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Measuring Systemic Risk: Past, Present and Future

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Abstract

Systemic risk has proven to be an elusive concept to define. Nevertheless, despite a lack of consensus on the definition of systemic risk, measuring and quantifying it has never been more important. In this paper, we present a survey of systemic risk measures. We explore the literature of current systemic risk measures and the history of the risk measurement to draw out implications for future research in quantifying systemic risk. We find two key conclusions; the first is that the balance sheet is a medium for systemic risk and this risk boils down to choices between debt and equity at the firm level. Finally, we propose a promising outlet of research by modelling balance sheet size growth as a bubble.

Keywords: Systemic risk, measures of risk.

1. Introduction

A financial institution or most other corporate entities for that matter, face two forms of financial distress: illiquidity and insolvency. Such firms pose a high risk of defaulting on obligations. When defaults occur across a system, the entire system faces annihilation. This is systemic risk: the risk of a system wide collapse.

Billio, Getmansky, Lo and Pelizzon [1] defines systemic risk as "any set of circumstances that threatens the stability or public confidence in the financial system" while the European Central Bank [2] defines systemic risk as financial instability risk 'so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffers materially.

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Other paradigms include experiencing systemic events, fragility, correlated exposures, feedback behavior, asset bubbles, contagion, externalities, information disruption and coordination failures, spillovers, and imbalances.

The problem to measurement is obvious as even a working definition or consensus definition of systemic risk is not even agreed upon. This lack of consensus about the exact defined nature of systemic risk creates unique problems in measurement. Specifically on how to measure something which the researcher cannot define. In this paper, we survey the literature on the measurement of systemic risk. We explore the history of measurement, current proposed measures and the future of measurement. We outline the importance of measurement and the need to measure systemic risk even when definitions are unclear at this point in time.

Exogenous or endogenous causes trigger a systemic event that becomes contagious and spread from one financial institution to another over a period of time. Systemic risk has a two dimensional character; the time series dimension that captures the evolution of systemic risk over time and the cross sectional dimension of risk that captures the distribution of risk in the financial system at a particular point in time [3]. Hence, the components of systemic risk can be inferred from the tools used to measure it, namely; leverage, liquidity, losses, linkages from the interconnectedness and interdependencies of institutions, capital shortfalls, correlations of assets and returns, susceptibility to external shocks, irrationality leading to bubbles and other behavioral components such as fraud leading to failures

The purpose of this paper is then to present a contemporary survey of the current state of systemic risk measurement in the context of past measures and to present new techniques and measures that may be helpful to future research in this area. Section 2 discusses the economic intuition behind systemic risk measurement. Section 3 presents the brief history of systemic risk measurement and theories of systemic risk. Section 4 presents a survey of current systemic risk measures, Section 5 presents the potential future of measurement and Section 6 concludes.

2. Economic Importance and Significance of Systemic Risk Measures

2.1. The Role of Systemic Risk Measures

Systemic risk is a topic of great interest to regulators, policy makers and to academic research simply because of the grave consequences of a financial crisis inflicted upon the masses in the form of foreclosures, loss of employment and bankruptcy, and the importance of systemic considerations in the context of prudential regulation and policies in risk management and financial intermediation. Hence, it is important to have measures that can assist in detecting, monitor and guide the orderly resolution of any financial crisis.

Systemic risk measures can be applied to policy applications by: identifying systemically important institutions, identifying specific structural deficiencies, identifying the potential shocks, provide an early warning signal. The decision making horizon of systemic risk measures span three categories according to an event; ex-ante, contemporaneous, and ex-post measures to an event.

Ex- Ante measures provide early warning signals by identifying any accumulating imbalances, fragilities or bubbles that may become a systemic threat if not given due attention and action. Examples are the macroeconomic boom-bust model of Alessi and Detken[4] and the distressed insurance premium model of Huang, Zhou and Zhu [5]. After a crisis or systemic event has occurred, crisis response by policymakers to monitor the risk situation becomes of paramount importance to ensure the crisis remains contained.

Contemporaneous systemic risk measures allows for monitoring of fragility of institutions and the system and also for crisis monitoring. Adrian and Brunnermeier's [6]CoVaR measures provide indications of fragility by being updated with frequent data. For the purpose of policy response, systemic risk measurement in the ex- post scenario of a crisis can help to calm markets and investor, shed light on the causes of the crisis and to ensure future accountability so that markets and regulations can be redesigned to avert future catastrophes [7]. Getmansky, Lo, and Makarov's [8] ex- post analysis of serial correlation and illiquidity in hedge funds and Sapra's[9] examination of the role of marked-to-market accounting in sowing the seeds of the crisis are excellent examples of post mortem crisis analysis. Figure 1 illustrates the role ofsystemic risk measures.

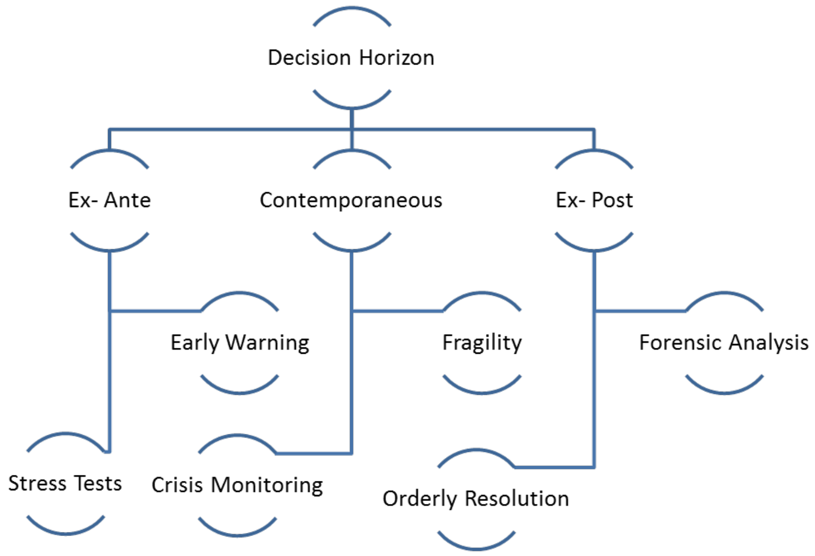

Figure 1: The role of systemic risk measures

2.2. Endogenous nature of Systemic Risk: The role of the balance sheet

Equity is the risk capital of a firm, contributing to stability and solvency. Debt is used as leverage to increase earnings by contributing more capital to finance assets. The most commonly used measurement that captures the relationship between equity and debt is the gearing ratio; total debt/ equity ratio or the leverage ratio; total assets/ equity ratio. The gearing ratio measures the risk of a firm's capital structure and serves as the most common screening device for financial condition. The higher proportion of debt, the greater the likelihood of insolvency, illiquidity and distress [10]. The choice between debt and equity and the optimal mixture of both is one of the most important managerial decisions. The balance sheet itself can become a source and mechanism of financial contagion that may lead to a system wide collapse [11].

Static tradeoff theory and the pecking order theory [12], [13] especially disagree when it comes to securities issuing and securities repurchase decisions. de Jong, Verbeek and Verwijmeren [14] investigate this issue and find that for issuing decisions, the pecking order theory prevails as firms prefer to increase debt although already above the targeted debt ratio. While for repurchase decisions, the static tradeoff theory prevails as firms prefer to repurchase the securities earlier issued to continue increasing leverage when below the target debt ratio. The debt overhang theory of Myers [15] predicts that higher leverage increases the probability of the firm underinvesting which affects future earnings and result in lower stock prices. There are disagreements on the impact of leverage change and future firm performance. Dimitrov and Jain [16] provide empirical evidence that increase in leverage is negatively related to deteriorating firm performance which impacts future stock prices negatively. However, Cai and Zhang [17] find no such evidence. The choice between the amount of debt and equity is clearly a source of risk. This risk emanates from the balance sheet and increases the default risk of firms as leverage increases. The importance of debt overhang was clearly illustrated in the global financial crisis when governments struggled to make the right decisions on whether to use asset purchase or equity interventions to efficiently recapitalized highly leveraged banks that failed [18].

Equity as the risk capital and liabilities posing liquidity and insolvency risks to the firm. Hence, assets are practically financed by risk. The interplay or entanglement of the relationship between assets, liabilities and equity creates systemic endogenously from the balance sheet where each element carries its own risk. The most common ratios used to assess financial condition are the leverage ratio, gearing ratio and the quick ratio or the current ratio. The inherent nature of risk in the balance sheet was formally exploited by Altman [19] in a seminal work that used ratios to predict corporate bankruptcy.

Systemic arises and propagates through the balance sheet due to the procyclical nature of the balance sheet being tied to the business cycle. This is due to the procyclical nature of leverage and capital [20], [21]. This is due to the expansion in good times and contraction of the balance sheet in bad times. This expansion of the asset side is financed by debt in the form of increased borrowing either through loans or selling asset backed securities. In the recent crisis, equity remained approximately the same throughout and hence played the role of the forcing variable and expansion took placed via debt instead of equity. The expansion of the balance sheet in fact points to active risk management by intermediaries in response price changes and perceived risk.

3. The Past: History and evolution of systemic risk measures

The history of measuring risk began earnestly more than five hundred years ago. Risk was viewed as the fate of humanity and required divine intervention to alter the nature risk. Risk was measured subjectively through emotive feelings. In 1654 Blaise Pascal and Pierre de Fermat laid the foundation of probability theory and this allowed for the first time the computation of event probabilities as the measure of risk. The next theoretical developments occurred in the 1700's when Jacob Bernoulli formulated the law of large numbers. Abraham de Moivre then derived the normal distribution or the bell curve which was then refined by Gauss and Laplace. The measure of risk was now the sampled probabilities of a population. In 1763, Thomas Bayes introduced Bayesian statistics where existing subjective beliefs are called prior probabilities and these values can be revised in light of new evidence was known as posterior or conditional probabilities. With this innovation, statistical measures of risk came in to being and were utilized by insurers to construct actuarial measures of expected losses that were based on historical data. In 1900, Louis Bachelier published his thesis, The Theory of Speculation. His random walk model is now standard in finance literature. Studying the behavior of stock and option prices, the measure of risk was the price variation over time. At about the same time, access and reliability of financial reports of corporations were much improved. This gave rise to the use of accounting information to construct financial ratios that were used as indicators of risk of a particular firm. Ratios such as profitability ratios (return on equity), and leverage (debt to capital) were used by ratings agencies to provide ratings on bonds as a risk indicator (see Damodaran [22] for a historical review of risk measures).

In the 1950's, Harry Markowitz introduced the Portfolio Theory (now called Modern or MPT). For the first time, risks in the context of stock returns were quantified. Markowitz [23] used standard deviations of stock returns as a proxy for risk. Building on the works of Markowitz, Jack Treynor, William Sharpe, John Lintner and Jan Mossin independently derived the core mechanics of asset pricing which we know as the Capital Asset Pricing Theory (CAPM) [24]. The CAPM models risk as the sensitivity of the expected excess asset return to the expected excess market return or the ubiquitous $\beta = \frac{Cov\ (R_i,R_m)}{Var\ R_m}$. Hence, β is a measure of stock return volatility.

Mandelbrot [25], [26] and Fama [27] proposed for more attention to be paid to heavy tails as a measure for risk of large price movements; rare events or disasters. They proposed that a symmetric Levy probability distribution function to be most appropriate to describe the stochastic properties of commodity changes and price changes. During the same period of the 1960's, accounting based financial ratios made a comeback as a measure or indicator for risk. Altman (1968) introduced the Z- score in a seminal paper that proposed the use of certain financial ratios from balance sheet items identified to be most relevant to bankruptcy risk by applying multiple discriminant analysis. In the 1970's Ross [28] developed the arbitrage pricing model (APT). The APT replaces the single market risk factor β (measures risk added by a single asset to the market portfolio) with multiple factor β (measures an asset's exposure to each individual market risk factor). Fama and French [29] then extended the factor model to explore firm specific characteristics in explaining stock returns. They found that market capitalization and its book to price ratios were the best proxies of risk measurement in explaining the difference in returns across stocks between 1962 and 1990 versus the CAPM βs.

The Value at Risk (VaR) measurement which was introduced by J.P. Morgan in 1994 became the standard adopted risk management tool even until today [30], [31]. In particular, VaR has been adopted as a risk measure in the Basel- II Accord for modeling credit, liquidity and operational risk.

A major breakthrough in the conceptual understanding of risk and the measurement of systemic risk came in 1999 when Artzner, Delbaen, Eber and Heath [32] proposed that for any acceptable measure of risk, it must be coherent and therefore satisfy four axioms of coherence which they propose to be positive homogeneity, subadditivity, monotonicity, and translational invariance. These axioms have major implications in the construct of a useful measure of risk especially in the diversification of portfolio risk. Risk management is usually performed at a micro level of individual assets or sub- portfolios, for example the risk at a single equity trading desk or a single subsidiary of a corporation. Therefore, the axioms of coherence are of utmost importance as risk should be measured in its aggregate across portfolios and the single entity of a corporation as risk is derived from the risk taking actions of economic agents within the same firm. Positive homogeneity requires that portfolio size should linearly influence risk; the larger the portfolio, the larger the risk. Subadditivity is the most important axiom for risk measures especially in risk management. A risk measure that is not subadditive may report that the sum of risk of two different portfolios may be more than the total risk of the individual two portfolios separately. Monotonicity is also intuitively reasonable in that if a certain portfolio X is always worth at least as much as Y, then surely Y cannot possess more risk than X. Translational invariance ensures the expression of risk measures is in the appropriate units. This means that adding or subtracting an amount α to the initial position and investing it in a reference instrument simply decreases or increases the risk measure by the similar α.

However, it is important to note these axioms of coherence are still much debated especially on the nature of its applications [33]. Bollerslev and Todorov [34] argue that coherence may apply to standard measures of tail risk that only depend on the actual probabilities for tail events to occur but not the pricing of these tail jumps. Moreover, while VaR has been criticized for being subadditive, Garcia, Renault and Tsafack [35] and Ibragimov[36] show that VaR can satisfy the subadditivity criteria if the tails of the marginal distributions are reasonably thin and asymmetric. Hence, when risks are not extremely heavy tailed, diversification is still preferred and VaR can satisfy subadditivity [37]. On the subject of mergers, subadditivity implies that corporate mergers do not create extra risk via diversification. However, Dhaene, Goovaerts, and Kaas [38] argue that, mergers may increase risk especially when there is bankruptcy protection for institutions. Notwithstanding the debate regarding the axiomatic approach, Chen, Iyengar, and Moallemi [39] propose an axiomatic approach to systemic risk measurement and demonstrate the application of these axioms in other risk measures such as VaR, CoVaR, expected shortfall, contagion models, and deposit insurance measures. The authors attempt to define the axioms for the single firm risk measure and extend it to a systemic context. Notable contributions by these authors include axioms on how risk is to be aggregated across the system, the representation of systemic risk measures and the attribution of systemic risk to individual agents in the economy.

Much of the past work had focused on the task of assessing the risk of financial positions at a point in time using historical data. Hence, measures such as VaR and coherent risk measures are static (one period) in nature [40]. To address this issue, a risk measure should be able to deal with the question of evaluations of risk at different or multiple periods are related as a sequence of conditional risk measures [41]. Risk measures have to be dynamic in adapting to changes in the market or within the firm so that risk management can be dynamic as well [42]. Cvitanic and Karatzas [43] propose a dynamic coherent measure of risk as the smallest expected discounted shortfall that can be achieved from a certain set of trading strategies from a class of admissible portfolios. [44]further expanded the conceptual framework of dynamic risk measures by introducing the element of time consistency where judgments made by individual based on the risk measure are consistent and not contradictory over time. .

Dynamic measures using continuous time methods include the familiar Merton [45] credit risk model (contingent claims and distance to default) based on geometric Brownian motion were also proposed. [45] proposed a model for assessing the credit risk of a non- financial firm by viewing the firm equity as a call option on its assets and this approach has been extended to model the equity of banks as a call option on the market value of its assets. This model of credit risk gave birth to two strands of literature on default risk; the structural models where bankruptcy is modeled as microeconomic model of the firm's capital structure and the reduced form models that model bankruptcy as a statistical process. The notable difference is that reduced form models assume that the key variable is the time to default that follows a Poisson process where the intensity of the process depends on exogenous variables [46]. Notable structural models include the models of Kim, Ramaswamy, and Sundaresan [47] where default is induced by liquidity when cash flows are insufficient to meet coupon demands. The most well-known reduced form model of default risk is the model of Jarrow and Turnbull [48] where the default event is modeled as a Poisson process; the default time is the first jump of a Poisson process that is independent of short term interest rates. This foundational cornerstone is utilized by modern systemic risk measures by numerous authors; [42], [49], [50], [51], and [52] among others to construct dynamic continuous time measures of systemic risk. Another novel method completely different from the Merton model using a dynamic geometric approach was proposed by Bahiraie, Azhar, and Ibrahim [53]; the Dynamic Risk Space (DRS) measure that allows the visualization of the evolution of transformation from the changes in financial ratio values where pairs of risk variables are represented on Cartesian coordinates.

3.1. Theories of systemic risk

Diamond and Dybvig [54] in their seminal paper on bank runs posit that banks are providers of insurance for depositors against liquidity shocks. A bank run is seen as a self-fulfilling prophecy triggered by the fear of early withdrawals by a sufficiently large number of depositors. Diamond and Rajan [55] study the optimal bank capital structure and its role in liquidity creation. In their model, they show that under uncertainty which increases deposit fragility to runs, bank capital which reduces the probability of financial distress to the bank also reduces liquidity creation and the amount the bank can induce borrowers to pay.

Diamond and Rajan [56] then further study the beneficial role demandable debt. They propose in an incentive framework without asymmetric information and loan liquidation costs that deposit contracts commits banks to liquidity creation by satisfying depositors' withdrawals needs while simultaneously shielding long term borrowers from liquidity shocks despite having relationship related power in loan collection. Based on this model, Diamond and Rajan [57] further argue that bank failures can trigger and propagate a systemic crisis even in the absence of a panic driven run. This is due to the inherent structure of banks that finance illiquid assets with demandable claims. In essence, illiquidity stems from the bank's asset side of the balance sheet. A common theme of these studies is the effect of illiquidity arising from bank runs on deposits as a manifestation of systemic risk being the trigger to a systemic crisis.

Lagunoff and Schreft [58] propose a model of financial fragility and show how overlapping claims on a firm can cause small shocks that lead to system wide bankruptcy. Allen and Gale [59] define financial system fragility when disproportionately large effects seen as defaults or asset price volatility are caused small aggregate shocks in the demand for liquidity. Bianchi [60] study 'over-borrowing' by private agents in a dynamic stochastic general equilibrium framework and show how it evolves into a systemic credit externality that amplifies the incidence and severity of a financial crisis.

Allen and Gale [61] proposes a model of bank contagion that addresses the role of interbank lending by focusing on the physical exposures among banks in different regions and the correlated liquidity needs of respective depositors. An inter- regional contagion of bank failures can then occur depending on the amount of liquidity a bank has in a particular region that experiences withdrawals and how much other banks in other regions will be affected if bank in the affected region begin to withdraw their interbank deposits.

Acharya and Yorulmazer [62] propose a theory of systemic risk without inter- bank linkages. The authors propose that systemic risk is reflected on the liability side of banks caused by a revision in borrowing costs of surviving banks in the wake of the failure of others.

Allen and Gorton [63] proposed a continuous time model with a finite time horizon where the agency problem between investors and portfolio managers produces bubbles although all participants are assumed to be rational. Shleifer and Vishny [64] within the context of originating and distributing of securities by banks in financial markets propose that systemic risk is created due to the profit maximizing behavior of banks catering to investor demand during good times which lead to balance sheet expansion. This profitable expansion during good economic times causes instability as these banks will have to liquidate their portfolio holding as fire sale prices which are below fundamental values in bad times leading to major downward revisions of security prices in a downward spiral.

Acharya [65] defines systemic risk as the risk of joint failures caused by the correlation of asset returns of bank balance sheets. Systemic risk arises from the preferences banks have for highly correlated asset returns which manifest as aggregate risk. The author proposes a theory of systemic risk where banks have a systemic risk shifting incentive that depends on the health of other banks as failure acts as negative externality.

4. The Present: Contemporary systemic risk measures

4.1. Paradigms of systemic risk measures by research methodology

Broadly, instruments to measure systemic by research methodology include probability distribution measures, contingent claims and default measures, illiquidity measures, network analysis measures, macroeconomic measure, financial fragility, contagion and tail risks and rare events measures. An alternative class of measurement stems for the interdisciplinary field of econophysics in the form of complexity.

4.1.1. Measures of systemic risk by research methodology

Adrian and Brunnermeier [6] propose to measure systemic risk by proposing the conditional value-at-risk (CoVaR) of the financial system, conditional on the distress of individual financial institutions. The authors measure the contribution of a single institution to system wide risk through the difference between the CoVaR conditional on the institution being in distress and the CoVaR in the median state. The authors find that the link between a single institutions's VaR and its contribution to systemic risk measured by CoVaR. Further analysis found that certain characteristics of the firm were good predictors of systemic risk in the form of CoVaR; higher leverage (total book assets/ total book equity ratio), higher degree of maturity mismatch between liabilities and assets and larger size as measured by total assets. While Adrian and Brunnermeier's CoVaR focuses on measuring system wide risks, Acharya, Pedersen, Philippon and Richardson [66] propose the systemic expected shortfall (SES) to measure an institutions' contribution to systemic risk. SES measures the likelihood that an institution will be undercapitalized in the event the whole system is undercapitalized as well. The authors use three data sources as proxies to construct the SES. They use the outcome of stress tests performed by regulators to determine the minimum required capital in the event of a crisis, daily returns of equities of financial firms and credit default swap spreads to develop two leading indicators of SES; the marginal expected shortfall (MES) of the firm and the leverage ratio. Cross sectional regression is performed with SES as the function of MES and leverage. Further analysis on the levels of systemic risk of financial firms found that surprisingly, insurance firms contribute the least systemic risk. Securities brokers were found to be the riskiest and leverage to be key driver of systemic risk.

Giesecke and Kim [67] propose a reduced form model to capture the timing of banking defaults, the effects of direct and indirect linkages among financial institutions and the regime dependent behavior of their default rates. The measure of systemic risk is the default rate jump intensity derived from a continuous time framework. Default is defined as a missed or delayed payment, bankruptcy, a distressed exchange where the issuer offers debt holders new securities with lessened obligations, or an exchange that is purposely created to prevent the borrower defaulting. Using a data of all corporate defaults from January 1, 1970 to December 31, 2008, the authors found that in the event of a failure, the default rate jumps and the magnitude of the jump is a function of the value of the default rate just before the event. Related measures by other authors on the Merton framework were also proposed by [49], [50] and [51]. Using a sample of international banks, Lehar [49] estimates the dynamics can correlations between bank asset portfolios. Taking a regulator's perspective, he models the individual liabilities that the regulator has on each bank as a contingent claim on the bank's assets by viewing the banks under the regulators supervision as a portfolio of banks. Empirical analysis found that larger and more profitable banks have lower systemic risk and additional equity reduces risk.

Hu, Pan, and Wang [68] propose to measure liquidity risk by examining the amount of capital available for arbitrage in the market and its impact on price movements in the U.S. Treasury securities market. This is based on the observation that in periods of crisis, the shortage of capital causes yields to deviate more freely from the yield curve which results in more 'noise' in the data in an otherwise low intrinsic noise market. They propose to use this noise as a measure of liquidity. Findings reveal empirically that noise indeed is closely related to crisis periods and tends to be heightened during such times to indicate the lessening of available capital in the bond markets.

More recently, Drehmann and Nikolaou [69] explore the issue of liquidity in banking and its relation to provisions of liquidity by central banks. The authors construct a measure of systemic risk that arises from the bidding of funds at central bank auctions by banks. A bank's bid for funds reveals its funding liquidity risk. They construct a measure of funding liquidity risk as the sum of the premium banks are willing to pay above the expected marginal rate times the volume bidden, normalized by the expected amount of money supplied by the central bank. This measure can be interpreted as the weighted average insurance premium against funding liquidity risk. Using a unique and confidential data set of all bids in all auctions by European banks conducted at the European Central Bank (ECB), they find that funding liquidity risk spiked around key events of crises.

Nier, Yang, Yorulmazer and Alentorn [70] investigate how systemic risk relates to the structure of the system; capitalization, degree of connectedness, size of interbank exposures, and the degree of concentration. The authors construct a banking system network consisting of 25 banks connected by interbank linkages as a simulation tool. They then simulate shocks and evaluate changes in the structural parameters. Key findings are that better capitalized banks support a more resilient system against contagion, small increases in interbank connectivity increases the contagion effect but only up to a certain threshold where connectivity actually increases system resilience, the larger the size of interbank exposures, the larger the risk of external shocks, and the more concentrated the system is, the levels of systemic risk is also higher.

Krause and Giansante[11] extend network analysis of banks even further by incorporating the structure of the balance sheet in construct a network of interbank loans. The amount of capital, cash, interbank loan exposure as lenders and borrowers are taken into account via simulation of the network. The authors measure contagion as the fraction of failing banks in the simulation. The key findings of the simulation point to bank size being the prime factor determining the occurrence of contagion in the system. But the extent of which contagion spreads is determined by the network structure of interbank loans which measure the degree of interconnectedness among banks.

Brunnermeier, Gorton, and Krishnamurthy [71] propose the risk topography of the financial system that involves the process of data acquisition and dissemination that informs policymakers, researchers, and market participants about systemic risk. They propose that to measure liquidity (or illiquidity), it is insufficient to just examine measure of current assets; volatility, spreads, etc. A liquidity index for a firm is constructed as the aggregate of the change in the firm's total assets to the change in the risk factor.

Maino and Tintchev [72] further expand stress testing of individual countries to co- stress testing related financial institutions. The authors model bank capital asset ratios (total capital/ risk weighted assets) which are used as regulatory capital requirements in Basel II as a function of future losses and credit growth using a generalized method of moments to calibrate adverse shocks to credit quality (represented by non- performing loans) and credit growth. Their proposed measure of systemic risk: the CoStress, mirrors the CoVar measure described earlier and captures the tail risk co- movements among banks in the system. They define this measure as the level of banking stress conditional on the distress of individual banks. The key finding from empirical analysis is that credit risk is a major systemic vulnerability. Banks with weak capital buffers and a high proportion of non- performing loans were vulnerable to moderate credit quality shocks and therefore very vulnerable to insolvency.

The relationship of liabilities, capital and assets to systemic risk was further explored by Geanakoplos [73]. The author points out that the collateral rate (leverage) is an equilibrium variable separate from interest rates. Major movements in the collateral rate are the result of the leverage cycle and hence can be an indicator of systemic risk. Geanokoplos and Fostel [74] further investigates the leverage cycle in the housing sector via agent based simulations from 1997 to 2009. The authors find that leverage as represented by the desired loan to value of the property ratio (LTV) was the key factor driving the boom and bust of 1997 to 2010 instead of interest rates.

Aspachs, Goodheart, Tsocomos and Zicchino [75] define financial fragility as a combination of high default probabilities and low profit variously measured that can be applied with necessary modifications to individual and aggregate levels. The authors propose a measure of fragility based on the economic welfare in a general equilibrium model. Fragility is then indicated by the adverse effect on an agent's welfare in the event of defaults that induce distress in the financial system. They find that exogenous shocks decrease welfare if the shocks induce distress in the system and that banks that are CAR constrained do not exhibit a fall in profit as expected. The interplay between capital and assets point that banks needing to maintain CAR would choose riskier investments to raise profit and this increases systemic risk in the form of increased default probabilities.

Moussa [76] within a network analysis context, propose a Contagion Index (CI) that measures the systemic importance of financial institutions in combination with both market and credit risk factors. The author defines CI as the expected loss of capital to the network triggered by the default of a financial institution when the whole system is hit by a market shock resulting in a cascade of defaults. Performing Monte Carlo simulations, it is found that the CI is heavy tailed indicating that only a few institutions pose a high contagion risk to the system.

De Jonghe [77] extends the tail- β methodology to focus on the micro level of banking to identify specific characteristics of banks that contribute to systemic risk specifically the diversification of revenue. Systemic risk is measured by the tail- β which indicates the probability of an extreme decline in a bank's stock price conditional on a crash of the banking index. Sampling balance sheet data (income sources, total assets, equity, and loans), bank daily stock returns and market capitalization of selected European banks from a period starting from 1992 to 2007, the author performs similar semi- parametric estimation. Key findings show the degree of non- interest income can increase the tail- β and therefore providing evidence that the increase in non- interest income increases systemic risk in agreement with other studies such as [78]. Additionally, the study provides evidence that smaller and better capitalized banks are able to cope better with extreme shocks.

5. The Potential Future: Alternative Measures of Systemic Risk

[80], [81], [82] and [83] study the properties of stock returns using high frequency data of all stock returns for all securities listed on the New York Stock Exchange (NYSE). [82] study overnight and daytime returns and hence use daily opening and closing prices for all stocks listed on the NYSE on December 31, 2007. They found that follows a power law distribution in its tails and return intervals display scaling and memory of past movements. Similar to climate and earthquake data, systemic risk as the occurrence of a rare event lying in the heavy tails is quantified from power law distributions. [81] show that the distribution of financial ratios and even Altman's (1968) Z-score is characterized by power laws and scaling. This suggests that future development of endogenous and systemic risk metrics should be based on the natural distribution of balance sheet variables at book values.

Caetano and Yoneyama [84] propose to detect the occurrence of an imminent stock market drawdown as a measure of systemic risk. With a wavelet decomposition method detecting abrupt changes in a time series of stock market indices; The Hong Kong Hang Seng and the Brazilian IBOVESPA covering the pre and post-crash of 1929 and the recent 2008 market crashes, the behavior of wavelet coefficients was found to be provide useful insights on the probability of a future drawdown. Aggregates of the information provided by the coefficients is used to create an index which showed good capabilities of monitoring crashes and drawdowns. Caetano and Yoneyama [85] propose a novel measure of systemic risk as a catalytic chemical reaction by modeling the Hong Kong Hang Seng, U.S. Dow Jones and the Brazilian IBOVESPA index from 1993 to 2007 based on this apporach. The measure of risk is the degree of influence of one index on the other. They show how a strong market represented by the Dow Jones as the reagent with high concentration in a chemical process can influence the behavior of lesser markets represented by the Hang Seng and IBOVESPA. Performing 200 Monte Carlo simulations, they calculate the VaR for each market and show that the larger market does significantly influence the dynamics of smaller markets.

The Fractional Market Hypothesis (FMH) was proposed to address the deficiencies of its Efficient predecessor. Blackledge [86] proposed the use of a non-stationary fractional dynamic stochastic model of economic signals to assess systemic risk. He models the time varying Fourier dimension of the fractional diffusion equation to measure market volatility. Increasing values of the Fourier dimension suggests that the probability of volatile market behavior increases. Performing a case study on the subprime credit default swap ABX index from July 24, 2006 to April 2, 2009, the model is able to show that the index exhibits a clear phase transition period or criticality which preceded the crash of 2008.

Log periodic models of price bubbles were proposed by [87]. Studying market crashes as analogous to earthquakes, the authors posit that similar to other large complex dynamic and non-linear systems, stock market crashes are caused by the slow accumulation of long range correlations that lead to a collapse in one critical moment. The challenge is to capture this self -critical instant and describe its behavior before and after the crash. Building on previous works; [88] among others, they propose a log- periodic power law (LPPL) model that models volatility as oscillations of the system.

The measure of a bubble is the faster than exponential rate of increase in asset prices driven by accelerating oscillations. The model is designed to capture the positive feedback loop of higher return expectations of participants and the negative feedback loop of crash expectations. Testing on the Shanghai and Shenzhen stock index between May 2005 and July 2009, they found the stock market evolved into critical states from around the middle of 2005 and November 2008 and predicting the bursting of the price bubble in October 2007 and August 2009. Gnacinski and Makowiec [89] showed that there is a third bubble called the inverted bubble where after drawdowns had occurred, extraordinary draw-ups occurred after the log- periodic behavior had ended.

6. Conclusion

While the measurement of systemic risk is ‘fuzzy’ and compounded by a lack of even an agreed definition, it is still nonetheless of utmost importance to attempt to measure and track its evolution. The simple reason of preventing catastrophe is sufficient enough. The key determinants of systemic risk identified in current literature are the components of leverage and liquidity. Specifically, debt in the form of short term debt is identified to be the major culprit. This is a shift from the past focus on the asset side of the balance sheet where much theory, measurement, policies and regulations have been put into place to keep assets safe to the liability side. For banks, Tier 1 capital requirements and deposit insurance were created to keep deposits less prone to runs and other measures to ensure borrowers repay their loans. However, the realisation that debt should receive more attention has been proven with Basel III liquidity and funding ratios due for implementation to ensure sufficient capitalization that depends less on debt or at least the less stable forms of debt.

The choice between the amount of debt and equity is clearly a source of systemic risk. This risk stems from the balance sheet and increases the default risk of firms as leverage increases. Default by systemically important firms or institutions can then cause risk to become systemic threatening the stability of an entire system. The importance of debt overhang was clearly illustrated in the global financial crisis when governments struggled to make the right decisions on whether to use asset purchase or equity interventions to efficiently recapitalized highly leveraged banks that failed [18].

A promising area we wish to draw the reader's attention to is the study of bubbles. Usually price bubbles are studied. We suggest that the key elements of the balance sheet be measured as a bubble, especially debt and equity. The LPPL methodology can be applied to the size of the balance sheet. Faster than exponential rate of balance sheet size expansion based on book values can be a promising measure of risk and thus reflect the magnitude of systemic risk. The LPPL methodology yield a potential method to measure both endogenous and systemic risk as the LPPL specification takes into account rational expectations, herding potential, and process of bifurcations and phase transitions. [90] use repo data to study the behavior of leverage bubbles with this method. Further research down this methodological line with book value balance sheet data could be promising.

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