated systemic risk by subtracting one index AR at a time from the group AR, and further check the validity of this analysis by running a panel regression with the Economic SentiMent index for each country as exogenous variable on the previously obtained differences.

Brownlees & Engle (2012) introduced a new empirical measurement instrument, the Systemic Risk - SRISK index. Systemic risk is therefore measured as the expected shortage of capital of an institution, determined by an important market decline. They compute SRISK for 94 financial institutions from US (depositories, insurance firms, brokers and dealers, others), between 2000 and 2010. Calculating SRISK requires data regarding equity, debt and the Marginal Expected Shortfall – MES (which in turn depends on the institution's leverage, size and equity loss in the event of a market decline). MES is modelled by means of GARCH-Dynamic Conditional Correlations (Engle et al., 2009) in order to deliver long-run and short-run dynamic volatility, correlations and tails for the returns. Summing up the computed SRISK values accounts for the aggregated systemic risk of the financial system as a whole. Later on, Brownlees & Engle (2016) reiterate the SRISK metric on a panel of US financial institutions with a capitalization greater than 5 billion USD (period 2003-2012), while they settle for the long run MES component (LRMES).

Engle, Jondeau & Rockinger (2015) run the SRISK methodology, this time on a broad selection of large European financial institutions and argue that in some instances government bailout costs become so high, that certain banks may be "too big to be saved".

Acharya et al. (2016) used equity and CDS market data to assess Systemic Expected Shortfall (SES) as a metric for the contribution of a financial institution to systemic risk, defined as "the propensity of that institution to be undercapitalized when the system as a whole is undercapitalized". The Systemic Expected Shortfall proposed by Acharya et al. (2016) is relatively similar to the SRISK, but according to Brownlees & Engle (2016) it may not be as practical, for it requires to observe a systemic crisis in order to measure the systemic risk of a firm. They put forward the argument that SES may overlook the significant aspect of risk building up in the background during low volatility periods and manifesting only when a crisis bursts. SES is calculated as the linear combination of leverage and one step ahead MES[2].

[2] *Computed quite similarly to MES for SRISK, based on a GARCH-DCC approach. The approach of Acharya et al. (2016) differs in that the MES they compute is time invariant.*

Adrian & Brunnermeier (2016) derive CoVaR, a measure of systemic risk, from the very common Value at Risk – VaR used by most financial institutions. CoVaR is the Value at Risk of the financial system conditional on an institution undergoing financial distress. Moreover, ΔCoVaR is the contribution of an institution to systemic risk computed as the difference between CoVaR conditional on the distressed financial institution and CoVaR conditional on the normal state of that institution. The authors compute ΔCoVaR using quantile regressions, but it can also be estimated through GARCH-type models. They compute ΔCoVaR based on weekly data (1971-2013) for US commercial banks, brokers and dealers, real estate companies and insurance companies, all traded on stock exchanges. The main difference between CoVaR and SES is hence the directional approach: Acharya et al. (2016) assess the firm's financial distress conditional on systemic distress, while Adrian & Brunnermeier (2016) measure the systemic distress generated by the individual firm's distress. Girardi & Tolga Ergün (2013) estimate Adrian & Brunnermeier's CoVaR by using both the normal distribution and the skewed-t distribution for the GARCH model. They find that using the skewed-t distribution, and thus taking skewness and kurtosis into consideration, provides for better consistency of the CoVaR obtained. Lopez-Espinosa et al. (2012) apply a generalized version of CoVaR on a sample of international banks and confirm that banks relying exceedingly on short-term debt bear higher risks, hence acting as primary sources of systemic risk. Hautsch, Schaumburg & Schienle (2014) build on the VaR methodology, in order to identify systemically important institutions. If an institution's incremental contribution to the VaR of the system is statistically significant and positive, then the institution is considered systemically relevant.

Authors such as Battiston et al. (2012), or Acemoglu et al. (2015) focused on the architecture of the financial network and how the shape and the nature of financial interlinkages favour shock transmission. Acemoglu et al. (2015) discover that once negative shocks surpass a specific threshold, dense financial linkages are more prone to contagion, whereas the same densely interconnected system is actually more resilient when shocks have a lower magnitude. This is in line with Battiston et al. (2012), who also conclude that moderately integrated systems are the most resilient to shocks. Allen, Babus & Carletti (2010) analyse whether financial institutions' debt maturity is in any way correlated with the shock resilience of the network structure.

They discover that for long-term debt, the network structure is rather irrelevant. Conversely, when banks rely on short-term financing, the network structure becomes of utmost importance, as positive or negative signals determine investors to (or not to) roll-over the debt. Results show that in the event of negative signals, investors are more inclined towards avoiding rolling-over the debt in densely interconnected systems. Cont, Moussa & Santos (2010) contribute to this strand of literature by introducing two measures aimed at localizing sources of systemic risk in an interconnected structure: the counterparty susceptibility (measuring creditors' sentiment towards the default probability of the liable institution), and local network frailty (measuring the upsurge of systemic risk when a network node defaults).

Anginer, Demirguc-Kunt & Zhu (2014) use the credit risk model of Merton (1974) to derive default risk and examine the risk-taking behavior of banks in relation to the network structure. They also approach the issue of financial architecture and systemic risk, but switch their attention to competition rather than financial interlinkages. They find that greater competition fosters stability, because it is an incentive for banks to diversify risk. It follows that the lack of competition makes banking systems less resilient to shocks.

Giglio, Kelly & Pruit (2016) compute several systemic risk measures proposed in the literature in order to examine their consistency in predicting changes in the distribution of macroeconomic shocks in the future. Relying on the hypothesis that these measures do not capture properly the latent systemic risk factor, they compute two estimators – the principal component quantile regression (PCQR) and the partial quantile regression (PQR). By running PCQR and PQR on the cross-section of systemic risk indices, they find that these are more consistent in predicting macroeconomic shocks, but only with the prerequisite of mild conditions. Tarashev, Borio & Tsatsaronis (2010) propose an existing measure that can be computed in conjunction with several systemic risk measures: the Shapley Value of Shapley (1953). They find that the Shapley Value feature of assigning to players their incremental impact on the wider groups makes it appropriate for measuring systemic risk. Intuitively, in terms of financial institutions, individual risk accounts for the difference between systemic risk of the group including the institution and the systemic risk of the group without it. Gauthier, Lehar & Souissi (2012) quantify macroprudential capital requirements by also computing Shapley Values, ΔCoVaR (Adrian &

Brunnermeier, 2012), the MES of Acharya et al. (2016)[3] and VaR (Jorion, 2007). They prove that capital requirements are able to reduce a bank's default probability by 25%, and the probability of simultaneous defaults of several banks by 41%. Rodriguez-Moreno & Peña (2013) compute and compare different systemic risk measures, and results show that methods based on credit default swaps (CDSs) are more consistent than stock or interbank market-based ones.

Providing meaningful systemic risk quantification methods has become an ambition of the academic field and the impressive amount of studies prove the difficulty of this task.

4. Concluding remarks

Systemic risk quantification has been addressed time and again in the academic field, in the attempt to offer valuable inputs for prudential policies. A central issue of this purpose is that any problem aimed at being solved needs to be clearly defined in the first place. The lack of a clear definition slackens the attempts of addressing and solving multifaceted problems like this. Given the continuously changing nature of the financial system, measurement tools have developed quickly to address diverse and progressively more complex aspects, thereby adding to the issue of establishing a universal framework of measuring systemic risk. It is clear that many risks stemming from different sources have provided for as many approaches and risk measurement tools built to emphasize various aspects.

In the aftermath of the 2008 crisis, the conspicuous underestimation of systemic risk has turned into a strong incentive for authors to develop comprehensive measurement techniques. Consequently, surveying the methods has proven to be a correspondingly difficult task. Among the most prominent challenges we emphasize the following: given the bewildering number of analyses, literature surveys cannot claim to be exhaustive, and secondly, complex methods become difficult to classify into broad categories. In

[3] *Time inconsistency in several instances throughout our paper is explained by the numerous earlier versions under working paper form of "Measuring Systemic Risk" by Acharya, V. V., Pedersen, L. H., Philippon, T., & Richardson, M. This is also the case for Adrian & Brunnermeier's "CoVaR" and Brownless & Engle's "Volatility, Correlation and Tails for Systemic Risk Measurement". Most of the times, for clarity purposes, we referenced the latest published versions.*

this respect, we tried to devise a brief overview of extant systemic risk approaches, from definition to a selection of measurement tools.

The conclusion that must be drawn is that systemic risk measurement is a worthy challenge for academia and policymakers alike, and a general consensus regarding the framework is neither attainable, nor desirable. Henceforward, although important steps have been made in this direction, systemic risk measurement and mitigation remain open issues.

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