ELLIS, S., SHARMA, S., and BRZESZCZYŃSKI, J. 2022. Systemic risk measures and regulatory challenges. *Journal of financial stability* [online], 61, article 100960. Available from: https://doi.org/10.1016/j.jfs.2021.100960

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ELLIS, S., SHARMA, S., and BRZESZCZYŃSKI, J.

2022

Systemic Risk Measures and Regulatory Challenges

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ABSTRACT

This paper discusses different definitions of systemic risk and identifies the challenges regulators face in addressing this phenomenon. We conducted a systematic literature review of 4,859 abstracts to categorise the various methodologies developed to measure systemic risk. In total, 60 systemic risk measures proposed post-2000 have been critically appraised to inform academics and regulators of their practical applications and model vulnerabilities. This review suggests that most of these methods focus on individual financial institutions rather than system stability. Those methodologies directly reflect the current regulations, which aim to ensure individual institutions' soundness. As macro-prudential regulation evolves, policy-makers face the issues of understanding contagion and how regulations should be implemented. This paper also discusses new systemic risk and regulatory challenges resulting from the current COVID-19 pandemic.

KEYWORDS
Systemic Risk; Systematic Literature Review; Data Requirements; Macro-prudential Regulation; COVID-19 Pandemic

JEL CLASSIFICATION
G01; G15; G2; G28; C58; C6

1. Introduction

Global crises have highlighted the need for a better understanding of systemic risk and regulation of the financial system. The financial crisis of 2008-09 and the current COVID-19 pandemic have posed unprecedented challenges to the financial system (Rizwan et al. 2020). However, these two crises visibly differ. The financial crisis originated from the vulnerabilities in the global financial system, which spilled over into the real economy. The COVID-19 pandemic is a worldwide health emergency that, together with the containment measures, imposes a severe shock on the real economy and threatens to impair the financial system's stability (Buch 2020).

Eisenberg and Noe (2001) highlighted the need for a comprehensive approach to determine the financial sector's exposure to systemic risk before the 2008-09 financial crisis and the present COVID-19 pandemic. Over the last two decades, the financial markets have fundamentally changed and expanded globally, which has created numerous challenges for policymakers. As a result, there has been a plethora of interest in systemic risk in the financial industry among academics (Anginer and Demirguc-Kunt 2014; Bongini et al. 2015; Ellis et al. 2014; Rizwan et al. 2020; Silva et al. 2017; Wilson et al. 2010) and regulators (BIS 2009; IMF 2020b; Tarashev et al. 2009) alike. In addition, the process of removing regulatory barriers affected the dynamics of the market structure, which significantly transformed financial institutions' risk management characteristics, which potentially adds to the unintended consequences of systemic risk and financial instability (Goldin and Mariathasan, 2015).

This paper presents a systematic literature review to identify 60 methodologies developed to measure systemic risk post-2000. The reviewed methods are categorised into five types, depending on the risk area, and they are critically appraised. An earlier systematic literature review on systemic risk conducted by Silva et al. (2017) analysed and classified 266 articles on systemic risk to categorise systemic risk and produce an author network. Unlike the objective of this paper, Silva et al. (2017) did not seek to identify or critique the techniques and methodologies created to measure systemic risk. In addition, we summarise and present the data requirements necessary to calculate each different measure. Silva et al. (2017) concluded and suggested more comprehensive and comparative research of systemic risk measures that would enhance financial institutions' monitoring by discussing the advantages and disadvantages of each approach and checking where they clash or complement each other. Before Silva et al.'s (2017) study, Bisias et al. (2012) provided an overview of 31 quantitative systemic risk measures to present concise definitions and model requirements with open-source Matlab code with the objective to promote experimentation and innovation[1]. The main finding of our systematic literature review is that most of these measures tend to focus on individual financial institutions' risk rather than the entire banking system's stability. In addition, we identify the data typically used to measure systemic risk and the areas for future development. The most commonly used information is equity and fundamental data. One of the least used data types is from the foreign exchange market, even though it usually yields interesting and significant results when it is used to measure systemic risk. Generally, most methods use the US and European banking system data, so generalising the results elsewhere is difficult. Therefore, more comprehensive empirical evidence would be welcome to assess the extent and usefulness of these systemic risk measures for future global crises of different natures. Finally, based on the critical review of the systemic risk measures and in the light of the regulatory responses to the financial crisis and COVID-19 pandemic, we identify several challenges for policy-makers moving forward.

The remainder of this paper is structured as follows. In section 2 the methodology of the systematic literature review is presented. Section 3 critically appraises the 60 different methods developed to measure systemic risk. Section 4 identifies the data required to measure systemic risk. Section 5 discusses the challenges faced by regulators concerning systemic risk. Finally, Section 6 describes the research gaps and future research directions and Section 7 concludes.

2. Literature Review Methodology

The main challenge regarding systemic risk assessment and measurement is limited consensus on a widely accepted definition of this phenomenon. One of the first definitions from the BIS G10 stated that "systemic financial risk is the risk that an event will trigger a loss of economic value or confidence in, and attendant increases in uncertainly about, a substantial portion of the financial system that is serious enough to quite probably have significant adverse effects on the real economy" (BIS 2001, p. 126). Alternative definitions of systemic risk include (but are not restricted to): (i) a failure of a significant part of financial institutions (Acharya et al. 2011; De Bandt and Hartmann 2000); (ii) The risk that a national or the global, financial system will break down (Scott 2010); (iii) An impairment of the financial system (Adrian and Brunnermeier 2008); (iv) A correlation of defaults within the financial system over time (Billio et al. 2010); (v) A malfunctioning of the entire financial system (Bach and Nguyen 2012; Rodríguez-Moreno and Peña 2013); and (vi) a loss of economic value or a widespread loss of confidence in the financial system (Cummins and Weiss 2014).

A standard view is that systemic risk can be categorised by cross-sectional and time-series dimensions (Hartmann et al. 2014). Cross-sectional dimensions relate to the correlation of risk types throughout the system at given points in time. Time-series measurements relate to risk types or market conditions changes throughout, for example, the economic cycle or the

[1]See Giglio et al. (2016) for a comprehensive empirical study of 19 systemic risk measure identified in this paper.

potential development of asset/liability bubbles. The likes of asset/liability price bubbles tend to be more dangerous when credit is involved (Anundsen et al. 2016; Jordà et al. 2015; Virtanen et al. 2018). Individual financial institutions can impact the systemic risk of the financial system in a range of different ways. They are categorised as a *contribution to* and *participation of* systemic risk. *Contribution to* systemic risk arises from institutions' actions having knock-on effects on other institutions, which is known as moral hazards. Examples of this behaviour could be liquidating a financial institution's assets under fire sale and volatile market conditions (Coval and Stafford 2007; Shleifer and Vishny 1992). *Participation of* systemic risk relates to the financial institutions' susceptibility to amplifying systemic risk due to their inability to absorb macroeconomic or other institutional shocks.

As the quality and quantity of research conducted and published within the systemic risk literature have increased exponentially over recent years (Silva et al. 2017), our systematic review was performed using a combination of scoping and keyword searches. We used the key phases formalised by the Cochrane Collaboration[2] to ensure comprehensiveness and robustness (Jesson et al. 2011). During the search phase, various online databases and search engines were used[3], with a range of keyword and Boolean search terms[4] similar to Silva et al. (2017). Overall, the search identified 139,647 research articles, however most were rejected because of their title (e.g. literature relating to medical science and information technology). In addition, some duplicates were pre-2000, non-English and there was a non-availability problem. From the above-identified research articles, 4,859 were related to systemic risk in banking. The abstracts of these 4,859 articles were reviewed, and ultimately 60 articles related to the source of systemic risk or a new method of measuring it were selected.

Given that the 60 articles that focused on systemic risk measures were confirmed, it suggests very little agreement amongst academics and regulators about systemic risk or how it is measured. Nevertheless, there are benefits of model diversity. For example, if regulators impose a situation where institutions apply the same models, they may analyse potential shocks similarly. A possible consequence of this situation is that institutions could react similarly and cause further problems. Also, if certain institutions were not obligated to use particular models, they could use other models and gain a competitive advantage.

3. Models Proposed to Measure Systemic Risk

This section provides a comprehensive review of the systemic risk models based on the 60 identified articles. Without a precise definition of systemic risk, some elements are present in the various definitions that make it possible to understand Silva et al.'s (2017) study and categorise the types of systemic risk models. The models are broken down into five categories: (i) early warning and credit default swap indexes (17 models); (ii) capital (12 models); (iii) liquidity (6 models); (iv) contagion (10 models) and (v) network (15 models).

3.1 Systemic Risk Early Warning Systems (EWS) and Credit Default Swap (CDS) Indexes

A range of existing indexes allows regulators to gauge a country's macro-economic health. Within Europe, for example, the European Central Bank produces individual *Country-Level Index of Financial Stress* for the 28 countries. Duca and Peltonen (2013) discuss their

[2] The key phases are: (i) mapping the field *via* a scoping review; (ii) a comprehensive search; (iii) quality assessment; (iv) data extraction; (v) synthesis; and (vi) write up.
[3] Databases searched included ScienceDirect (10/12/18), Taylor & Francis Online (10/12/18), Business Source Premier (14/12/18), Emerald Insight (14/12/18), Scopus (15/12/18), Social Science Research Network (16/12/18) and Google Scholar (19/12/18). A further scoping search was conducted on 02/10/19, 12/11/2020 and 03/05/2021 to identify more recent systemic risk measures.
[4] Search terms included 'measuring' AND 'systemic risk', 'estimating' AND 'systemic risk', 'modelling' AND 'systemic risk', 'indicators' AND 'systemic risk', 'contagion' AND 'systemic risk'. Additionally 'systemic risk' was used as a sweeping search.

financial stress index benefits using global and domestic macroeconomic data. Their methodology takes into account policy makers' preferences. Hollo et al.'s (2012) Composite Indicator of Systemic Stress (CISS) proposed new ways to determine critical levels during a crisis. Their index based on portfolio theory aggregates five market-specific sub-indices, including indicators from the money, bond, equity, and foreign exchange markets and financial institutions' book value to market price ratio. Rizwan et al. (2020) exampled the usefulness and ease of EWS for quick results by applying the macro index of systemic risk ($CATFIN$) developed by Allen et al. (2012) to the largest banks and financial service providers of eight countries during the first six months of the COVID-19 pandemic. Using this EWS, they evidenced that those policy interventions helped to contain systemic risk. Thus, it shows that EWS can be used practically to gauge increased systemic risk and help policymakers understand if their interventions have promptly had the desired effect. Systemic risk indexes have their practical uses as a potential warning tool. However, because a significant element of systemic risk is centred around the economic cycle (Persaud 2013), such EWS may only reflect this and have a limited scope in identifying potential systemic risk indicators. Also, in a comparative study of early warning systems, Davis and Karim (2008) found that empirical results vary according to the dataset applied and the definition used for a financial crisis. Alessi et al. (2015) compared nine alternative early warning models, reporting in-sample and out-of-sample statistics for the exuberance indicators. In their many forms (e.g. probit or logit models), the authors found that multivariate models have great potential and add value over simple signalling models. Virtanen et al. (2018) results, relying on testing if bubble theory can predict the crisis, corroborate previous EWS literature findings. They indicated that periods of accelerated growth in variables such as real estate, price-to-income, credit-to-GDP ratio, or debt service costs are linked strongly to the financial crisis.

Therefore, these EWS cannot offer precise predictions; however, they can indicate heightened vulnerability. Alessi and Detken (2009) concluded that central bankers, on average, tend to have a stronger preference for the missing crisis than to act on noisy signals for various reasons. These measures assume that the US financial system is a primary indicator of the global financial conditions due to its far-reaching impact. Outside of the US, regulators face a conundrum when developing an EWS. Do they pursue their indicators used in the US, or indicators developed from their more significant trading partner? Depending on their priorities, this could leave a specific part of their domestic policy isolated.

Furthermore, an EWS, as with any statistical model (two- or three-dimensional), has the limitations of including a chronological or cross-sectional dimension and the ability to assess multiple countries over time. In advancing this literature, Constantin et al. (2018) advocated for having estimated tail dependencies networks to EWS. They consistently outperformed models covering vulnerabilities solely from bank-specific, sector-level, and macro-financial imbalances to predict bank distress events. Like systemic risk indexes, others have used the CDS indexes, premia and spreads to assess institutions' systemic risk or the industry. As a proxy indicator of how risky an institution is, CDS premia reflect the market participant's view of the likelihood of default. Bhansali et al. (2008) quantify the relative magnitude of systemic risk embedded in the relatively liquid US (CDX) and European (iTraxx) credit derivative indices through a linear three-jump model. They concluded that systemic crises had become a much larger function of overall total credit risk. Trapp and Wewel (2013) also used CDS premia from the US and Europe to conclude that firms' exposure to the same shared risk factors contributes to systemic risk. Their results imply that regulators should aim to address international bank dependencies arising from shared risk factors. Alternatively, Huang et al. (2009) measured systemic risk of the financial system by the theoretical price of insurance against financial distress, Distress Insurance Premium (DIP). They estimated the probability of default which is derived from the institution's CDS premia. Table 1 presents an overview of the systemic risk indexes, EWS, and CDS indexes proposed to measure systemic risk. The main advantage of using CDS premia instead of equity return is that the CDS premium is closer to a firm's default. For example, the firm's equity price can trade at a non-zero price level even after defaults on debt payments. Similar to equity prices, the CDS premia may reflect factors other than just the firms' default risk (e.g. investor sentiment and economic conditions). Rodríguez-Moreno and

Peña (2013) tested high-frequency market-based indicators, including equity price, interbank rates, and CDS premia. Their results suggest that the CDS premium is a more accurate indicator of systemic risk than the others.

CDS premia as systemic risk indicators are limited to CDS trading institutions located in developed economies to broader applicability. Also, the CDS market may sometimes send wrong signals (Li and Tang 2016) and ultimately provide inaccurate prices due to irrational exuberance or panics. These phenomena were highlighted during the COVID-19 pandemic, which led to a sharp increase in CDS spreads; however, these increases were not uniform across firms, with non-financial firms recording the highest debt-rollover-risk (Liu et al. 2021). Therefore, the CDS market's efficiency, transparency, and quality become an issue of paramount importance. In addition, numerous studies such as Giglio (2016), Trapp and Wewel (2013), Schneider et al. (2010), among other things, document that CDS premia are non-normally distributed. Thus, when using CDS premia data, authors should acknowledge this and, as part of their diagnostic testing, seek to test for non-normality first or make use of non-parametric methods such as Trapp and Wewel (2013).

Table 1. Systemic Risk Indexes, Early Warning Systems and using Credit Default Swaps to Measure Systemic Risk

Author	**Model**	**Methodology**	**Sample**	**Empirical Findings**
Bhansali et al. (2018)	The measure of systemic risk *via* indexes of CDS	Implementing a simple linear version of a three-jump model and calibrating it to assess market indexes and tranche spread levels.	A CDS index and tranches of investment-grade US CDX and European iTraxx from March 2007 to December 2007.	They provided evidence to show that the information in credit derivatives about the market's expectations of systemic credit risk can be extracted.
Huang et al. (2009)	Distress Insurance Premium (DIP)	Systemic risk is measured by the price of insurance against financial distress (a situation in which at least 15% of total liabilities of the financial system are in default) *via* estimating the probability of default (from CDS spreads) and the equity return correlations.	Weekly CDS spreads and high-frequency intraday, equity price data from 12 major US Banks between January 2000 and May 2008.	DIP was evidenced to be higher when the average actual failure rate increases or when the exposure to common factors in the system increases.
Alessi and Detken (2009)	Early warning indicator for asset price boom/bust cycles	This analyses various indicators (5 macroeconomic and 13 financial variables), the relative performance of global versus domestic equity markets, and money market versus credit-based liquidity indicators. A warning signal is issued when an indicator exceeds a certain threshold.	Quarterly data from 18 OECD countries between 1970 Q1 to 2007 Q4.	The global liquidity measures (private credit gap) are among the best performing systemic risk indicators and displayed forecasting abilities. In addition, evidence suggested that the best indicators are global variables. This can be explained by the fact that asset price boom/bust cycles are largely international phenomena.
Gaganis et al. (2010)	A Stability Classification Model	There are eleven indicators of; the banking sector's macroeconomic, institutional, regulatory environment, and characteristics within three multi-criteria decision techniques to classify banking stability.	114 countries' banking sectors during 2008	In line with the Economist's Banking Sector Risk Rating, their model could correctly classify between 75.60% and 79.81% of the observations, outperforming discriminant analysis and logistic regression methods.
Kritzman and Li (2010)	Mahalanobis Distance to measure financial turbulence	The average joint returns of securities were obtained and then applied a tolerance boundary. Observations outside of that boundary are statistically unusual and are thus likely to be characterised as turbulent periods.	Monthly returns of six asset-class indices: US Equities; non-US Equities; US bonds; non-US bonds; commodities; and US real estate from 1980 to 2009.	They provide evidence that their measure of financial turbulence coincides with well-known episodes of market turbulence.
Kritzman et al. (2011)	The measure of implied Systemic risk called the Absorption Ratio	The systemic risk was inferred from asset prices, defined as equal to the fraction of a set of assets' total variance explained (or absorbed) by a finite number of eigenvectors. A high value for the absorption ratio corresponds to a high level of systemic risk because it implies that the sources of risk are more unified.	Equity returns from 51 US industries in the MSCI USA index (1998 to 2010) and 14 US housing markets data, along with the Case-Shiller 10-City National Composite Index (1992 to 2010).	This measure predicted the most significant equity market declines and consolidations in the housing market. Also, the absorption ratio systematically rose in advance of market volatility.

Author	Model	Methodology	Sample	Empirical Findings
Hollo et al. (2012)	Composite Indicator of Systemic Stress (CISS)	Based on portfolio theory to aggregate five market-specific sub-indices, which included 15 individual financial stress measures.	Based on European data from 1982 to 2011	CISS identified the recent financial and economic crisis as well as the other stressed periods. This method can also determine crisis levels.
Allen al. (2012)	Macroindex of systemic Risk (*CATFIN*)	*CATFIN* is constructed using an average of three VaR and ES estimates: (i) a parametric extreme value method using estimates of the generalised Pareto distribution; (ii) a parametric estimate of the skewed generalised error distribution; and (iii) a non-parametric approach.	Out-of-sample tests were conducted using U.S., European, and Asian equity bank returns data from January 1973 to December 2009.	*CATFIN* systemic risk measures forecast macroeconomic downturns (measured by GDP, industrial production, the unemployment rate, and an index of 85 existing monthly economic indicators) approximately six months before they occurred.
Duca and Peltonen (2013)	The Financial Stress Index (FSI)	A country-specific composite index, covering five segments of the financial market including (i) Short-term interbank and government bill spreads; (ii) negative equity returns; (iii) volatility of the main equity index; (iv) realised volatility of the nominal effective exchange rate; (v) realised volatility of the yield on short-term government bills.	Based on 28 countries, both emerging and advanced economies using quarterly data from 1990 to 2009.	Domestic and global macro-financial vulnerabilities indicators significantly improved the models' ability to forecast a systemic financial crisis during known crises.
Trapp and Wewel (2013)	Measurement of systemic risk *via* CDS Premia	Applying a copula approach to focus on downside risk (extreme value theory). This method is used as previous studies have highlighted that CDS premia are non-normally distributed.	Based on 550 US and European companies from 9 industries, daily CDS bid quotes from 2004 to 2009.	They provided evidence that suggested banks are exposed to common risk factors that play a significant role in systemic risk within the banking sector. The dependence between the banking sector and a wide range of real sectors is limited.
Bagliano and Morana (2014)	A US Summary Index of Financial Fragility	A country-specific composite index including (i) Short-term interbank and government bill spreads as a measure of credit and liquidity risk; (ii) government agency long-term bond spreads; (iii) yield difference between BAA and AAA rating bonds; (iv) a range of global macroeconomic condition factors; (v) eight sources of US financial disturbances and fundamental imbalances; (vi) 10 oil market variables.	Based on US quarterly data from 1986 to 2010. The global macroeconomic factors are time-series data from 50 different countries.	Fluctuations in the financial fragility index can be attributed to global and domestic macroeconomic (20%), financial disturbances (40-50%) over both short- and long-term horizons, as well as to oil supply shocks in the long-term (25%).
Sensoy et al. (2014)	Financial Fragility Index (FIX)	A principal component analysis and dynamic conditional correlations of five variables which include: (i) stock market indexes; (ii) exchange rate against the US dollar and Euro; (iii) CDS quotes of the 5-year sovereign bond; (iv) overnight interbank rates; (v) 2-year bond yields.	Based on Turkish daily data covers the period from September 2006 to April 2014.	FIX is not an absolute measure of financial stress, but it does serve as a relative measure (due to dynamic weighting). They also evidenced that except for the overnight interest rate, all variables play almost equally important

Author	Model	Methodology	Sample	Empirical Findings
				roles in determining the financial fragility of the system.
Eder and Keiler (2015)	A Spatial Econometric Approach	This method can decompose the variance of a bank's CDS premiums into contagion, systematic and idiosyncratic risk components.	5-year monthly CDS spread data for 15 global systemically important financial institutions from 2004 to 2009.	Results indicate that contagion is important in the CDS market. The considerable risk of spillovers was due to the interconnectedness of the financial institutions.
Alessi and Detken (2018)	Random Forest Technique	An Early Warning System (EWS) uses binary classification trees to identify whether the financial system is particularly vulnerable due to aggregate credit and asset price developments. It uses macroeconomic indicators, property prices, and interest rate market-based indicators.	Based on crisis timing from 28 EU members during 1970Q1 and 2012Q4.	The main advantages of this approach are that it considers the conditional relations between various indicators when setting early warning thresholds. It models the non-linear relationship between credit, asset prices, and the occurrence of banking crises more accurately than standard linear regression models.
Gibson et al. (2018)	Systemic vulnerability for selected EU banking systems	This measure is based on the banks' performance's covariance (measured by daily market value) *via* a univariate GARCH estimation.	57 Banks from 9 European countries: Austria; France; Germany; Greece; Italy; Ireland; the Netherlands; Spain; and the United Kingdom. Data from 2000 to 2016.	The index often rises before stressful events (shocks) and captures elevated vulnerability levels before certain events.
Papanikolaou (2018)	EWS of banking bankrupt and bailout	Regressing a range of bank-level, macroeconomic and financial variables against distress scores or bailout dummies.	7,602 US banks, of which 167 were bankrupt, 824 were bailed out, and 6,611 were non-distressed, using quarterly data from 2003Q1 to 2009Q4.	Banks with inadequate capital, illiquid and risky assets, poor management, low levels of earnings, and high sensitivity to market conditions have a higher bankruptcy probability. Neither the managerial expertise nor the quality of assets is relevant to the probability of bailout.
Tölö, E. (2020).	Recurrent neural networks (RNN)	Long-Short Term Memory (RNN-LSTM) and the Gated Recurrent Unit (RNN-GRU) neural nets were used. A crisis dummy for the dependent variable and five explanatory variables for the systemic financial crisis prediction model: (1) loans to non-financial private sector divided by GDP; (2) actual equity prices; (3) actual house prices; (4) current account-to-GDP ratio; and (5) real GDP.	Their model used Jordà et al.'s (2017) dataset, containing crisis dates and an annual macroeconomic series of 17 countries over the 1970–2016 period (with the main subsample for analysis covering years 1970–2016).	From their model, they identified that time-series input could lead to more accurate predictions. Also, they find that the RNNs, especially the gated RNNs (RNN-LSTM and RNN-GRU), outperform the logit model and the multilayer perceptron neural nets.

3.2 Capital Measures of Systemic Risk

Before the financial crisis, banking regulation followed a microprudential approach in assessing the resilience of financial institutions. Thus, the original generation of stress testing models usually focused on individual banks' solvency risk (Anand et al. 2018). However, capital measures can identify the organisations exposed to systemic risk, and such tools are helpful for regulators to identify institutions that could significantly be affected by market shocks. Table 2 presents an overview of the credit and capital risk measures of systemic risk. VaR models can be applied to measure financial stability as a simpler alternative to structural econometric models. VaR allows for dynamic interaction between a few variables with interaction driven by a set of exogenous shocks. A VaR analysis can generate a probability distribution of outcomes for the dependent variable through simulations, measuring the probability of distress over the given time horizon. Aymanns et al. (2016) further suggest that VaR risk measurements could have caused the financial crisis.

Adrian and Brunnermeier (2008) developed an aggregate Co-Risk Approach developed based on Conditional VaR (CoVaR). However, this measure directly focused on individual institutions or minor clusters that cannot be combined to measure system-wide risk. In other words, adding the CoVaRs of all the institutions in a system will not lead to the system-wide VaR. Instead, their set of explanatory variables, such as market to book, return on equity, quick liquidity, and maturity mismatch ratios were shown to be significant predictors of systemic risk. López-Espinosa et al. (2015) proposed an extension to CoVaR, which captures the asymmetric response of the banking system to both positive and negative shocks in the market-valued balance sheets of the individual financial institutions. However, they found that Adrian and Brunnermeier's (2008) CoVaR assumption of a simple linear representation in which individual returns are proportional to system-wide returns is excessively restricted to larger banks.

The empirical evidence in López-Espinosa et al. (2015) did, however, suggest that CoVaR may provide a realistic approximation for smaller banks and cannot capture the heteroscedasticity characteristic of financial assets, which may severely underestimate systemic risk. Girardi and Ergün (2013) change the definition of CoVaR, using another strand of literature that attempts to explore contagion by Generalized Autoregressive Conditional Heteroscedastic (GARCH) models (Dimitriou et al. 2013; Mobarek et al. 2016). However, this method alone ignores the extreme tail risks, leading to underestimating systemic risk (Girardi and Ergün 2013). Combining CoVaR with ADCC-GARCH models allows for possible changes over time in the linkage between individual markets and the global economy, making CoVaR more robust in assessing systemic risk and allowing for backtesting.

Brownlees and Engle (2012) used the same explanatory variables as Adrian and Brunnermeier (2008) plus Marginal Expected Shortfall (MES) in developing the SRISK index, which measures the expected capital shortage of an institution conditional on a substantial market decline. MES estimates the expected loss an equity investor of the institution would experience if the market declined substantially. This measure is helpful for ranking firms according to their systemic risk level but, again, does not identify specific systemic risk indicators. The MES concept has been known in the actuarial literature for quite some time as the conditional tail expectations methodology (Tasche 2002). Tasche (2002) introduced expected shortfall as an alternative measure of VaR, which builds on Acerbi et al. (2001) work in response to VaR critics. For example, Heath et al. (1999) commented that VaR could not be considered a sound methodology for allocating economic capital in financial institutions.

Acharya et al. (2010, 2017) provided evidence that capital-based techniques could estimate the systemic risk contribution of institutions through their Systemic Expected Shortfall (SES) approach, which aims to measure the extent to which firms impose negative externalities on the system *via* increased leverage and MES. Closely related to MES, Weiß et al. (2014) propose a measure of extreme systemic risk, which captures an individual institution's Lower Tail Dependence (LTD) concerning the sector index. In other words, it captures the respective banks and the sectors' joint probability to crash together. However, this measure evaluates an institution's systemic relevance based on extreme events rather than moderate tail co-movements with the market. Pierret (2015) provides evidence that SRISK as a measure of capital shortfall outperforms CoVaR in determining how much short-term debt (liquidity) a financial institution can raise in a crisis period. SRISK, unlike CoVaR, is a function of size and leverage, which is relevant to regulators who want to measure solvency risk. Regulators employ capital ratios such as Tier 1 ordinary capital and Tier 1 leverage to assess the solvency risk; however, Pierret (2015) found that they do not appear to be related to either side of the financial institutions' short-term balance sheet. $SRISK_{it}$ represents the expected capital shortfall of the financial institution i at time t in a crisis, which is when the respective equity market index falls by 40% over the next six-month period.

In such market conditions, Acharya et al. (2012) state that *SRISK* is based on the assumption that long-term book value debt D_{it} of the financial institution remains constant over the six months while its market capitalisation MV_{it} decreases by its six-month returns during a crisis, which is also known as long-run marginal expected shortfall (*LRMES*). Rather than focusing on relative losses in the capital (equity or market capitalisation) in the way CoVaR, MES, and *SRISK* do, Kreis and Leisen (2018) introduce Conditional Expected Default Frequency (*CEDF*), which focuses exclusively on the default risk of the banking system using equity return data. Kreis and Leisen (2018) back-tested their *CEDF* measure as well as CoVaR and SRISK during the two years beforehand and subsequent to the Lehman bankruptcy (September 2008); SRISK appeared to be a better EWS as it started increasing from June 2007 and fairly smoothly trended upwards until July 2008 while CoVaR only significantly reacted after the event. On the other hand, *CEDF* was more volatile (during December 2007- September 2009) with several peaks and troughs. This volatility could send mixed messages; however, the original substantial increase in December 2007 could have sent a strong signal of possible future threats in the financial system. Kleinow et al. (2017) examined four different systemic risk measures (Co-dependence Risk (Co-Risk), delta CoVaR , LTD, and MES), using 122 US financial institutions data (2005-2014) and concluded that the alternative measurement approaches produced heterogeneous estimates of systemic risk. Das et al. (2019) also found similar results whilst comparing the same measures as well as SRISK.

Furthermore, different metrics may lead to contradicting assessments regarding different financial institution riskiness types (i.e. banks, non-depository financial institutions, and insurance companies). Kleinow et al.'s (2017) findings suggest that assessing systemic risk based on a single risk metric should be approached cautiously. MES appears intuitively most appealing (out of four credit risk-based systemic risk measures). It accurately outlined the financial crisis timeline by producing consistently high systemic risk estimates for three industry sectors. The main challenge of these capital models is that a vast amount of data and intensive computing are required. The majority of the information comes in the form of proxies and dummies from accounting data. It is common practice to judge the soundness of an institution by looking at its accounting data which the regulatory agencies evaluate. However, it is worth observing that this approach is only as reliable as the accounting standard within that country. The measures discussed within this section are empirically tested using data from developed countries; therefore, applying these measures to other countries with poor accounting standards may produce unreliable results. A lack of consistent accounting practices across countries and standards may have direct implications for systemic risk evaluation. For example, under Basel III, capital adequacy is calculated using total assets derived from risk-weighting formulas specified by the Basel Accord, not the International Financial Reporting Standards (IFRS)[5]. Yet, most systemic risk measures use bank fundamentals, generally calculated according to IFRS. Thus, the effects of different accounting standards on measuring systemic risk could be further investigated. Also, the impact of shadow banking can skew the data. For instance, before the recent financial crisis, the financial institutions covertly increased leverage by moving risk onto the balance sheets of special-purpose vehicles that were ultimately backstopped by credit lines from the same institutions. Subsequently, many institutions moved such shadow bank assets back onto their balance sheets (Adrian 2015). After the recent financial crisis, the regulators considered restricting the shadow banking system activity, which was regarded as a gap in the previous regulatory structure (Rixen 2013). Further, from a systemic risk perspective, Bianchi and Sorrentino (2020) found differences in the ranking defined by the ΔCoVaR and the GSIBs bucket allocation, even if the ΔCoVaR seems to segregate good banks from bad ones.

Regarding the computing power required, the minimal number of observations to verify an internal risk management model is 250 (recommended by BIS (2010)). Hence, the ability to compute this number of observations largely depends on the feasibility of the operational capabilities of the institution. However, Kupiec (1995) states that even using 250 observations for testing often provides a low statistical power. Furthermore, Borio and Drehmann (2009) argue that the use of VaR models does not address the dynamics of distress. They are unable to incorporate the likes of boom-boost economic cycles. Additional constraints on leverage arise from several regulatory policies. According to Aymanns et al. (2016), the following measures effectively impose a risk contingent leverage constraint: (i) if institutional investors trade collateralised loans, they must maintain margin on its collateral; (ii) regulators such as the Basel Committee for Banking Supervision (BCBS) impose a risk-contingent capital adequacy ratio; and (iii) another possibility is that internal credit risk management procedures may adopt a VaR constraint on leverage.

[5] see Mugge and Stellinga (2015) for an overview of the most important accounting standard negotiations and modifications.

Table 2. Credit and Capital Measures of Systemic Risk

Author	**Model**	**Methodology**	**Sample**	**Empirical Findings**
Bartram et al. (2007)	Presented three methods to quantify the risk of a systemic failure	The first approach examines the equity returns of unexposed banks during a financial crisis. The second approach is based on the likelihood of systemic failure based on a structural credit risk model (Merton, 1974). The third approach estimates bank default probabilities implied by equity option prices.	334 banks from 28 countries. The five global financial crises within the sample included the Mexican devaluation in 1994, the Asian crisis in 1997/98, the Russian long-term capital Management default in 1998, and the Brazilian devaluation in 1999.	It was found that small increases in estimated default probabilities of unexposed banks during crisis generated little risk of a systemic failure. There also provided possible explanations for this, i.e. the shocks might not be large enough. Effective policy responses might have limited the risks, or their approach might not accurately measure risk, and CoVaR estimates show those characteristics.
Adrian and Brunnermeier (2008)	Δ CoVaR, defined as the difference between the Conditional VaR of the financial system conditional on an institution being in distress	Panel quantile regression of equity prices and balance sheet fundamental data used.	15 US financial institutions using quarterly data from 1971Q1 to 2013Q2 and daily equity data over the same period.	Factors such as leverage, size, maturity mismatch, and asset price booms significantly predict systemic risk contribution.
Segoviano Basurto and Goodhart (2009)	Joint Probability of Default (JPoD) and the Bank Stability Index (BSI)	JPoD represents the probability of all the banks in the system (as a portfolio) becoming distressed, i.e., the tail risk of the system. This uses an entropy-based copula approach that matches marginal default probability constraints from the CDS markets. The BSI reflects the expected number of banks becoming distressed, given that at least one bank has become distressed.	Based on CDS data from 2005 to October 2008 for major American and European banks (as foreign banks). The foreign banks impact sovereigns in Latin America, Eastern Europe, and Asia.	Using very limited datasets, their measures allow users to analyse (define) stability from three different yet complementary perspectives.
Acharya et al. (2010, 2017)	Each financial institution's contribution to systemic risk can be measured as its Systemic Expected Shortfall (SES)	Measures the extent to which an institution imposes negative externalities on the system. They calculated Marginal Expected Shortfall (MES) and SES on daily equity returns, volatility, and Beta. They compare these with fundamental data such as leverage, assets, and market value of equity.	102 US financial Institutions using equity and CDS data from June 2005 to December 2008.	SES increases with the institution's leverage and its expected loss in the tail of the system's loss distribution, i.e. its tendency to be under-capitalised when the system as a whole is under-capitalised.
Khandani et al. (2010)	Consumer Credit Risk Measure	Application of machine-learning techniques to construct non-linear, non-parametric forecasting models of consumer credit risk.	Customer transactions and credit bureau data from January 2005 to April 2009 for a sample of a major commercial bank's customers. The sample is a small	Time-series patterns of estimated delinquency rates from this 2008-09 financial crisis model suggest that aggregated consumer credit risk analytics may have critical

			percentage of the bank's total customer base (unique dataset).	applications in forecasting systemic risk.
Brownlees and Engle (2012)	SRISK Index. The expected capital shortage of an institution conditional on a substantial market decline	SRISK is an index that is a function of fundamental data such as the degree of leverage, size, marginal expected shortfall (MES), equity returns, market capitalisation, liquidity ratios, and book value.	94 US financial institutions from July 2000 to June 2010.	Their results provided evidence that SRISK is valid for ranking systemically risky institutions at various stages of the financial crisis.
Puzanova and Düllmann (2013)	The financial sector is treated as a portfolio of debt represented by financial institution" liabilities	The systemic risk capital contribution was derived *via* a credit portfolio approach using a Gaussian factor model. Systemic risk is gauged by the tail risk of the portfolio loss distribution, which is based on the book value of the bank's liabilities.	54 out of 86 of the world's major commercial banks from Europe, North America, South America, Africa, Japan and Asia & Pacific. Using monthly data from 1997 to 2010.	Their evidence suggests that macroprudential supervision should focus on a solid capital base throughout the financial cycle and the decorrelation of banks' asset values.
Girardi and Ergün (2013)	Multivariate GARCH estimation of CoVaR	This modification of Adrian and Brunnermeier (2008) *Delta* CoVaR by using it in conjunction with ADCC-GARCH models.	74 US financial institutions data from June 2000 to February 2008.	This adaptation allows the *Delta* CoVaR model to consider more severe distress events (those beyond the institution's VaR and farther in the tail), to back-test, and to improve consistency (monotonicity) concerning the dependence parameter (Mainik and Schaanning 2014).
Jobst and Gray (2013)	Systemic Contingent Claim Analysis	This measures systemic solvency risk generated by aggregate estimates of the joint default risk of multiple institutions as a conditional tail expectation using multivariate extreme value theory. Based on equity prices and balance sheet data.	Thirty-three large US commercial and investment banks, insurance companies, and special purpose financial institutions using daily data between January 1, 2007, to January 2010.	This measure helps quantify the individual contributions to contingent liabilities and systemic risk of the financial sector during times of stress.
Avramidis and Pasiouras (2015)	Puzanova and Dű llmann (2013) model was extended.	The Gaussian approach was developed by proposing a model that accounts for the extreme event dependence and they quantify the level of capital shortfall when this characteristic is ignored.	Eighty-two of the largest commercial banks in the world, data from January 2000 to December 2012.	This method can calculate systemic risk in potential credit losses and allocate total systemic risk to the financial system participants based on their contributions.
Kreis and Leisen (2018)	Conditional Expected Default Frequency (*CEDF*)	They structurally model the banking system, assuming that defaults of individual banks are linked through correlated (changes in) asset values.	A core sample of 15 U.S. banks (largest by assets during 2004 and 2016) and an extended sample of an additional 15 U.S. Banks. Daily equity prices and quarterly asset values between 1980 and 2016 (extended sample from 1996).	Average asset loadings (correlation) considerably increased over the last 36 years, while their heterogeneity decreased. Due to the limited focus, *CEDF* will not capture all dimensions of systemic risk in the banking system. Still, it proved to be a valuable complement to existing systemic risk measures.

High leverage levels can exacerbate risk because, in bear markets, leverage increases when asset prices decrease. Such a drop in stock prices can then impact leverage constraints, which may force institutions to sell such assets into falling markets (quick-fire sales), amplifying declines in prices further. In addition, due to the nature of the demand and supply curves, they tend to be stronger when the leverage of the financial intermediary is pro-cyclical (when leverage is high during bull markets and low during bear markets). There are two main ways institutions can reduce their balance sheet leverage: by selling risky assets (potentially impacting profitability) or raising more capital (Sharma et al. 2010). Adrian and Shin (2008) found that most institutions tended to do the former in practice during and before the financial crisis of 2008-09. Barth and Seckinger (2018) investigated the unintended consequences of more stringent leverage ratios; for example, a binding leverage ratio might create an incentive for an originate-and-distribute strategy. They suggested that higher-quality institutions cannot absorb the entire debt supply if it is too costly to issue new equity. This can effectively enhance the market share of lower-quality institutions, raising interest in them from regulators and adding to the competition of higher-quality institutions.

3.3 Liquidity Measures of Systemic Risk

Historically, most financial institutions and regulators rarely viewed liquidity risk as a priority (Vento and La Ganga 2009). Recently, many studies have argued that to prevent another systemic crisis, banks and financial institutions introduce liquidity requirements to reduce the reliance on short-term refinancing and decrease the maturity mismatch between assets and liabilities (Acharya and Yorulmazer 2008; Acharya 2009; Acharya and Richardson 2009; Wagner 2009). In addition, Cao and Illing (2010) proposed that if all institutions held extra liquidity, the system on aggregate would be more resilient. However, the empirical findings of Distinguin et al. (2013) based on a sample of 781 US and European banks from 2000 to 2006 suggest that liquidity risk is a predictor of bank failure. To avoid such shortcomings, liquidity risk should be minimised at an individual bank and a macro banking system level. Berger and Bouwman (2009) used US bank data to develop several liquidity measures for customers by capturing banks' illiquidity. They showed that larger banks (total assets $1Bn) comprise 80% of the sector's liquidity (despite accounting for a small percentage of all US banks). Bai et al. (2018) used their Liquidity Mismatch Index (LMI) similarly to find that the top 50 banks largely determine the US banking sector's liquidity.

Most systemic liquidity risk measures focus on negative externalities caused by maturity mismatches (Table 3 provides an overview). For example, Brunnermeier and Pedersen (2009) proposed using the institutions' CoVaR measure to calibrate charges for maturity mismatches to manage systemic liquidity risk. However, it is unclear whether this capital-oriented measure like CoVAR can be applied for such a purpose. Also, based on financial institutions' fundamentals, Pierret (2015) empirically investigated the link between solvency and liquidity in line with the bank-run literature (Allen and Gale 1998). Pierret (2015) provided evidence that financial institutions lose access to short-term funding (liquidity) when markets expect them to become insolvent, using the difference between short-term liabilities and short-term assets as a proxy for liquidity risk. Perotti and Suarez (2011) proposed mandatory liquidity insurance funded by taxation of short-term wholesale funding. This simple model requires institutions to pay different rates based on their contribution to negative externalities. However, institutions are funded by many different channels, so the assumption of short-term borrowing as the sole source of an institution's funding oversimplifies the issue and makes it difficult to interpret the results in terms of regulatory recommendations. Also, Jobst (2014) argues that there is limited knowledge of empirically measuring the systemic risk of wholesale funding. Jobst (2014) introduced a risk-adjusted liquidity measure that aims to assess the marginal contribution of each institution to total systemic liquidity risk. This approach is based on option pricing theory, wherein the model can fail due to irrational market behaviour.

The Basel Committee on Banking Supervision (BCBS) agreed the Basel III framework (BIS 2011), which sets out several consistent liquidity monitoring tools, which are expected to capture information related to cash flow issues, balance sheet structure, availability of encumbered collateral, market liquidity indicators and disclosure standards (Adalsteinsson 2014). The BCBS's primary approach to reducing funding concentration focuses on the more significant wholesale funding sources (both on a counterparty and product basis). Basel III set out international liquidity requirements, including the introduction of the Liquidity Coverage Ratio (LCR) (BIS 2013) and the Net Stable Funding Ratio (NSFR) (BIS 2014) to be implemented by 2015 and 2018, respectively. LCR focuses on financial institutions' short-term liquidity levels (over the next 30 days) in the event of shocks. To do this, it adds behavioural assumptions to the asset and liability categories, which makes it a more dynamic tool than alternative balance sheet ratios (Adalsteinsson 2014).

In comparison, the NSFR monitors the long-term funding stability (Ashraf, Rizwan, and L'Huillier 2016) and identifies maturity mismatches that could impact funding risk (Schmitz and Hesse 2014). Ultimately, both ratios have been formulated to encourage more stable funding sources and ensure that financial institutions access funding when required. Blundell-Wignall and Atkinson (2010) and Schwerter (2011) believed that introducing Basel III liquidity requirements would reduce systemic risk at times of liquidity tension and reduce dependence on central banks for funding. Härle et al. (2010) evidenced that implementing the new liquidity requirement would lead to more capital and liquidity efficient business models and products. Schwerter (2011) and King and Tarbert (2011) also argue that introducing liquidity standards is the most critical aspect of the new Basel III framework. In their view, the financial crisis was more a liquidity shock than a credit crisis, yet increasing the capital requirement for credit risk remains the appropriate solution from the regulator's point of view. Pakravan (2014) supports King and Tarbert's (2011) notion, suggesting that the new liquidity measures attempt to avoid a repeated future crisis. Chiaramonte and Casu (2017) empirically evidenced this as the NSFR was found to be a significant determinant of bank sector fragility using EU bank-level data, thus supporting the need for such liquidity requirements.

Several empirical studies have assessed the impact of the new liquidity regulations. With the challenges of determining the LCR over 30 days, regulators would propose focusing on the NSFR. Goodhart et al. (2012) found the NSFR an excellent pre-emptive macro-prudential tool compared to cyclical variation in capital requirements or underwriting standards. King (2013) tested NSFR levels for larger financial institutions in 15 countries. On average, representative banks in 10 out of 15 countries appear to have an NSFR below the minimum threshold at year-end 2009.

Similarly, Dietrich et al. (2014) explored the potential impact of the prescribed funding structures under Basel III on the performance of the banking industry in Western Europe with the sample of 921 banks during the period between 1996 and 2010 to find that the majority of the banks have historically not fulfilled NSFR minimum requirements. By assessing US bank data prior to the introduction of Basel III regulations, DeYoung et al. (2018) found that, on average, banks increased their NSFR following adverse shocks to their risk-based regulatory capital ratios. However, there was no evidence to suggest that banks increase their NSFR following adverse shocks to their simple accounting (leverage) equity ratios. The authors argue that these results indicate that capital and liquidity have been historically treated as substitutes. Thus, implementing both capital and liquidity requirements will be a challenge to banks and financial institutions. Alternatively, Dietrich et al. (2014) reported that banks with higher capital ratios, lower loan growth, more interest-bearing business, and branches operating in their native country have higher NSFRs. In other words, banks with a traditional business model (based on lending and deposit-taking) should have a higher NSFR than banks with a high share of non-interest income.

Several concerns have been raised regarding the liquidity requirements (König and Pothier 2016). Concerning LCR, Keister and Bech (2012) suggest that this requirement should increase demand for central bank funding impacting open market operations (e.g., using the money markets). Also, Malherbe (2014) argues that cash hoarding to maintain a certain level of funding may reduce market liquidity. In relation to NSFR, Härle et al. (2010) suggest that banks and financial institutions with substantial capital markets and trading businesses will be impacted the most due to the NSFR requirement. King (2013) also shared this sentiment and argued that universal banks with diversified funding sources and high trading assets would be penalised the most. In addition, Blundell-Wignall and Atkinson (2010) proposed that the liquidity requirements may significantly lower banks' returns. Also, Gideon et al. (2013) expect financial institutions to raise lending rates to keep their return on equity in line with market valuations and reduce credit supply to lower the share of risky assets on the balance sheet.

Wei et al. (2017) showed that the NSFR requirement might unintendedly negatively affect banking profitability due to higher funding costs, thus affecting stability. Also, Schmitz and Hesse (2014) noted that banks tend to hold on to liquidity during periods of systemic uncertainty, increasing costs for banks seeking more stable funding. Another potential reason for it may arise from the banks changing their funding habits if they require a specific type of funding. For example, Donaldson and Micheler (2018) argue that if banks increased non-resaleable debt (repos) as a source of financing, it could create new credit networks[6] which can act as a source of systemic risk, i.e. a bank's default will impact its counterpart creditor and that creditor's creditors. The consultation process and implementation of NSFR were also questioned as the calculation requires a highly detailed classification of the funding, which banks do not disclose or even did not collect for their balance sheets (Gobat et al. 2014; Härle et al. 2010). In addition, analysts were unsure regarding the weights given to assets and liabilities to reflect appropriate liquidity risk assumptions (Gobat et al. 2014). Therefore, weighting changes will ultimately impact bank-level risk. Wei et al. (2017) demonstrated that if a short-term debt is given a sufficiently low weight as an example within the available stable funding, NSFR can lower the use of short-term debt and thus reduce banks' exposure to excess roll-over risk.

Despite the introduction of liquidity requirements in Basel III, according to Jobst (2014), systemic liquidity risk from a macro-prudential perspective remains largely unaddressed. Distinguin et al. (2013) argued that liquidity risk predicts bank failure. The previous regulations do not go far enough in the US and Europe as liquidity at the system level was not addressed.

In an attempt to build a further liquidity buffer within the Global Systematically Important Banks (G-SIBs), the Financial Stability Board (PSB) announced additional liquidity standards in the form of Total Loss Absorbing Capacity and Minimum

[6] If a bank makes a loan *via* non-resaleable debt and needs liquidity, it cannot sell the loan but must borrow.

Requirement for Own Funds and Eligible Liabilities (MREL) (FSB, 2014a, 2014b). These require financial institutions to hold an excess level of risk-weighted assets. Additionally, Schmitt and Schmaltz (2016) found that such weightings revisions significantly reduced the number of non-compliant banks and the magnitude of shortfall. TLAC is designed to minimise the *participation of* institutions in systemic risk from a liquidity perspective. This standard intention is to ensure that in the event of failure of a larger, interconnected and complex financial institution, it can be resolved in an orderly manner without the need for public-funded support.

Following these initiatives, supervision authorities and central banks have been developing newer stress-testing models and tools that rigorously consider the interconnections between banks and the interactions between banks' liquidity and solvency risk. For example, the European Central Bank's *Stress-Test Analytics for Macroprudential Purposes in the Euro area (STAMP)* (Dees et al. 2017) comprises five different analytical assessments: (i) dynamic dimension that takes into account banks' responses to a particular scenario; (ii) the interaction with the real economy; (iii) the interconnections between financial institutions; (iv) the integration of system-wide liquidity assessment and (v) the interaction with non-financial sectors.

Table 3. Liquidity Measures of Systemic Risk

Author	Model	Methodology	Sample	Empirical Findings
Brunnermeir and Pedersen (2009)	A model that links an assets market liquidity and traders funding liquidity	Market asset liquidity was defined as the difference between the transaction price and the fundamental value. They define funding liquidity as speculators' shadow cost of capital.	S&P 500 futures margins from 1982 to 2008. Funding requirement data from hedge funds, commercial & investment banks and market makers.	Their model predicts that market liquidity declines as implied volatility increases (negative correlation). They also provided evidence that, under certain conditions, margins are destabilised and that market and funding liquidity are mutually reinforcing, leading to liquidity spirals.
Aikman et al. (2009)	A Risk Assessment Model for Systemic Institutions (RAMSI)	RAMSI assesses the impact of macroeconomic and financial shocks on individual banks and the banking system using Bayesian VAR (BVAR). They also regress bank fundamental data against credit rating.	The ten largest UK banks from 1972 Q2 to 2007 Q4.	They demonstrate how rising funding costs and liquidity concerns can amplify other sources of risk.
Perotti and Suarez (2011)	A Pigovian tax on short-term funding	An analysis of the relative performance of realistic price-based and quantity-based approaches to regulating systemic externalities associated with the bank's short-term funding strategy was developed.		They provided evidence that a Pigovian tax on short-term funding efficiently contains risk and preserves credit quality, while quantity-based funding ratios are distortionary.
Lee (2013)	Systemic liquidity Shortages due to Interbank interconnectedness	A comparative analysis of six different types of network structures. Their models are described by several exogenous parameters such as reserve ratios, deposit shares, surplus funds, and cross-holdings.		The evidence showed that a more significant bank liquidity imbalance across banks aggravates a deficit bank's liquidity shortage. Also, banking systems become more vulnerable to liquidity shocks as their interbank network becomes more ill-matched.
Hu et al. (2013)	Noise as Information for Illiquidity	Market-wide liquidity measure by exploiting the connection between the amount of arbitrage capital in the market and observed noise (deviations from a given pricing model) in US Treasury bonds.	US daily cross-sections of end-of-day treasury bill and bond (1 Month to 10-year maturities) prices from 1987 to 2011. Total of 163 treasury bills and Bonds.	Their noise measure captures episodes of liquidity crisis from different origins across the financial market, providing information beyond existing liquidity proxies.
Jobst (2014)	Systemic Risk-Adjusted Liquidity (SRL) Model	Option price theory and the institutions required and available stable funding ratios were used. This approach quantifies an individual institution's time-varying contribution to expected losses from system-wide liquidity shortfalls and insurance premia that incentivises banks to internalise the social cost of their individual funding decisions.	13 largest US commercial and investment banks' data from January 2005 to December 2010	The SRL model provides a tractable framework for assessing system-wide valuation effects arising from joint liquidity risk.

3.4 Contagion Measures of Systemic Risk

The emergence of systemic risk in financial networks has also received increasing attention in the literature (Acemoglu et al. 2015a; Allen and Babus 2009; Stiglitz 2010) and among regulators (IMF 2012; Yellen 2013). Within the banking sector, financial institutions' interconnectedness can have broader implications in the event of financial shocks. This is because exogenous or endogenous shocks can be intensified in various ways (Roukny et al. 2018). For example, funding concentration can spread bank runs and capital flight (Diamond and Dybvig 1983); similar asset portfolios (both indirect interconnectedness) can be exposed to suppressed valuations *via* fire sales and deleverage (Caccioli et al. 2014), and intertwined balance sheets (*via* derivatives and loans) and can result in cascading defaults (Allen and Gale 2000). Further, Cai et al. (2018) argue that syndication increases the overlap of bank loan portfolios and makes them more vulnerable to contagious effects. On the other hand, indirect interconnectedness is limited by reducing the reliance on mark-to-market accounting or promoting incredible business strategies.

Possible channels of contagion in the banking sector can originate from a range of sources, both on the liability side (e.g. bank runs) and the asset side (e.g. interbank lending, derivative exposure, and settlement systems). Garriga (2017) argues that delays in revising banks' prudential regulation provide opportunities for banks to elude regulation and adopt risky behaviour. This effect increases a country's vulnerability to a systemic banking crisis. The majority of measures for systemic risk that relate to contagion are based on the assumption that the greater the correlation of indicators, the greater the systemic risk. This assumption was noted by the IMF (2020b), which stated that during the COVID-19 crisis, correlations across risky assets exceeded the 2008–09 financial crisis levels and warned the higher correlations could reduce portfolio diversification opportunities and, therefore, increase contagion risk. Table 4 presents an overview of the proposed contagion measures of systemic risk.

Nicoló and Kwast (2002) argue that an institution's interdependencies indicate systemic risk, using equity return correlations of large and complex US financial institutions. Their claim is based on the assumption that increased equity return correlation may increase the potential for a shock to become systemic. The use of equity returns does reflect market participants' collective evaluation of an institution. However, it is unclear to what extent this captures the total impact of its interactions with other institutions, as this may be private information. Patro et al. (2013) also conducted a similar study and found that daily equity return correlation is a simple, robust, forward-looking, and timely systemic risk indicator. Based upon Reinhart and Rogoff's (2009) measurement of banking instability (equity pricing) and defined crisis periods in the UK over 181 years, Campbell et al. (2016) made the following five observations: Firstly, on average two years before any crisis that tends to be substantial, the equity gains are followed by considerable declines in the year of the crisis. Secondly, economic indicators (real interest rates, inflation, and GDP growth) are higher than historical averages two years before a crisis, as economic activity tends to accelerate before a crisis. Thirdly, the money supply is consistent with improved averages in the years before the crisis. Fourthly, proxies for commodities display negative growth two years before a crisis, however one year before and during a crisis, price growth is considerably above historical averages. Lastly, in the years leading up to a crisis, financial institutions' lending and house price growth rates were above average, supporting the view that significant credit growth fuels a housing asset bubble in the lead-up to the financial crisis. Lehar (2005) measures risk at the banking system level rather than at the individual institution level by estimating the dynamics and correlations between institution asset portfolios following Merton's (1973) equity method as a call option of institution's assets. This does not attempt to capture systemic risk, but the measure enables regulators to track and compare the risk of the system. This method was extended by Allenspach and Monnin (2008), who assessed the co-movement of banks' assets to debt ratio as they believe that changes in the assets to debt ratio can be considered as a good summary of changes in the overall financial health of an institution. Allenspach and Monnin's (2008) finding warns against viewing systemic risk as a pure correlation phenomenon and highlights the danger of high and volatile leverage at the individual institution level. It is worth noting that the studies that use equity indexes returns to assess the contagion across different markets provide evidence consistent with studies focused on international diversification.

Ye et al. (2014) used a Multivariate Conditional Autoregressive Value at Risk (MV-CAViaR) model to assess contagion from the US equity market to five other countries (China, Japan, UK, France, and Germany) during a crisis period. They found that contagion from the US increased the market risk of the other tested countries during the crisis except for China; however, this contagion effect was reduced and varied during the recovery period. These findings were consistent with previous results from Bae et al. (2003). Assuming that a crisis period reflects a bear equity market and the recovery period reflects a bull market, these results are similar to You and Daigler (2010). Their study empirically investigated the theory of international diversification using dynamic correlation away from the US equity market during bull and bear periods. Their findings provided evidence that investors can get diversification benefits from Asian markets but limited benefits from the European market. They also found that the tested indexes became increasingly correlated during bear periods (crisis periods) and bull periods. This phenomenon is not just isolated to equity prices (Riadh et al., 2011). For example, Eder and Keiler (2015) found that financial contagion strongly affected CDS premia in European and US financial institutions, while Asian financial institutions were relatively independent.

A more recent assessment of contagion at the industry level was conducted by Tonzer (2015), who used the BIS aggregate bilateral cross-border asset and liability positions reporting and macro-economic data regressed against industry bank risk (as measured by the Z-Score). He found that countries that are connected *via* foreign borrowing or lending positions to more stable banking systems overseas are significantly affected by positive spillovers. This implies that linkages in the banking system can be beneficial; however, this may not be the case in a crisis period.

Table 4. Contagion Measures of Systemic Risk

Author	Model	Methodology	Sample	Empirical Findings
Nicolo and Kwast (2002)	Institution Interdependencies	For the dynamics of interdependencies, they use equity return correlation. Then they relate the correlations to their consolidation activity by estimating measures of the consolidation elasticity of correlation through time and cross-sectionally.	Major US Banks from 1988 to 1999, taking into account 22 consolidation events.	They provide evidence of a positive trend in equity return correlations net of diversification effects, which suggests that the systemic risk potential in the financial sector may have increased during the sample periods.
Bae et al. (2003)	Contagion captures the coincidence of extreme returns	Significant positive and negative daily equity returns were observed, then calibrated the joint occurrences of excessive returns using Monte Carlo simulation followed by multinomial logistic analysis against economic indicators.	Based on 17 Asian and Latin American markets from April 1992 to December 2000.	They found contagion is predictable and depends on regional interest rates, exchange rate changes, and conditional equity return volatility. In addition, contagion is more substantial for extreme negative returns than for excessive positive returns, which is mixed.
Gropp and Moerman (2004)	Co-incidence of extreme shocks to bank's risk to examine contagion	Bank's risk is measured by the first difference of weekly distances to default and abnormal returns, applying Monte Carlo simulations to the observed frequency of large shocks experienced by two or more banks simultaneously. This is consistent with the assumption of a multivariate normal or a student t-distribution.	Sixty-seven of the largest EU banks from 1991 to 2003.	Their measure may accurately measure contagion among any bank pair, as long as the probabilities of an idiosyncratic shock hitting the two banks are quite similar. Also, their measure can be used to identify banks that have systemic importance within countries and across countries.
Lehar (2005)	Standard tools that regulators require banks to use for their internal risk management are applied at the level of the banking system to measure the risk of a regulator's portfolio	Estimate the dynamics and correlations between bank asset portfolios. Fundamental data included bank size, ROA, the book value of equity over total assets, long term debt, and regulatory capitalisation.	149 International Banks (50 US, 40 Europe, 45 Japan, 14 Other) from 1988 to 2002.	The sample period showed that the North American banking system gains stability in line with market events while the Japanese banking sector becomes more fragile.
Rodriguez (2007)	A Copula approach to measure contagion	Copula approach with time-varying parameters that change with the variance states to identify shifts in the dependence structure in times of crisis was used. This method can capture increases in tail dependence.	Five East Asian equity indices during the Asian crisis (1/1/96 to 30/6/98) and four Latin American equity indices during the Mexican crisis (1/1/93 to 31/12/95).	They provided evidence that the dependence structure between the equity market returns of Asia and Latin American countries changed during the crisis. They argue that structural breaks in tail dependence are an actual dimension of the contagion phenomenon.

Author	Model	Methodology	Sample	Empirical Findings
Schwaab, Koopman, and Lucas (2011)	A coincident measure and an indicator for the likelihood of simultaneous failure	Using a dynamic factor framework based on state-space methods. The indicators of systemic risk are based on underlying macroeconomic (8 US and 8 European indicators) and credit risk components such as exposure and actual default count.	Dataset of 450 US and 400 EU-27 area financial firms, compared with non-financial firms from 1984Q1 to 2010Q4.	They found that decoupling credit risk from macro-financial fundamentals may serve as an early warning signal of systemic risk.
Giesecke and Kim (2011)	Dynamic hazard model of failure	The formulation attempts to capture the spillover effects channelled through a complex network of relationships in the economy. The model is based on actual failure rates compared against macroeconomic and sector-specific risk factors.	US default timing data from 1987 to 2008.	Their evidence indicated that the model provides accurate out-of-sample forecasts of the term structure of systemic risk. Also, the cause of systemic distress is the correlated failure of institutions to meet obligations to creditors, customers, and trading partners.
Billio et al.(2012)	Econometric measures of connectedness	Several econometric measures of connectedness based on principal component analysis and Granger-causality networks.	Monthly returns of US value-weighted indexes of hedge funds, banks, broker/dealers, and insurance companies data from 1994 to 2008.	Their evidence suggests that the four sectors have become highly interrelated over the sample period, likely increasing the level of systemic risk in the finance and insurance industries.
Ye et al. (2014)	MVMQ-CAViaR Method	Multivariate Conditional Autoregressive Value at Risk (MV-CAViaR) models was used to analyse market risk variation among different countries at different stages of the crisis. This is based on the equity index daily return data.	Equity market indices include the S&P 500 (US), CSI300 (China), Nikkei 225 (Japan), FTSE-100 (UK), CAC-40 (France), and DAX (Germany).Over several periods including Pre-crisis (January 2006 to December 2007); Crisis Period (January 2008 to June 2009), and the Recovery phase (July 2009 to July 2013).	Their evidence shows that their estimated coefficients became more significant or that the market risks of the tested countries increased during the crisis except for China. Also, their model demonstrated the changes in market risk were consistent with market events.
Tonzer (2015)	Linkages in interbank markets affect the stability of interconnected banking systems (not individual banks)	A spatial modelling approach was used to test for spillovers in cross-border interbank markets, using the banking system's international balance sheet positions data, i.e. total cross-border positions disaggregated from the BIS bilateral cross-border asset and liability positions data. They also used a range of macroeconomic data with dependant variables to bring the industry Z-Score to measure Bank Risk.	Data from the US, 15 European countries, Canada and Japan from 1994 to 2012.	The results suggest that foreign exposures in banking play a significant role in channelling banking risk. Countries that are linked through foreign borrowing or lending positions to more stable banking systems abroad are significantly affected by positive spillover effects. This implies that linkages in the banking system can be beneficial in stable times, while they have to be taken with caution in times of financial turmoil affecting the whole system.

3.5 Network Measures of Systemic Risk

In the early 2000s, the simulation models of systemic risk or network theory emerged in which parameters such as connectivity, concentration, and financial institutions' size were considered. Our paper tends to focus on systemic risk through contagion effects following a shock. Generally, there are five types of network structures that can be tested (See figure 1).

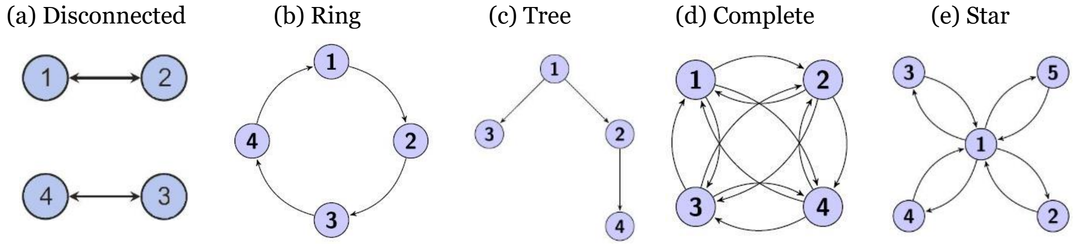

Figure 1. Network Structures

Simulations provide policymakers with a rough indication of whether contagion could become a possible consequence of endogenous or exogenous shocks. Thus, such methods can be used to identify potential financial institutions whose failure could potentially cause system contagion and other institutions to fail (e.g. node 1 in figure 1e). Unlike other models, simulations can consider simultaneous factors, such as balance sheet data and interaction with interbank markets. However, the simulation studies tend to be based on similar underlying solid assumptions, leading to different biases. Moreover, data availability is a severe issue with simulations. The simulation method may be sophisticated, however limited access to the data may make models useless. Data on bilateral exposures within, for example, the interbank market is currently limited, especially for over-the-counter bilateral agreements. Therefore, some financial institutions' exposures are intrinsically unobservable. In time, as more bilateral agreements are conducted *via* central platforms, the data availability could improve. Table 5 presents an overview of the current network measures of systemic risk.

A more recent study by Roukny et al. (2018) introduces a conceptual model to compute the probability of default for individual financial institutions and systemic defaults within a network of banks connected *via* credit contracts. This model is designed to be applied using actual data with adjustable parameters depending on the data available within the assets/credit portfolios and balance sheet. The main advantage of this technique is that regulators can access both the level of individual risk and systemic risk and identify any uncertainty arising from the interconnectedness.

Barroso et al. (2018) proposed a method of identifying systemic risk from insolvency contagion arising from aggregated cross-border debt exposure networks. Using BIS's Consolidated Banking Statistics database and aggregated capital buffer data, they found that the US and UK hold the most cross-border risk-bearing with the potential to cause a shock/damage within a global network. Their approach is valuable for monitoring cross-border financial systems but does not identify interconnectedness among individual financial institutions.

Poledna et al. (2015) and Poledna et al. (2021) provide a robust example of this research area, using a unique dataset covering four different types of exposure in the Mexican banking system. This dataset is only available to supervisors or for systemic risk research purposes. Uniquely, they provided evidence that focusing on a single layer network underestimates the total systemic risk by up to 90%. Furthermore, their results demonstrated that the exposures related to the cross-holding of securities and FX transactions (both traded over-the-counter) are crucially important components of the systemic risk. However, it would be dangerous to generalize such findings to larger banking systems like the US and Europe. Nevertheless, recent work has shown how network research can be advanced.

Aldasoro and Alves (2016) analysed the multiplex network structure of 53 anonymous large European banks (as of year-end 2011), presenting exposures partitioned (layered) according to maturity and instrument type. They found a high similarity between the different layers, a core-periphery structure comprising a large core and positively correlated multiplexity. Similarly, Berndsen et al. (2018) investigated coupling financial institutions' multiplex networks with financial market infrastructures' networks. They found that central financial institutions overlap across financial networks; thus, their systemic importance may be greater than envisaged. In both cases, the layout was similar to the star structure in Figure 1, but with some central nodes with similar exposures (instrument and maturity) from other smaller nodes. These methods can demonstrate which institutions play an essential role within a network and identify correlated transmission channels. Their granular level data was compiled by two regulatory bodies for such purpose; therefore, it is not public and is difficult to criticize. Even if more interconnection data were available, practical issues such as the computing power required for larger banking systems would be substantial. For example, estimating loss distributions and methods such as Monte Carlo simulation would be required.

Table 5. Network Measures of Systemic Risk

Author	Model	Methodology	Sample	Empirical Findings
Eisenberg and Noe (2001)	A network approach to introduce a single clearing mechanism that produces the number of defaults required to induce a firm to fail	An algorithm was developed that clears the financial system computationally efficient and provides information on the systemic risk faced by the individual system firms.		They provided comparative statics, which implies that, in contrast to single-firm results, even unsystematic, non-dissipative shocks to the system will lower the total value of the system.
Elsingere et al.(2006)	To assess two sources of systematic risk by analysing the market and credit portfolios of all banks simultaneously	Eisenberg and Noe's (2001) model was extended to include indirect linkages through correlation.	Austrian interbank lending exposure cross-sectional data (881 reporting banks) for September 2002 (plus three additional times for robustness).	Correlation in bank asset portfolios dominates contagion as the primary source of systemic risk. They also computed the VaR for a lender of last resort and found that the funds necessary to prevent contagion were unpredictably low.
Chen and Wang (2009)	CDS market network model to study systemic risk	An algorithm was developed in which a bilateral connection matrix is generated stochastically to simulate a plausible CDS network reflecting the real market. The node links are the bilateral obligations from the CDS market.	FDIC data and market share data of 26 banks to create a US CDS market with the incorporation of 'non-US bank' nodes.	The network model of the CDS market shows how specific parameters of a network can affect the expected loss of the system relative to the initial loss caused by default.
Canedo and Jaramillo (2009)	Systemic Risk Network Model (SyRNet)	A network model to analyse systemic risk in the banking system seeks to obtain the probability distribution of losses resulting from the shock/contagion process for the financial system.	Mexican interbank exposure data (25 banks) from January 2004 to December 2006 (unique dataset).	Their model allows them to perform stress tests along with both the bank default probabilities and the interbank exposures and assess the risk of the system.
Mart ́inez-Jaramillo et al. (2010)	Model systemic risk *via* random shocks that weakens one or more financial institutions and a transmission mechanism that transmits such effects to the rest of the system	Canedo and Jaramillo's (2009) model was enhanced to make it more robust by incorporating CVaR to evaluate if the system has become more or less fragile.	Mexican Interbank exposure data (27 banks) from December 2007 to June 2009 (unique dataset).	Their results suggest that the probability distributions of the initial shock, the size of the losses, and the correlations, play a key role in determining the robustness or fragility of a financial system.
Bluhm and Krahnen (2014)	A macroprudential risk management approach building on a system-wide value at risk (SVaR)	This model incorporates multiple sources of systemic risk, including the size of financial institutions; direct exposure from interbank lending; asset fire sales using a Shapley value-type measure; and fundamental data (assets such as liquid, non-liquid assets, and interbank lending; liabilities such as deposits, interbank borrowing, and equity).		Using SVaR, they provide evidence that a fair systemic risk charge proportional to a bank's contribution to systemic risk diverges from the optimal macroprudential capitalisation of the banks. Also, the bank's size and interconnections in interbank lendings and fire sale spirals are driven by a mark-to-market mechanism.
Poledna et al. (2015) Poledna et al (2021)	Quantify the daily contributions to systemic risk from four network layers	The four network layers include deposits & loans, security cross-holdings, derivatives (swaps, forwards, options, and repo transactions), and foreign exchange (FX) transactions.	Applying Mexican banking system data from 2007 to 2013. A unique dataset (confidential to regulators and supervisors).	They provide evidence to show that focusing on a single layer network underestimates the total systemic risk by up to 90%. Furthermore, their results demonstrated that the exposures related to the cross-holding of securities and the exposures arising from FX transactions are crucial components of the systemic risk.
Hautsch et al. (2015)	A systemic risk beta as a measure of financial companies contribution to systemic risk, given the network interdependence between firms' tail	The realised systemic risk beta was defined as the total time-varying marginal effect of a firm's Value-at-risk (VaR) on the system's VaR. They use a wide range	59 US financial institutions from 2000 to 2008.	They provide evidence to highlight how interconnected the US financial system is and marked channels of relevant potential spillovers. In particular, this method can classify companies into major risk producers, transmitters, or recipients within

Author	Model	Methodology	Sample	Empirical Findings
	risk exposures	of publicly accessible macroeconomic market, equity return, and fundamental data.		the system.
Acemoglu et al. (2015)	A theoretical framework for the study of the economic forces shaping the relationship between the structure of the financial network and systemic risk	The focus was on an economy consisting of banks (simulating different network structures), which lasted for three periods. In the initial date, banks borrow funds from one another to invest in projects that yield returns both in the intermediate and final dates. The liability structure that emerges from interbank loans determines the financial network, capturing the pairwise counterparty relationships between institutions.		They found that a highly interconnected complete financial network is the configuration least prone to contagion. This is due to the fact that losses of a distressed bank are passed to a more significant number of counterparties, guaranteeing more efficient use of the excess liquidity. On the other hand, ring networks tend to be the most fragile. However, they provided evidence that networks do not aid the system in the case of more significant shocks.
Constantin et al. (2018)	Estimated network linkages into an EWS model to predict bank distress	The approach estimates tail-dependence networks *via* equity returns and combines them with a bank-level early-warning model (mainly focused on the CAMELS variables).	EWS was produced using 171 European banks' data from 1999Q1 to 2012Q3. The broader sample includes 243 European banks.	The EWS, including estimated tail dependencies, consistently outperforms the EWSs that solely cover vulnerabilities from bank-specific, sector-level, and macro-financial imbalances to predict bank distress events.
Roukny et al. (2018)	A theoretical model to compute the individual and systemic probability of default	Using a theoretical financial network of over-the-counter (OTC) credit contracts, the authors compute the individual and systemic probability of default in a system of banks connected in a generic interbank network.		Their main contribution shows that multiple equilibria can arise from closed chains of debt within the network. For example, suppose the default conditions of a set of banks mutually depend on credit contract cycles. In that case, a range of external shocks exist, such as the equilibrium where all those banks default and none of those defaults co-exists.
Barroso et al.a (2018)	Insolvency contagion within Financial Networks	This method decomposed drivers of systemic risk from insolvency contagion. In addition, they assessed the drivers of systemic risk from financial institutions' debt network exposures and capital buffers.	Quarterly data on cross-border debt exposures and aggregated tier 1 capital buffers from 26 countries from 2005 to 2014.	Their findings suggest that network debt topology explains most of the volatility of contagion risk and that capital buffers effectively reduce contagion risk.
Covi et al. (2021)	Contagion Mapping (CoMap)	This method demonstrates the architecture of banking networks through bilateral linkages primarily on a balance sheet simulation approach to map contagion, following the approach by Eisenberg and Noe (2001).	A unique dataset of euro area banks' significant exposures within the global banking system. Using Q3 2017 as a reference point, capturing granular bank and exposure level information.	They highlighted that the degree of bank-specific contagion and vulnerability depends on network-specific tipping points directly affecting the magnitude of amplification effects.
Moratis and Sakellaris (2021)	Individual Systemic Risk (ISR)	This is the sum of CDS shocks the bank sends to and receives from banks in a network. They employ Bayesian VAR to address the dimensionality problem in large networks of banks and for every pair of banks in the system maps the shocks that they exchange.	Seventy of the world's largest 150 banks from 19 developed and seven emerging economies. Including all the G-SIBs. Using their publicly traded CDS US dollar contracts and their CDS spreads to cover the period from January 2008 to June 2017.	Their findings suggest ISR has solid explanatory power for standard variables of systemic risk and can act as an early warning signal. In addition, more interconnected banks, as measured by the size of their systemic network, tend to be of higher systemic importance. They also find a high level of coherence between ISR and Acharya et al. (2012) Long-run marginal expected shortfall (LRMES) and to a lesser extent between ISR and SRISK.
Vodenska et al. (2021)	Using stress test data to network portfolio overlaps.	The model for systemic risk propagation is based on common bank exposures to	They use data from the 2011 EBA stress tests. This European data	The model can identify critical thresholds for asset risk and bank response to a shock beyond which the system transitions

Author	Model	Methodology	Sample	Empirical Findings
		specific asset classes. Their model has two parameters: (i) the size of the initial shock to the banking system and (ii) the spreading or spillover parameter.	included exposure of 90 different banks in the following seven investment categories: sovereign debt, financial institutions, corporate, retail, residential mortgage, retail revolving, small and medium-sized enterprises (retail SME), and commercial real estate (CRE).	from stable to unstable. They also determined that the tier 1 capital ratio deterioration prompts a banks' reaction, putting stress on their portfolios and further enhancing the crisis.

4. Data Requirements

Table 6 summarises the different data types required to compute and empirically test the methods proposed for calculating systemic risk. It includes 54 models, rather than the 60 models noted previously, because six of them are theoretical and they were not empirically tested with real-world data. The most common indicators are equity prices (55% of models) and financial institution fundamental data (45% of models), which is likely related to its availability *via* stock exchanges or from a range of subscription databases (e.g. Thomson Reuters Datastream and Bloomberg Professional Service). As mentioned previously, they have certain limitations, which are widely acknowledged in the literature. For example, using equity relies on the assumption of rational markets, which is not always the case, especially in times of crisis. Zhang et al. (2015) questioned whether purely equity-based measures capture systemic risk adequately from an empirical perspective.

Furthermore, as global equities become more correlated (Roll 2013; You and Daigler 2010), these could impact the models' reliability and statistical significance. For example, Born et al. (2014) used the bank equities dataset to conduct an event study focusing on the central bank's dissemination, the Financial Stability Report publication (and ad hoc speeches/interviews) and further affecting equity markets increasing correlation returns and reducing market volatility. As some EWS (e.g. FSI and CISS) use correlation and realized volatility, such models may also be indirectly affected by such issues.

Many papers that apply fundamental data from financial institutions[7] , balance sheets items, or their combination, are used as proxies for risk. In some cases, there is little consistency (e.g. the decision to utilise the natural log function or not). Also, some methodologies require interpolation, extrapolation, or disaggregating from yearly to quarterly or monthly data. Given the operational nature of the financial institutions, this technique could provide misleading observations. Macroeconomic data is used within 27% of the models and, again, this data is widely available within the public domain. However, similar to fundamental data, the frequency and time of publication varies across different countries, often impacting comparability. It is also worth noting that most models used interest rate/bond yield data during positive interest rate environments. However, following the financial crisis and COVID-19 pandemic, several jurisdictions lowered interest rates close to zero and some central banks even introduced negative rates (Demiralp et al. 2021). Therefore, the effectiveness of such models may need to be tested in negative interest rate environments.

The contagion and network methods of measuring systemic risk tend to use unique datasets. Poledna et al. (2015) and Poledna et al. (2021) applied the Mexican Central Bank data. Khandani et al. (2010) used customer transactions and credit bureau data from the US commercial banks. Covi et al. (2021) used the European regulator credit and counterparty exposure datasets. Canedo and Jaramillo (2009), Elsinger et al. (2006) and Tonzer (2015) used the interbank market data. Such research provides insight into specific cases relying on data that is not readily available in the public domain; they provide interesting and significant findings. Thus, an argument for more data transparency and availability. Previous literature (Aldasoro and Alves 2016; Covi et al. 2021), among other things, has argued the need to use more granular data by noting that banks interconnectedness can range differently in different layers (different asset or liability types). Therefore, focusing on a single layer may be misleading (Poledna et al. 2015; Poledna et al. 2021). Still, vital information can be obtained from one layer dataset, and in particular, if one can decompose global systemic importance, regulators can identify institutions to investigate further. Nevertheless, without unique/granular level data Aldasoro and Alves (2016) provided evidence that simple network measures can be an excellent second best.

Foreign exchange data is rarely used in the systemic risk models and this data tends to be in the form of an index or a currency pair price. As foreign exchange transactions are conducted over the counter, such indexes/prices tend to aggregate the bid/offer prices. In attempts to capture inter-

[7] Silva et al. (2017) identified that out of the 266 articles reviewed, banks out of all institutions were the prominent focus being used in 174 studies

day volatility, the spot price is often compared to the 30 minutes earlier price or the futures price. Interestingly, despite the occasional use of foreign exchange market data, when it is employed, it tends to be in studies covering the developing countries and is found to be a significant indicator of systemic risk (Bae, Karolyi, and Stulz 2003; Poledna et al. 2015; Sensoy, Ozturk, and Hacihasanoglu 2014, *among other things*). In addition, Laeven and Valencia (2013) noted that most financial crises within developing economies initially originate from either sovereign default and currency depreciation. Therefore, incorporating foreign exchange data may provide valuable insight into the future development of systemic risk models. Lastly, all the current systemic measurement techniques do not consider any new data developments and the abundance of non-financial data, including digital footprints that banks now access (Stulz, 2019). Such data is generated from the Fintech sector, which is starting to utilize machine learning and artificial intelligence techniques, which gives rise to economies of scale in data usage (Boot *et al.,* 2021). Thus, future systemic risk models could exploit such new data and techniques. However, Beutel, List, and Schweinitz (2019) warned that further enhancements to machine learning techniques in early warning models are needed before they can offer a valuable addition for predicting systemic banking crises.

Table 6. Data Requirements

Author(s) and Year of Publication	Credit Default Swaps	Equity	Macroeconomic	Fundamental	Bond Market	Interbank Market	Commodities Market	Foreign Exchange Market	Real Estate	Hedge Fund	Regulation Environment	Futures Margins	Credit Rating/Default Timing	Consolidation Timing	Unique/Granular Dataset
Nicolo and Kwast (2002)		x												x	
Bae et al. (2003)		x	x					x						x	
Gropp and Moerman (2004)		x		x											
Lehar (2005)				x											
Elsinger et al. (2006)						x									x
Chan et al. (2006)										x					
Bartram et al. (2007)		x													
Rodriguez (2007)		x													
Bhansali et al. (2008)	x														
Adrian and Brunnermeier (2008)		x		x											
Huang, Zhou, and Zhu (2009)	x	x		x											
Alessi and Detken (2009)			x	x											
Segoviano Basurto and Goodhart (2009)	x														
Brunnermeier and Pedersen (2009)												x			
Aikman et al. (2009)		x	x	x									x		
Canedo and Jaramillo (2009)						x									x
Chen and Wang (2009)	x														
Gaganis et al. (2010)			x	x							x				
Kritzman and Li (2010)		x			x		x		x						
Acharya et al. (2010, 2017)	x	x		x											
Khandani, Kim, and Lo (2010)													x		x
Martınez-Jaramillo et al. (2010)						x									x
Kritzman et al. (2011)		x								x					
Schwaab et al. (2011)			x										x		
Giesecke and Kim (2011)		x	x			x							x		
Allen, Bali, and Tang (2012)		x	x												
Hollo, Kremer, and Lo Duca (2012)		x		x	x	x		x							
Brownlees and Engle (2012)		x		x											
Billio et al. (2012)										x					
Duca and Peltonen (2013)		x		x	x	x	x								
Trapp and Wewel (2013)	x														
Girardi and Ergun (2013)		x		x											
Puzanova and Dullmann (2013)		x		x											
Jobst and Gray (2013)		x		x											
Hu et al. (2013)					x	x									
Sensoy et al. (2014)	x	x			x	x		x							
Jobst (2014)				x											
Ye et al. (2014)		x													
Avramidis and Pasiouras (2015)		x		x									x		
Poledna et al. (2015) Poledna et al (2021)															x
Hautsch et al. (2015)		x	x	x											
Tonzer (2015)			x	x		x									
Eder and Keiler (2015)	x	x	x	x	x	x									
Aldasoro and Alves (2016)															x
Kreis and Leisen (2018)		x		x											
Alessi and Detken (2018)			x		x				x						
Constantin et al. (2018)		x	x	x											
Gibson et al. (2018)		x													
Papanikolaou (2018)			x	x							x		x		
Barroso et al. (2018)				x											x
Tölö, E. (2020).		x	x						x						
Covi et al. (2021)															x
Moratis and Sakellaris (2021)	x														
Vodenska et al. (2021)											x				

5. Challenges for Regulation and Systemic Risk Measurement

In reacting to the initial shock of the COVID-19 pandemic, governments worldwide have responded with unprecedented scope and magnitude of policies to support the real economy, prevent permanent damage to the balance sheets of firms, and maintain the flow of credit to the real economy.

Government actions have included: promoting increased capital levels by publishing voluntary guidelines requiring banks not to pay a dividend, lowered or waived capital holdings on some risk-weighted assets,[8] and freeing some of the capital buffers such as the countercyclical capital buffer that is designed to be used during downturns (IMF, 2020a). These policies allowed banks to free up capital to provide liquidity and continue a credit line to a more risky sector. However, regulatory easing *via* these policies reduced minimum requirements below Basel framework levels in some jurisdictions (IMF, 2020b). Such unconventionality risks undermining the credibility of the internationally agreed standards. Thus far, most regulatory responses are consistent with the core standards implemented after the global financial crisis, focusing on the soundness of individual institutions. Assessing the CoVaR on European banks, Borri and Di Giorgio (2021) formulated a reasonable conclusion that the new regulation implemented after the financial crisis, which set higher capital requirements for banks and more stringent stress tests, had proved successful at avoiding another financial crisis. However, Didier et al. (2021) warned that the current regulatory infrastructure was not designed to deal with an exogenous systemic shock, such as the COVID-19 pandemic. On the contrary, they suggested that it could amplify the problem as it penalises firms that face difficulties, leading to inefficient bankruptcies and excessive relationship destruction in the COVID-19 pandemic. As a result, policy-makers face several challenges in reducing overall systemic risk and the coordination between jurisdictions.

Firstly, a policy response to systemic risk is a global issue. A collaborative partnership of central banks, regulators, and governments with a harmonised supervisory style would need to lead a macro-prudential approach. Following the global financial crisis, there were repeated calls to strengthen the cooperation between national regulators as part of the policy response (Arner 2009). There have been several proposals to develop cross-border regulations (mainly focused on the G-SIB), including recommendations by the WTO, BIS, and IMF (Arner and Taylor 2009); however, such harmonized supervisory approach is currently a long way off. The reasons could include: culture (for example, Carretta et al. (2015) found that among the European banks there is a substantial number of different supervisory cultures); attitudes to risk (Clark and Jokung (2015) noted that, globally, regulators' risk aversions differ significantly) and a reluctance to hand over power (Masciandaro and Volpicella (2016) found that some governments tend to be cautious when placing too much power in the hands of independent and discretionary central banks).

Secondly, the idea of harmonisation and the term macro-prudential regulation can be interpreted in different ways. It means controlling financial instability inherent to financial markets and institutions using a top-down approach from a systemic risk perspective. However, macro-prudential regulation often focuses on mapping and managing the economic cycle while sceptics treat it meaningless. Therefore, a consensus on the precise definition of macro-prudential regulation would be desirable. Recent findings from Meuleman and Vennet (2020) showed the importance of macro-prudential measures as they confirm that macroprudential policy is also effective in containing bank systemic risk (as assessed by stock market investors). In contrast, previous studies had mainly documented the moderating effect of macroprudential measures on banks.

As previously discussed in this paper, the wide range of systemic risk measures available, coupled with many proposed policy instruments to address a specific type of risk, leave policy-makers facing a conundrum, which results in the main problem of deciding on a universally accepted regulatory instrument (or a combination of instruments) that would be cost-effective in mitigating systemic risk.

[8] Mainly assets such as loans covered by government guarantees or loan exposures to specific sectors.

Thirdly, when determining what type of regulation to implement, policymakers face the challenge regarding which banks need further regulation or whether the 'one size fits all approach is sufficient. Traditionally, regulators have been focusing on the indicators related to banks' financial health, such as balance sheet and liquidity indicators (Silva et al. 2017), irrespective of size. Empirical evidence has sought to address this challenge, however more could be done using a range of systemic risk measures identified in this paper. In previous studies, Vazquez and Federico (2015) found that smaller and larger banks (in the US and Europe) were susceptible to failure for different reasons, i.e. smaller banks due to liquidity problems and large banks due to insufficient capital buffers. Demirguc-Kunt et al. (2013) found that robust capital reserves are linked with better equity price performance for larger banks and Chiaramonte and Casu (2017) report that for the G-SIBs the Basel III capital and liquidity standards have proven to be important in reducing a bank's probability of default.

Fourthly, another relevant issue is whether regulators should target banks as *contributors to* (reducing moral hazard) or *participants of* (making individual banks safer) systemic risk. As Covi et al. (2021) warn, current financial regulations seek to limit each institution's risk in isolation, which underestimates the systemic risk contribution to overall fragility.

Finally, stress-testing has also become an important new challenge in light of the COVID-19 pandemic. Following the outbreak of the COVID-19 virus, the regulators who regularly conducted stress-test exercises on banks had to adjust their approach. They initially performed *ad hoc* tests to assess the vulnerability of banking sectors as a whole and to measure the system-wide impact of the COVID-19 pandemic on the banking sector, which was different from the usual stress-tests in terms of their objectives, design, methodologies, and also communication (Baudino, 2020). In addition, they aimed to evaluate the immediate impact of the COVID-19 pandemic at the aggregate level. However, as the COVID-19 pandemic develops and nears its end following the mass vaccination programmes worldwide, the authorities should further adjust their stress tests and refine their key features to allow for more granular bank-level evaluations (Baudino, 2020).

6. Research Gaps and Future Research Directions

Based on our review of the systemic risk measures and challenges which regulators face, we have identified the following gaps in the available literature. We also point towards the possible future research directions which they open.

Firstly, systemic risk measurement, especially when linked with the capital requirements for banks (and other financial institutions), is still a critically important research field. As discussed in this review, the research on bank capital requirement and its associated regulations to prevent institutions from being *participants of* systemic risk continually evolves, and will continue to do so in light of new macroeconomic environments and changes to the sector.

Secondly, in a strict sense of the systemic risk and the network measures, there are also issues relating not only to 'Too Big To Fail' (TBTF) but also the 'Too Interconnected To Fail' (TITF), 'Too Big To Regulate'(TBTR) and 'Too Many To Fail' (TMTF). More papers covering data from different international markets would be helpful to address these issues, given the majority so far are from the US and European banking sectors.

Thirdly, is essential to better understand the pro-cyclicality of regulations (more specifically, regarding the capital regulations and the provisioning for credit risk) and how to counteract the pro-cyclicality with using, for example, the anti-cyclical buffers. This problem can be perceived more broadly, i.e., as the convergence of the microprudential and macroprudential policies, noted in Section 5.

Fourthly, from a liquidity perspective, TLAC and MREL are particularly important in understanding the risk contagion (within the banking sector and among sectors), so more research would be welcome in this area.

Fifthly, it is also essential to verify whether recent regulatory reforms and responses to the COVID-19 pandemic were successful and if they have been appropriately implemented. Questions remain whether the capital and liquidity requirements were correctly calibrated and if TLAC/MREL are justified and adequately play their role.

Sixthly, another related issue is that if the requirements for banks are being relaxed, there would be a question if the thresholds were previously not set too high. Although it has been argued that the buffers were used temporarily, there seems to be currently too much capital in banks (and perhaps also too much liquidity). The use of systemic risk measures to test the appropriate capital and liquidity requirements would be desirable.

Seventhly, the stress tests and reverse stress tests (necessary for both the banks and the regulators/supervisory institutions and in the micro and macroprudential perspectives) need to be investigated more intensively (Baudino, 2020). This issue gained importance following the COVID-19 pandemic and more research on the effectiveness of stress tests in the current economic conditions would be very welcome.

Furthermore, an increasing new problem following the COVID-19 pandemic is the likelihood of negative interest rates. With most systemic risk measures being created and empirically tested during positive interest rate environments, they may not be effective in a negative interest rate scenario. Moreover, negative interest rate environments have broader implications on banking models and levels of liquidity (Demiralpa et al. 2021; Gilman, 2021), which directly relate to risk, thus will be captured in a range of other systemic risk measures.

In addition, despite not being directly addressed in this paper, an emerging area following on from the development and enhancement of the network systemic risk measures is machine learning and artificial intelligence and how these methods can be used to measure systemic risk. This may help overcome the challenges noted in Section 4, such as applying techniques which can use large data sets. Thus, incorporating multiple variables in future systemic risk measures may allow one to analyse risk from micro and macro perspectives. Similarly, the current systemic risk measures only address the banking sector. Thus, understanding the impact of the Fintech sector on risk (including systemic risk) is another critical new research topic. As highlighted by the network systemic risk measures, it is challenging to identify the routes of transmission of risk; thus, the integration of Fintech within the banking network should be taken into account.

The current COVID-19 pandemic highlighted many of the aforementioned problems or even exposed them on a grander scale. Moreover, given that there will be more pandemics in the future, these issues should be taken into account by banks and financial institutions as well as regulators in the understanding of the *ex-ante* risks. Finally, it needs to be mentioned too that it is not entirely unlikely that the COVID-19 pandemic (and other future pandemics on a global scale) may also lead to some social and political instabilities, which is another important consideration that can have a significant impact on the systemic risk. Hence, this problem should be taken into consideration as well in the proper measurement of risk.

7. Conclusion

In this paper, a systematic literature review was conducted to identify the post-2000 systemic risk measures as well as to better understand systemic risk and its regulation. Since 2000, and more so following the 2008-09 financial crisis, there has been an over-abundance of different definitions, identified sources, and systemic risk measurements. The main challenge regarding measuring systemic risk is that there is no single definition and the wide range of measures developed provides no consistency of understanding systemic risk. Ultimately, the systemic risk measures designed so far only sought to address specific aspects of systemic risk. The more recent approaches are moving in the right direction to create a more holistic measurement of the institution and market risk by incorporating a range of typical market indicators. However, to enhance the effectiveness of the measures, there is a need for improved data availability, transparency, and empirical testing. With most of the models using the US and European banking data, additional research to apply the more comprehensive models identified in the context of alternative jurisdictions would be welcome. In addition, with the spread of the novel coronavirus resulting in an unprecedented shock to the global economy, new empirical evidence of the effectiveness of the systemic risk measures covered in this paper using data from the COVID-19 period may validate their usefulness in practice. From a regulatory perspective, continued progress is needed for policy-makers to improve their understanding of the current reforms and macro-prudential regulation to move towards a more globally harmonised approach. Without macro-prudential regulation, policy-makers will continue to focus on individual institutions. This was noticeable in the varied international response to the COVID-19 pandemic when respective jurisdictions mainly concentrated on relaxing institutions' capital and liquidity buffers to minimise the financial impact on the real economy. However, such relaxation could leave individual institutions unable to withstand additional shocks in the future, which may have broader repercussions for financial stability in an adverse scenario.

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