A Survey of Systemic Risk Analytics*

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Abstract

We provide a survey of 31 quantitative measures of systemic risk in the economics and finance literature, chosen to span key themes and issues in systemic risk measurement and management. We motivate these measures from the supervisory, research, and data perspectives in the main text, and present concise definitions of each risk measure—including required inputs, expected outputs, and data requirements—in an extensive appendix. To encourage experimentation and innovation among as broad an audience as possible, we have developed open-source Matlab code for most of the analytics surveyed, which can be accessed through the Office of Financial Research (OFR).

Keywords: *Systemic Risk; Financial Institutions; Liquidity; Financial Crises; Risk Management JEL Classification: G12, G29, C51*

1. Introduction

In July 2010, the U.S. Congress enacted the *Dodd Frank Wall Street Reform and Consumer Protection Act* (Dodd Frank Act), the most comprehensive financial reform bill since the 1930s. Among other things, the Dodd Frank Act created the Financial Stability Oversight Council (FSOC) and Office of Financial Research (OFR). The FSOC has three broad mandates: (1) to identify risks to financial stability arising from events or activities of large financial firms or elsewhere; (2) to promote market discipline by eliminating participants' expectations of possible government bailouts; and (3) to respond to emerging threats to the stability of the financial system.[1] The starting point for all of these directives is the accurate and timely measurement of systemic risk. The truism that "one cannot manage what one does not measure" is especially compelling for financial stability since policymakers, regulators, academics, and practitioners have yet to reach a consensus on how to define "systemic risk". While regulators sometimes apply Justice Potter Stewart's definition of pornography, i.e., systemic risk may be hard to define but they know it when they see it, such a vague and subjective approach is not particularly useful for measurement and analysis, a pre-requisite for addressing threats to financial stability.

One definition of systemic risk is "any set of circumstances that threatens the stability of or public confidence in the financial system" (Billio, Getmansky, Lo, and Pelizzon, 2010). The European Central Bank (ECB) (2010) defines it as a risk of financial instability "so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially". Others have focused on more specific mechanisms, including imbalances (Caballero, 2009), correlated exposures (Acharya, Pedersen, Philippon, and Richardson, 2010), spillovers to the real economy (Group of Ten, 2001),

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[1] *See Section §112(a)(1) (Pub.L.111-203,H.R.4173). The full range of detailed mandates, constraints, and authorities for the FSOC and OFR are covered in Sections §112–156 of the Act.*

information disruptions (Mishkin, 2007), feedback behavior (Kapadia, Drehmann, Elliott, and Sterne, 2009), asset bubbles (Rosengren, 2010), contagion (Moussa, 2011), and negative externalities (Financial Stability Board, 2009).

This partial listing of possible definitions suggests that more than one risk measure will be needed to capture the complex and adaptive nature of the financial system. Because systemic risk is not yet fully understood, measurement is obviously challenging, with many competing—and sometimes contradictory—definitions of threats to financial stability.

Moreover, a single consensus measure of systemic risk may neither be possible nor desirable, as such a "Maginot" strategy invites a blindsided surprise from some unforeseen or newly emerging crisis mechanism. Instead, a robust framework for monitoring and managing financial stability must incorporate both a diversity of perspectives and a continuous process for re-evaluating the evolving structure of the financial system and adapting systemic risk measures to these changes. At the same time, to be useful in *measuring* systemic risk, a practical implementation must translate economic concepts into very particular choices: one must decide which attributes of which entities will be measured, how frequently and over what observation interval, and with what levels of granularity and accuracy. Summary measures involve further choices on how to filter, transform, and aggregate the raw inputs.

In this paper, we take on this challenge by surveying the systemic risk measures and conceptual frameworks that have been developed over the past several years, and providing open-source software implementation (in Matlab) of each of the analytics we include in our survey. These measures are listed in Table 1, loosely grouped by the type of data they require, and described in detail in Appendixes A–F. The taxonomy of Table 1 lists the analytics roughly in increasing order of the level of detail for the data required to implement them. This categorization is obviously most relevant for the regulatory agencies that will be using these analytics, but is also relevant to industry participants who will need to supply such data.[2] For each of these analytics, Appendixes A–F contain a concise description of its definition, its motivation, the required inputs, the outputs, and a brief summary of empirical findings if any. For convenience, in Appendix G we list the program headers for all the Matlab functions provided.

Thanks to the overwhelming academic and regulatory response to the Financial Crisis of 2007–2009, we face an embarrassment of riches with respect to systemic risk analytics. The size and complexity of the financial system imply a diversity of legal and institutional constraints, market practices, participant characteristics, and exogenous factors driving the system at any given time. Accordingly, there is a corresponding diversity of models and measures that emphasize different aspects of systemic risk. These differences matter.

Systemic Risk Measure	Section
Macroeconomic Measures:	
Costly Asset - Price Boom/Bust Cycles	A.1
Property - Price, Equity - Price, and Credit - Gap Indicators	A.2
Macroprudential Regulation	A.3
Granular Foundations and Network Measures:	
The Default Intensity Model	B.1
Network Analysis and Systemic Financial Linkages	B.2
Simulating a Credit Scenario	B.3

[2] *An obvious alternate taxonomy is the venerable Journal of Economic Literature (JEL) classification system or the closely related Econ Lit taxonomy. However, these groupings do not provide sufficient resolution within the narrow subdomain of systemic risk measurement to be useful for our purposes. Borio and Drehmann (2009b) suggest a three-dimensional taxonomy, involving forecasting effectiveness, endogeneity of risks, and the level of structural detail involved. Those three aspects are reflected in the taxonomies we propose in this paper.*

Systemic Risk Measure	Section
Simulating a Credit-and-Funding-Shock Scenario	B.4
Granger-Causality Networks	B.5
Bank Funding Risk and Shock Transmission	B.6
Mark-to-Market Accounting and Liquidity Pricing	B.7
Forward-Looking Risk Measures:	
Contingent Claims Analysis	C.1
Mahalanobis Distance	C.2
The Option iPoD	C.3
Multivariate Density Estimators	C.4
Simulating the Housing Sector	C.5
Consumer Credit	C.6
Principal Components Analysis	C.7
Stress-Test Measures:	
GDP Stress Tests	D.1
Lessons from the SCAP	D.2
A 10-by-10-by-10 Approach	D.3
Cross-Sectional Measures:	
Co VaR	E.1
Distressed Insurance Premium	E.2
Co-Risk	E.3
Marginal and Systemic Expected Shortfall	E.4
Measures of Illiquidity and Insolvency:	
Risk Topography	F.1
The Leverage Cycle	F.2
Noise as Information for Illiquidity	F.3
Crowded Trades in Currency Funds	F.4
Equity Market Illiquidity	F.5
Serial Correlation and Illiquidity in Hedge Fund Returns	F.6
Broader Hedge-Fund-Based Systemic Risk Measures	F.7

Table 1: Taxonomy of systemic risk measures by data requirements.

For example, many of the approaches surveyed in this article assume that systemic risk arises endogenously within the financial system. If correct, this implies that there should be measurable inter-temporal patterns in systemic stability that might form the basis for early detection and remediation. In contrast, if the financial system is simply vulnerable to exogenous shocks that arrive unpredictably, then other types of policy responses are called for. The relative infrequency with which systemic shocks occur make it all the more challenging to develop useful empirical and statistical intuition for financial crises.[3]

[3] *Borio and Drehmann (2009a) observe that there is as yet no single consensus explanation for the behavior of the financial system during crises, and because they are infrequent events in the most developed financial centers, the identification of stable and reliable patterns across episodes is virtually impossible in one lifetime. Caruana (2010a) notes two studies indicating that, worldwide, there are roughly 3 or 4 financial crises per year on average. Most of these have occurred in developing economies, perhaps only because smaller countries are more numerous.*

Unlike typical academic surveys, we do not attempt to be exhaustive in our breadth.[4] Instead, our focus is squarely on the needs of regulators and policymakers, who, for a variety of reasons—including the public-goods aspects of financial stability and the requirement that certain data be kept confidential—are solely charged with the responsibility of ensuring financial stability from day to day. We recognize that the most useful measures of systemic risk may be ones that have yet to be tried because they require proprietary data only regulators can obtain. Nevertheless, since most academics do not have access to such data, we chose to start with those analytics that could be most easily estimated so as to quicken the pace of experimentation and innovation.

While each of the approaches surveyed in this paper is meant to capture a specific challenge to financial stability, we remain agnostic at this stage about what is knowable. The system to be measured is highly complex, and so far, no systemic risk measure has been tested "out of sample", i.e., outside the recent crisis. Indeed, some of the conceptual frameworks that we review are still in their infancy and have yet to be applied. Moreover, even if an exhaustive overview of the systemic risk literature were possible, it would likely be out of date as soon as it was written.

Instead, our intention is to present a diverse range of methodologies, data sources, levels of data frequency and granularity, and industrial coverage. We wish to span the space of what has already been developed, to provide the broadest possible audience with a sense of where the boundaries of the field lie today, and without clouding the judgments of that audience with our own preconceptions and opinions. Therefore, we have largely refrained from any editorial commentary regarding the advantages and disadvantages of the measures contained in this survey, and our inclusion of a particular approach should not be construed as an endorsement or recommendation, just as omissions should not be interpreted conversely. We prefer to let the users, and experience, be the ultimate judges of which measures are most useful.

Our motivation for providing open-source software for these measures is similar: we wish to encourage more research and development in this area by researchers from all agencies, disciplines, and industries. Having access to working code for each measure should lower the entry cost to the field. We have witnessed the enormous leverage that the "wisdom of crowds" can provide to even the most daunting intellectual challenges—for example, the Netflix Prize, the DARPA Network Challenge, and Amazon's Mechanical Turk—and hope that this survey may spark the same kind of interest, excitement, and broad engagement in the field of systemic risk analytics. Accordingly, this survey is intended to be a living document, and we hope that users will not only benefit from these efforts, but will also contribute new analytics, corrections and revisions of existing analytics, and help expand our understanding of financial stability and its converse. In the long term, we hope this survey will evolve into a comprehensive library of systemic risk research, a knowledge base that includes structured descriptions of each measurement methodology, identification of the necessary data inputs, source code, and formal taxonomies for keyword tagging to facilitate efficient online indexing, searching, and filtering.

Although the individual models and methods we review were not created with any classification scheme in mind, nonetheless, certain commonalities across these analytics allow us to cluster the techniques into clearly defined categories, e.g., based on the types of inputs required, analysis performed, and outputs produced. Therefore, we devote a significant amount of attention in this paper to organizing systemic risk analytics into several taxonomies that will allow specific audiences such as policymakers, data and information-technology staff, and researchers to quickly identify those analytics that are most relevant to their unique concerns and interests.

However, the classifications we propose in this paper are necessarily approximate. Each risk measure should be judged on its own merits, including the data required and available, the sensitivities of the model, and its general suitability for capturing a particular aspect of financial stability. Because our goal for each taxonomy is to assist users in their search for a particular risk measure, creating a single all-inclusive classification scheme is neither possible nor desirable. A number of papers we survey are internally diverse, defying unique categorization. Moreover, the boundaries of the discipline are fuzzy in many places and expanding everywhere. An organizational scheme that is adequate today is sure to become obsolete tomorrow. Not only will new approaches emerge over time, but innovative ideas will reveal blind spots and inadequacies in the current schemas, hence our taxonomies must also evolve over time.

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[4] *Other surveys are provided by Acharya, Pedersen, Philippon, and Richardson (2010), DeBandt and Hartmann (2000) and International Monetary Fund (2011, Ch. 3)*

For our current purposes, the most important perspective is that of policymakers and regulators since they are the ones using systemic risk models day-to-day. Therefore, we begin in Section 2 with a discussion of systemic risk analytics from the supervisory perspective, in which we review the financial trends that motivate the need for greater disclosure by systemically important financial institutions, how regulators might make use of the data and analytics produced by the OFR, and propose a different taxonomy focused on supervisory scope. In Section 3, we turn to the research perspective and describe a broader analytical framework in which to compare and contrast various systemic risk measures. This framework naturally suggests a different taxonomy, one organized around methodology. We also include a discussion of non-stationarity, which is particularly relevant for the rapidly changing financial industry. While there are no easy fixes to time-varying and state-dependent risk parameters, awareness is perhaps the first line of defense against this problem. For completeness, we also provide a discussion of various data issues in Section 4, which includes a summary of all the data required by the systemic risk analytics covered in this survey, a review of the OFR's ongoing effort to standardize legal entity identifers, and a discussion of the trade-offs between transparency and privacy and how recent advances in computer science may allow us to achieve both simultaneously. We conclude in Section 5.

2. Supervisory Perspective

The Financial Crisis of 2007–2009 was a deeply painful episode to millions of people; hence, there is significant interest in reducing the likelihood of similar events in the future. The Dodd Frank Act clearly acknowledges the need for fuller disclosure by systemically important financial institutions (SIFIs), and has endowed the OFR with the statutory authority to compel such entities to provide the necessary information (including subpeona power). Nevertheless, it may be worthwhile to consider the changes that have occurred in our financial system which justify significant new disclosure requirements and macroprudential supervisory practices. A number of interrelated long-term trends in the financial services industry suggest that there is more to the story than a capricious, one-off “black-swan” event that will not recur for decades. These trends include the gradual deregulation of markets and institutions, disintermediation away from traditional depositories, and the ongoing phenomenon of financial innovation.

2.1 Trends in the Financial System

Innovation is endemic to financial markets, in large part because competition tends to drive down profit margins on established products. A significant aspect of recent innovation has been the broad-based movement of financial activity into new domains, exemplified by the growth in mortgage securitization and “shadow banking” activities. For example, Gorton and Metrick (2010) document the strong growth since the 1980s in repo and money-fund assets, and Loutskina and Strahan (2009) demonstrate that the widespread availability of securitization channels has improved liquidity in mortgage markets, reducing the sensitivity of credit supply to the idiosyncratic financial conditions of individual banks. Facilitating these institutional changes are underlying advances in modeling portfolio credit risk, legal and technical developments to support electronic mortgage registration, and the expansion of markets for credit derivatives. Another factor is the burden of supervision and regulation, which falls more heavily on established institution types such as traditional banks and broker-dealers, and relatively lightly on hedge funds and private equity firms.

As innovation and alternative investments become more significant, the complexity of the financial system grows in tandem—and size matters. In many cases, financial innovation has effectively coincided with deregulation, as new activities have tended to expand most among less regulated, non-traditional institutions. For example, in the 1980s, the hedge-fund industry was well established but small enough that its activities had little effect on the rest of the system. By the late 1990s, hedge-fund assets and activities had become so inter- twined with global fixed-income markets that the demise of a single hedge fund—Long Term Capital Management (LTCM)—was deemed potentially so disruptive to financial stability that the Federal Reserve Bank of New York felt compelled to broker a bailout. Securitization is particularly important in this context: it effectively disintermediates and deregulates simultaneously by moving assets off the balance sheets of highly regulated, traditional depositories, and into less regulated special purpose vehicles. Adrian and Shin (2009) connect the growth in shadow banking to securitization, arguing that the latter has enabled increases in leverage by reducing idiosyncratic credit risk at originating institutions. As securitization activity expanded, the balance sheets of securities firms such as Lehman Brothers ballooned, potentially increasing the fragility of the system as a whole. Adrian and Shin (2009) demonstrate the procyclicality of this (de-)leveraging effect through the recent boom and crisis. The collapse in the asset-backed securitization market that followed the crisis was, in effect, a re-intermediation, and re-regulation has emerged in the form of the Dodd Frank Act in the U.S. and similar legislation in the United Kingdom and the European Union. Even innovation has taken a holiday, with structured products falling out of favor and investors moving closer to cash and its equivalents.

Over the longer term, however, broader trends have also involved disintermediation. Feldman and Lueck (2007) update an earlier study of long-term structural trends in financial markets by Boyd and Gertler (1994), and using adjusted flow-of-funds data, they show that banks have employed a variety of techniques, including securitization, to recover market share lost in the 1980s and 1990s. However, their statistics also show dramatic growth in market share for "other financial intermediaries", which increases from less than 10% in 1980 to roughly 45% in 2005 (see Feldman and Lueck (2007, Figure 3)). Even this is a gross underestimate because "other financial intermediaries" does not include the hedge fund industry. Accompanying this broader trend of disintermediation is the secular growth in the finance and insurance industries as a share of the U.S. and global economies. There is considerable anecdotal evidence for this growth in recent years—in numbers, assets, employees, and diversity—and more objective measures such as per capita value-added and salary levels confirm this informal impression. Total employment of the finance and insurance sectors has continued to rise, even in recent decades as the spread of automation has eliminated many back-office jobs. This pattern is part of a larger trend in the U.S. economy where, according to nominal U.S. GDP data from 1947 to 2009, service industries have become an increasingly larger proportion of the U.S. economy than goods-producing industries since the post-war period. The finance and insurance have grown almost monotonically during that period, in contrast to many other goods-producing sectors such as manufacturing. One implication of these trends is that the repercussions of sector-wide shocks to the financial system are likely to be larger now than in the past.

Closely related to the growth of the financial sector is the intensity of activity in that sector. This is partly the result of innovations in telecommunications and computer technology, and partly due to financial innovations that encourage rapid portfolio rebalancing, such as dynamic hedging, portfolio insurance, and tracking indexes.[5] Whether measured by trading volume, number of transactions, the total assets deployed, or the speed with which transactions are consummated, the pace of financial activity has increased dramatically, even over the last decade. Improvements in computation, connectivity, trading, social and financial networking, and globalization have facilitated ever faster and more complex portfolio strategies and investment policies. The co-location of high-frequency trading algorithms at securities exchanges is perhaps the most extreme example, but the "paperwork crisis" of the late 1960s was an early indication of this trend. The implication for regulatory supervision is that the relatively leisurely pace of quarterly financial reporting and annual examinations is becoming increasingly inadequate. Moreover, legacy supervisory accounting systems sometimes fail to convey adequately the risk exposures from new complex contingent contracts, and from lightly regulated markets with little or no reporting requirements. In fact, supervisors do not even have consistent and regularly updated data on some of the most basic facts about the industry, such as the relative sizes of all significant market segments.

A related concern is whether the systemic consequences of shocks to these sectors might be more or less severe than among the more traditional institutional segments. This is largely an open question because so little is known about systemic exposures in the shadow banking sector. Feldman and Lueck (2007, pp.48–49) conclude with a plea for more detailed information, since "good policy on banking requires a solid sense of banks' market share." In a world of interconnected and leveraged institutions, shocks can propagate rapidly throughout the financial network, creating a self-reinforcing dynamic of forced liquidations and downward pressure on prices.

Lack of transparency also hampers the ability of firms to protect themselves. Market participants may know their own counterparties, but no individual firm can peer more deeply into the counterparty network to see all of the interconnections through which it can be affected. Two familiar examples illustrate this more general problem. Participants who had purchased CDS protection from AIG Financial Products were unknowingly exposed to wrong-way risk because they could not see the full extent of AIG's guarantee exposures to others, and Lehman Brothers disguised the full extent of its leverage from other participants via its "Repo 105" transactions. Because trading firms must maintain secrecy around their portfolio exposures to remain profitable, the opaqueness of the financial network will never resolve itself solely through market mechanisms.

[5] *Even the simplest measure, such as the average daily trading volume in the S&P 500 index exhibits an increase of three orders of magnitude over the last half century, from 3 million shares in 1960 to just over 4 billion shares as of September 1, 2011. The growth in equity market trading is only a lower bound for the growth in total financial-market activity. It does not include the explosive growth in the many exchange-traded and over-the-counter derivatives since the 1970s, including the introduction of S&P 500 index futures contracts. It also ignores the broad expansion of securitization techniques, which have converted large swaths of previously illiquid loan contracts into bonds that trade actively in secondary markets.*

2.2 Policy Applications

Having made the case for additional disclosure by SIFIs, a natural response by industry stakeholders is to ask how such disclosure and systemic risk analytics be used and why the financial industry should be a willing participant? While the details of macroprudential and systemic risk policy decisions are beyond the scope of this paper, a few general observations about uses and abuses may be appropriate. Alexander (2010) provides a useful perspective on this issue in his outline of four distinct policy applications of systemic risk measures:

(a) by identifying individual institutions posing outsized threats to financial stability (i.e., SIFIs), metrics can help in targeting heightened supervisory standards; (b) by identifying specific structural aspects of the financial system that are particularly vulnerable, metrics can help policymakers identify where regulations need to be changed; (c) by identifying potential shocks to the financial system posing outsized threats to stability (e.g., asset price misalignments), metrics may help guide policy to address those threats; and (d) by indicating that the potential for financial instability is rising (i.e., providing early warning signals), metrics can signal to policymakers a need to tighten so-called macroprudential policies.

The benefits of systemic risk measures in *expost* forensic analysis of market performance and behavior in the wake of systemic events should not be underestimated. Such analyses are routinely performed in other industries such as transportation, and may help identify institutional weaknesses, regulatory lapses, and other shortcomings that lead to much-needed reforms.[6] In fact, apart from occasional Inspector General's reports and presidential commissions, we have not institutionalized regular and direct feedback loops between policymaking and their outcomes in the financial sector. The ability to identify underperforming policies and unintended consequences quickly and definitively is one of the most effective ways of improving regulation, and measurement is the starting point.

With respect to early warning indicators of impending threats to financial stability, three important caveats apply. First, reliable forecast power alone will not solve the supervisory decision problem because there is no single "pressure gauge" that captures the full state of an intricate, multifaceted financial system. There will always be noise and conflicting signals, particularly during periods of financial distress. Moreover, since many of the metrics described here can be used with different time periods, firms, countries, asset classes, market sectors, and portfolios, the "curse of dimensionality" applies. In a real decision environment, techniques will be needed for sifting through such conflicting signals.

Second, there is the problem of statistical regime shifts, which are particularly relevant for systemic events. Adding model structure can improve conditional forecasts, especially in a shifting environment, but even if we know the correct structural model—a heroic assumption, particularly *ex ante*—obtaining a reliable statistical fit is a nontrivial matter. Of course, in practice, we can never be sure about the underlying structure generating the data. For example, in the run-up to the recent crisis, knowledgeable and credible experts were found on both sides of the debate surrounding the over- or under-valuation of U.S. residential real estate.

Third, to the extent that the Lucas critique applies (see Section 2.3), early warning indicators may become less effective if individuals change their behavior in response to such signals. Apart from the question of whether or not such indicators are meant for regulators' eyes only or for the public, this possibility implies an ongoing need to evaluate the efficacy of existing risk analytics and to develop new analytics as old measures become obsolete and new systemic threats emerge. This is one of the primary reasons for the establishment of the OFR.

As to why the financial industry should willingly participate in the OFR's research agenda, perhaps the most obvious and compelling reason is that all financial institutions benefit from financial stability, and most institutions are hurt by its absence. For example, the breakdown in stability and liquidity, and the collapse of asset prices in the fall and winter of 2008–2009 were an enormous negative-sum event that imposed losses on most participants.

In the aftermath of this crisis, there is near unanimity that firm-level risk management and supervision have limitations, and that the fallacy of composition applies: patterns exist in market dynamics at the system level that are distinct from the simple aggregation of the behavior of the individual participants.[7]

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[6] *See Fielding, Lo, and Yang (2011) for a detailed description of how the National Transportation Safety Board has played a critical role in improving safety in the transportation industry despite having no regulatory responsibility or authority.*

[7] *See Danielsson and Shin (2003) for an evocative example of the fallacy of composition. This basic principle is reflected in many of the measures here.*

Moreover, while all firms share the benefits of financial stability, market mechanisms do not exist to force firms to internalize the full cost of threats to stability created by their own activities. To address these externalities, systemic risk measures may be used to provide more objective and equitable methods for calibrating a Pigouvian tax on individual SIFIs, as proposed by Acharya and Richardson (2009), or the Basel Committee's (2011) capital surcharge on global systemically important banks (G-SIBs). These proposals are controversial. The Clearing House—a trade association of 17 of the world's largest commercial banks responded that, "there are significant open questions regarding the purported theoretical and policy foundations, as well as the appropriate calibration, for a G-SIB surcharge". As with any policy intervention, we should always be prepared to address the possibility of unintended consequences.

Another reason firms are not always penalized for their risky behavior is the existence of a safety net, created by government policy either explicitly (e.g., deposit insurance) or implicitly (e.g., too-big-to-fail policies). It has long been recognized that both deposit insurance and the discount window can encourage banks to take risks that might endanger their solvency.[8] In hindsight, it is clear that, throughout the recent crisis, both regulators and market participants failed to act in a timely fashion to curtail excessive leverage and credit expansion.

It is tempting to attribute such supervisory forbearance to some form of regulatory capture.[9] However, forbearance might also be motivated by indecisiveness, which can be exacerbated by limited information and penalties regulators may face for making mistakes.

Regulatory action in the face of unsafe or unsound practices typically involves formal interruptions of ongoing business activities, e.g., via cease-and-desist orders or the closure of an institution. Such decisions are not lightly made because they are fraught with uncertainty and the stakes are high. Waiting for unequivocal evidence of trouble can allow losses to accumulate, especially if the state of the institution is observed infrequently and measured with error, and managers and regulators are gambling on a significant reversal (Benston and Kaufman, 1997).

In fact, the loss function for supervisory mistakes is highly asymmetric between Type-I (premature closure) and Type-II (forbearance) errors. Regulators expect to be punished, e.g., reprimanded or sued, for acting too soon by closing a solvent firm. The opposite mistake—waiting until after a firm defaults on its obligations—puts the regulator in the role of cleaning up a mess created by others, but the perceived penalty is much smaller. At any point in time, this asymmetry creates strong incentives for supervisors to wait one more day, either for the arrival of unequivocal information to support a particular choice, or for the decision to become moot through the failure of the institution.[10] In these circumstances, improved techniques for measuring threats can significantly reduce the likelihood of policy mistakes.

While economic incentives alone can create a bias toward forbearance, these tendencies are likely to be exacerbated by well-known behavioral tendencies. "Prompt corrective action" can avert large accumulated losses, but such prophylactic responses always introduce the possibility of errors in supervisory decisions, with negative short-and long-term consequences to the regulator. Hardwired behavioral responses to "double down" and become more risk-tolerant when faced with sure losses only make matters worse in these situations.[11]

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[8] *Acharya and Richardson (2009) discuss the general role of government mispricing of risk in encouraging Risky behavior, and the papers in Lucas (2010) propose better pricing models for government guarantees. For a recent analysis of the moral hazard inherent in deposit insurance, see Demirguc Kunt, Kane, and Laeven (2008). On the historical understanding of the moral hazard issues at the time of the FDIC's creation, see Flood (1992). Regarding the moral hazard inherent in the lender of last resort function, see Rochet and Vives (2004). For an analysis of the historical understanding, see Bordo (1990) or Bignon, Flandreau, and Ugolini (2009).*

[9] *There is an extensive literature on forbearance and regulatory capture, well beyond the scope of this paper. For examples dating from the aftermath of the 1980s S & L crisis, see Kane (1989) and Boot and Thakor (1993). Two recent studies consider these arguments in the context of the recent crisis: Huizinga and Laeven (2010) and Brown and Din (2011).*

[10] *In the words of Shakespeare's Hamlet (Act III, Scene 1), "Thus conscience does make cowards of us all." Boot and Thakor (1993) present a similar argument in the context of a detailed model, in which regulators act to preserve their valued reputations, which would be damaged by the revelation of a premature closure. The result is a pooling equilibrium in which the asymmetric reputational costs of a premature closure vs. forbearance lead all regulators to mimic each other's closure policies. However, their model allows no possibility for regulators to improve their monitoring technology. Incentives are also supported in the model by a second period after the close/wait decision that allows bankers to "gamble for resurrection".*

[11] *See Kahneman and Tversky (1979) for the loss aversion phenomenon, and Lo (2011, Section 5) for a discussion of its relevance for risk managers, policymakers, and rogue traders.*

More generally, accurate systemic risk metrics can foster better ex post accountability for regulators: if they knew, or should have known, of systemic dangers ex ante, but failed to act, systemic risk metrics can provide the basis for remedial action. However, once again, there may be an unintended consequence in that silence from an informed regulator might be construed as tacit consent. Therefore, systemic risk monitoring must be structured so as not to absolve market participants of responsibility for managing their own risks.

2.3 The Lucas Critique and Systemic Risk Supervision

No policy discussion would be complete without addressing the potential impact of feedback effects on human behavior and expectations, i.e., the Lucas (1976, p. 41) critique, that "any change in policy will systematically alter the structure of econometric models". Of course, we have little to add to the enormous literature in macroeconomics on this topic, and refer readers instead to the excellent recent essay by Kocherlakota (2010) in which he reviews this important idea and its influence on modern macroeconomics and monetary policy.

As a starting point, we presume that the Lucas critique applies to systemic risk supervision. Measurement inevitably plays a central role in regulatory oversight and in influencing expectations. Imagine conducting monetary policy without some measure of inflation, GDP growth, and the natural rate of unemployment. Given that systemic risk monitoring will provoke institutional and behavioral reactions, the relevant questions revolve around the nature and magnitude of the impact. The first observation to be made about the Lucas critique is that it has little bearing on the importance of accurate metrics for systemic risk. By yielding more accurate inputs to policy decisions, these measures should have important first-order benefits for systemic stability, regardless of whether and how fully individual and institutional expectations might discount the impact of such policies.

The second observation regarding the Lucas critique is related to the fact that many of the analytics contained in this survey are partial-equilibrium measures. Therefore, by definition they are subject to the Lucas critique to the extent that they do not incorporate general-equilibrium effects arising from their becoming more widely used by policymakers. The same can be said for enterprise-wide risk management measures—once portfolio managers and chief risk officers are aware of the risks in their portfolios and organizations, they may revise their investment policies, changing the overall level of risk in the financial system. This may not be an undesirable outcome. After all, one of the main purposes of early warning signals is to encourage individuals to take action themselves instead of relying solely on government intervention. However, this thought experiment does not necessarily correspond to a dynamic general equilibrium process, but may involve a "phase transition" from one equilibrium to another, where the disequilibrium dynamics takes weeks, months, or years, depending on the frictions in the system. The Lucas critique implies that the general-equilibrium implications of systemic risk policies must be studied, which is hardly controversial. Nevertheless, partial-equilibrium measures may still serve a useful purpose in addressing short-term dynamics, especially in the presence of market imperfections such as transactions costs, non-traded assets, incomplete markets, asymmetric information, externalities, and limited human cognitive abilities.

Finally, rational expectations is a powerful idea for deducing the economic implications of market dynamics in the limiting case of agents with infinite and instantaneous cognitive resources. However, recent research in the cognitive neurosciences and in the emerging field of neuroeconomics suggest that this limiting case is contradicted by empirical, experimental, and evolutionary evidence. This is not particularly surprising in and of itself, but the more

informative insights of this literature have to do with the specific neural mechanisms that are involved in expectations, rational and otherwise.[12] This literature implies that rational expectations may only be one of many possible modes of economic interactions between

Homosapiens, and the failure of dynamic stochastic general equilibrium models to identify the recent financial crisis seems to support this conclusion.

For these reasons, we believe the Lucas critique does not vitiate the need for measures of systemic risk; on the contrary, it buttresses the decision to create the OFR as a research-centric institution. We are still in the earliest days of understanding the elusive and multi-faceted concept of systemic risk, and the fact that markets and individuals adapt and evolve in response to systemic measurement only reinforces the need for ongoing research.

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[12] *For example, Lo (2011) provides a review of the most relevant research in the cognitive neurosciences for financial crises, in which recent studies have shown that the regions of the brain responsible for mathematical reasoning and logical deduction are forced to shut down in the face of strong emotional stimuli.*

2.4 Supervisory Taxonomy

A second taxonomy for the analytics reviewed in this survey is along the lines of supervisory scope, which is of particular interest to policymakers. Institutionally, individual regulators' responsibilities and activities are typically segregated by industry subsector. The jurisdictional boundaries that separate the regulatory purview of the individual agencies provide clarity for regulated entities, and allow supervisors to develop focused expertise in particular areas of the financial system.

A given systemic risk metric may be more or less relevant for a particular regulator depending on the regulator's supervisory jurisdiction. Because it is likely that a given crisis will be triggered by events at a specific institution with a clearly identified primary regulator, e.g., LTCM or Lehman, having metrics that are tailored to specific institutional types and business models may help pinpoint dangers in those institutions and sound the alarm for the relevant regulator. For example, measures of equity market liquidity will likely interest the securities market supervisors more than housing regulators. However, by definition, threats to financial stability involve many institutions simultaneously and typically affect the system as a whole. Among others, Brunnermeier, Crockett, Goodhart, Persaud, and Shin (2009, pp. 6–10) emphasize the distinction between micro-prudential regulation (especially the capital-focused Basel system), and macroprudential regulation. The former is focused on prudential controls at the firm level, while the latter considers the system as a whole.[13] Although the impact of systemic events is a macroprudential concern, particular metrics of threats to financial stability may by applicable at either a microprudential or a macroprudential level (or sometimes both).

To this end, grouping systemic risk analytics by supervisory scope will yield two broad categories, microprudential and macroprudential analytics, and within the former category, we can further categorize them by institutional focus: securities and commodities, banking and housing, insurance and pensions, and general applications. This new taxonomy is summarized in Table 2, and we describe each of these categories in more detail below.

2.4.1 Microprudential Measures: Securities and Commodities

Securities and commodities market regulators have jurisdiction over a broad range of secondary market and inter-institution trading. For example, the U.S. Securities and Exchange Commission (SEC) and Commodities Futures Trading Commission (CFTC) together regulate a range of markets, including equities, commodities, and currencies, along with the securities firms active in those markets such as investment managers, mutual funds, broker/dealers, and, post-Dodd Frank, hedge funds. Similar supervisors exist in other countries, although the details of regulatory authority naturally vary across geopolitical boundaries. Several of the measures of fragility surveyed here focus on this market segment. Pojarliev and Levich (2011) look for patterns of coordinated behavior, i.e., “crowded trades”, in high- frequency trading data for currency funds.

Systemic Risk Measure	Section
Microprudential Measures—Securities and Commodities:	
Crowded Trades in Currency Funds	F.4
Equity Market Illiquidity	F.5
Serial Correlation and Illiquidity in Hedge Fund Returns	F.6
Broader Hedge-Fund-Based Systemic Risk Measures	F.7
Microprudential Measures—Banking and Housing:	
Network Analysis and Systemic Financial Linkages	B.2
Simulating a Credit Scenario	B.3
Simulating a Credit-and-Funding-Shock Scenario	B.4
Bank Funding Risk and Shock Transmission	B.6
The Option iPoD	C.3
Multivariate Density Estimators	C.4

[13] *See also Hanson, Kashyap, and Stein (2011), and Bank of England (2009).*

Systemic Risk Measure	Section
Simulating the Housing Sector	C.5
Consumer Credit	C.6
Lessons from the SCAP	D.2
A10-by-10-by-10 Approach	D.3
Distressed Insurance Premium	E.2
Microprudential Measures—Insurance and Pensions:	
Granger-Causality Networks	B.5
Mark-to-Market Accounting and Liquidity Pricing	B.7
Microprudential Measures—General Applications:	
The Default Intensity Model	B.1
Contingent Claims Analysis	C.1
Mahalanobis Distance	C.2
CoVaR	E.1
Co-Risk	E.3
Marginal and Systemic Expected Shortfall	E.4
Risk Topography	F.1
The Leverage Cycle	F.2
Macroprudential Measures:	
Costly Asset-Price Boom/Bust Cycles	A.1
Property-Price, Equity-Price, and Credit-Gap Indicators	A.2
Macroprudential Regulation	A.3
Principal Components Analysis	C.7
GDP Stress Tests	D.1
Noise as Information for Illiquidity	F.3

Table 2: Taxonomy of systemic risk measures by supervisory scope.

Khandani and Lo (2011) consider two distinct measures of liquidity in equity markets. Getmansky, Lo, and Makarov (2004) and Chan, Getmansky, Haas, and Lo (2006b, 2006b) also focus on liquidity, in this case for hedge funds, where serial correlation in reported returns can appear as an artifact of reporting conventions in illiquid markets.

2.4.2 Microprudential Measures: Banking and Housing

Depository institutions form the core constituency for the cluster of banking regulators, including central banks, deposit insurers, and bank chartering agencies. Residential mortgage originators, such as thrifts, building and loan societies, and mortgage banks also fall into this grouping, along with housing GSEs such as Fannie Mae, Freddie Mac, and the Federal Home Loan (FHL) banks in the U.S. Within this class, Fender and McGuire (2010a) look for binding funding constraints in aggregate balance sheet data for international banking groups. Merton and Bodie (1993) focus on the corporate financing, especially leverage, of insured depositories. Khandani, Kim, and Lo (2010) consider aggregate patterns in consumer lending via credit-risk forecasts estimated from detailed credit-card data. Huang, Zhou, and Zhu (2009a) calculate a hypothetical insurance premium based on firms' equity prices and CDS spreads; they apply this to a sample of banks. Khandani, Lo, and Merton (2009) examine coordinated increases in homeowner leverage, due to a one-way “ratchet” effect in refinancing behavior. Capuano (2008) and Segoviano and Goodhart (2009) use techniques from information theory to extract implied probabilities of default (iPoD) from equity and equity option prices, applying this technique to samples of commercial and investment banks. Chan-Lau, Espinosa, and Sole (2009) and Duffie (2011) construct financial network models, and take banking firms as the primary sample of interest.

2.4.3 Microprudential Measures: Insurance and Pensions

Pension and insurance regulators, such as the European Insurance and Occupational Pensions Authority (EIOPA) in Europe and the Pension Benefit Guaranty Corporation (PBGC) and state insurance departments in the U.S., are the focus of the third microprudential category in our taxonomy. Relatively few of the studies in our sample deal directly with pension funds or insurance companies, despite the fact that the recent crisis actively involved these institutions. An exception is Billio, Getmansky, Lo, and Pelizzon (2010), who include insurance as one of four industry sectors in a latent factor model used to identify patterns of risk concentration and causation. An insurance company subsidiary, AIG Financial Products, played a prominent role in the recent crisis as a seller of credit protection on subprime mortgage securitizations, and pension funds were among the buyers of the same.[14] The lack of easily accessible data in these industries is a significant factor: pension-fund and insurance-company portfolio holdings are not widely available, unlike equity and bond market benchmark indexes that would broadly track their performance. Sapra (2008) considers issues arising from historical and mark-to-market accounting for both insurance companies and banks.

2.4.4 Microprudential Measures: General Applications

On the other hand, accounting and market price data for large financial firms are widely available, and a number of fragility measures based on stock-market data could be applied to any or all of the microprudential categories just listed. Like Merton and Bodie (1993), Geanakoplos (2010) similarly focuses on institutional leverage, but he envisions a much broader scope of applicability than just banks. Gray and Jobst (2010) use CDS spreads in a contingent claims analysis of financial firm risk. Adrian and Brunnermeier's (2010) conditional value at risk (CoVaR) and the International Monetary Fund's (2009b) related "Co-Risk" models of shared exposures similarly rely on firm-level market prices.[15] The

Mahalonobis distance metric of Kritzman and Li (2010) is a statistical model that could, in principle, be applied to any time series.

2.4.5 Macroprudential Measures

Although the boundaries that support efficient institutional specialization among regulators serve many practical purposes, nevertheless they sometimes create the jurisdictional gaps within which risky activities are most likely to go undetected. These gaps are covered by macroprudential regulation, which is, of course, not new.[16] Two of the oldest elements of the

U.S. regulatory safety net are motivated by macroprudential concerns. The discount window, which provides emergency liquidity support to "innocent bystander" banks in a systemic crisis, was created with the founding of the Federal Reserve in 1913. Deposit insurance— created at the federal level in 1933 with the Federal Deposit Insurance Corporation (FDIC)— discourages bank runs and provides for orderly resolution of failing depositories.

However, it has been almost eighty years since the creation of the FDIC, and nearly a century since the founding of the Fed, and the intervening decades have witnessed a steady disintermediation away from traditional depository institutions. Recent decades have shown strong growth in direct capital-market access by large borrowers, derivatives markets, managed

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[14] *AIG Financial Products (AIGFP) is an example of a firm that does not fit neatly into the micro prudential regulatory framework. Although it was an insurance company subsidiary, it was supervised by a domestic housing regulator, the Office of Thrift Supervision (OTS), without deep expertise in the credit derivatives that were AIGFP's specialty. Moreover, AIGFP was headquartered in London, adding a geographic obstacle. Ashcraft and Schuermann (2008) describe subprime securitizations with the example of a pension fund investor.*

[15] *The default intensity model of Giesecke and Kim (2009), the distressed insurance premium (DIP) of Huang, Zhou, and Zhu (2009a), and the systemic expected shortfall (SES) of Acharya, Pedersen, Philippon, and Richardson (2010) also satisfy this general description.*

[16] *Clement (2010) traces the usage of the term "macroprudential" back to the 1970s, citing (p.61) in particular a Bank of England background paper from 1979, "This 'macroprudential' approach considers problems that bear upon the market as a whole as distinct from an individual bank, and which may not be obvious at the micro-prudential level." Etymology aside, macroprudential supervision has a longer history.*

investment portfolios (including mutual funds, ETFs, and hedge funds), and various forms of collateralized borrowing (including asset-backed and mortgage-backed securitization and repurchase agreements). As a result, when the crisis struck in force in the Fall of 2008, large segments of the financial system did not have immediate access to orderly resolution (FDIC) or lender-of-last-resort (Fed) facilities.

Macro-level metrics tend to concentrate on aggregate imbalances. As a result, they are frequently intended to serve as early-warning signals, tracking the buildup of unsustainable tensions in the system. For the same reason, there is also a tendency to use macroeconomic time series and official statistics in these measures. For example, Borio and Drehmann (2009b) look for simultaneous imbalances in broad indicators of equity, property, and credit markets. Alfaro and Drehmann (2009) examine the time series of GDP for signs of weakening in advance of a crisis. Hu, Pan, and Wang (2010) extract an indicator of market illiquidity from the noise in Treasury prices. The absorption ratio of Kritzman, Li, Page, and Rigobon (2010) measures the tendency of markets to move in unison, suggesting tight coupling. Alessi and Detken (2009) track anomalous levels in macroeconomic time series as possible indicators of boom/bust cycles.

2.5 Event / Decision Horizon Taxonomy

Decision-making is a critical activity for policymakers, who must choose whether, when, and how to intervene in the markets. In this context, the informativeness of a systemic risk metric over time—especially relative to a decision horizon or the onset of a systemic event—is significant. Accordingly, we can classify risk analytics into three temporal categories: pre-event, contemporaneous, and post-event analytics. There is obvious benefit from measures that provide early warning of growing imbalances or impending dangers; forewarned is often forearmed. However, even strictly contemporaneous signals of market turmoil can be useful in allocating staff and other supervisory infrastructure during an emerging crisis; reaction time matters, particularly as events are unfolding. And there is also a role for ex-post analysis in maintaining accountability for regulators (see the discussion in Section 2.2 and Borio (2010)) and generating forensic reports of systemic events. This event- and decision-horizon classification scheme is summarized in Table 3.

2.5.1 Ex Ante Measures: Early Warning

In an ideal world, systemic monitoring would work like the National Weather Service, providing sufficiently advance notice of hurricanes for authorities and participants to intervene by pre-positioning staff and resources, minimizing exposures, and planning for the impending event and immediate aftermath. This may be too much to hope for in the case of financial stability. Systemic shocks can arrive from many directions, such as the sovereign default that triggered the LTCM crisis, the algorithmic feedback loop of the May 6, 2010 "Flash Crash", or the speculative attacks that have repeatedly plagued small-country financial systems. Moreover, unlike hurricanes, many significant threats involve active subterfuge and evasive behavior. For example, institutions vulnerable to contagious runs, like Lehman Brothers in the run-up to its 2008 collapse, have strong incentives to avoid revealing information that could trigger a self-reinforcing attack.[17] Therefore, tracking a multitude of threats will require a diversity of monitoring techniques.

We define "early warning" models as measures aspiring to a significant degree of forecast power. Several of the macroprudential measures mentioned above are intended to identify accumulating imbalances, and thereby to have some forecast power for systemic events while using an observation or update interval longer than daily or weekly. These include Borio and Drehmann (2009b) and Alessi and Detken (2009), who use quarterly data, and Alfaro and Drehmann (2009), whose model is updated only annually. Higher-frequency measures with some potential forecast power include Khandani, Kim, and Lo's (2010) model of consumer credit risk, the default intensity model of Giesecke and Kim (2009), Huang, Zhou, and Zhu's (2009a) DIP metric, the hedge fund measures of Chan, Getmansky, Haas, and Lo (2006b, 2006b), the mortgage ratcheting model of Khandani, Lo, and Merton (2009), the cross-funding network analysis of Chan-Lau, Espinosa, and Sole (2009), and Getmansky, Lo, and Makarov's (2004) model of serial correlation and illiquidity in hedge fund returns.

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[17] *Per the bankruptcy court report, Valukas (2010, p.732), "Lehman employed off-balance sheet devices, known within Lehman as 'Repo 105' and 'Repo 108' transactions, to temporarily remove securities inventory from its balance sheet, usually for a period of seven to ten days, and to create a materially misleading picture of the firm's financial condition in late 2007 and 2008."*

Systemic Risk Measure	Section
Ex Ante Measures—Early Warning:	
Costly Asset-Price Boom/Bust Cycles	A.1
Property-Price, Equity-Price, and Credit-Gap Indicators	A.2
The Default Intensity Model	B.1
Network Analysis and Systemic Financial Linkages	B.2
Simulating the Housing Sector	C.5
Consumer Credit	C.6
GDP Stress Tests	D.1
Distressed Insurance Premium	E.2
The Leverage Cycle	F.2
Serial Correlation and Illiquidity in Hedge Fund Returns	F.6
Broader Hedge-Fund-Based Systemic Risk Measures	F.7
Ex Ante Measures—Counterfactual Simulation and Stress Tests:	
Simulating a Credit Scenario	B.3
Simulating a Credit-and-Funding-Shock Scenario	B.4
Lessons from the SCAP	D.2
A10-by-10-by-10Approach	D.3
Marginal and Systemic Expected Shortfall	E.4
Contemporaneous Measures—Fragility:	
Granger-Causality Networks	B.5
Contingent Claims Analysis	C.1
The Option iPoD	C.3
Multivariate Density Estimators	C.4
CoVaR	E.1
Co-Risk	E.3
Contemporaneous Measures—Crisis Monitoring:	
Bank Funding Risk and Shock Transmission	B.6
Mahalanobis Distance	C.2
Principal Components Analysis	C.7
Noise as Information for Illiquidity	F.3
Crowded Trades in Currency Funds	F.4
Equity Market Illiquidity	F.5
Ex Post Measures—Forensic Analysis:	
Macroprudential Regulation	A.3
Mark-to-Market Accounting and Liquidity Pricing	B.7
Ex Post Measures—Orderly Resolution:	
Risk Topography	F.1

Table 3: Taxonomy of systemic risk measures by event/decision time horizon.

2.5.2 Ex Ante Measures: Counterfactual Simulation and Stress Tests

Predictive models assign probabilities to possible future events, conditional on current and past observations of the system. Another prospective approach to assessing the vulnerability of a system is to examine its behavior under counterfactual conditions. Stress testing is codified in regulation and international standards, including the Basel accord. It is applied, for example, in the Federal Reserve's (2009) SCAP study. As a matter both of regulatory policy and traditional risk management, the process can be viewed as a means to identify vulnerabilities in the portfolio—i.e., combinations of external factor outcomes causing un- acceptably large losses—and ways to defend against those influences. A related approach is reverse stress testing, in which a portfolio outcome (typically insolvency) is fixed, and a search is undertaken for scenarios that could provoke this level of distress. A stress test typically draws its scenarios either from actual historical stress episodes or hypothesizes them via expert opinion or other techniques. Breuer, Janda ̌cka, Rheinberger, and Summer (2009), for example, emphasize three characteristics of well designed stress scenarios—plausibility, severity, and suggestiveness of risk-reducing action—and present an algorithm for searching within a "plausible" subset of the space of external factor outcomes for the scenario that generates the largest portfolio loss. Simultaneously targeting both severity and plausibility introduces a natural tension, since outlandish scenarios are likely to have painful ramifications. As a policy matter, if the goal of the exercise is simply to explore portfolio sensitivities (i.e., not to calibrate required capital or other regulatory constraints), then this trade-off is less immediate.

Stress scenarios are frequently stated in terms of possible values for macroeconomic fundamentals. A straightforward example is Alfaro and Drehmann (2009), who consider the behavior of GDP around 43 post-1974 crises identified by the Reinhart and Rogoff (2009) methodology. This is a high-level analysis that does not break out the detailed composition of GDP or institutional portfolio holdings. Although GDP growth often weakened ahead of banking crises, there is nonetheless a large fraction of banking crises not preceded by weakening GDP, suggesting additional forces are at play, such as macroeconomic feedback effects. Output drops substantially in nearly all of the observed crises once stress emerges. They next use a univariate autoregressive forecasting model of GDP growth in each country, and use its worst negative forecast error as a stress scenario to be compared with the historical sample. In two-thirds of cases, the real crises were more severe than their forecasts, suggesting that care should be taken in balancing the severity-vs.-plausibility trade-off.

Another policy application of stress testing is the identification of risky or vulnerable institutions. The Supervisory Capital Assessment Program (SCAP) described by Hirtle, Schuermann, and Stiroh (2009) also applies macroeconomic scenarios—GDP growth, unemployment, and housing prices—but is more sophisticated in several important respects. First, the SCAP was a regulatory exercise to determine capital adequacy of 19 large financial institutions in the spring of 2009; the results had immediate implications for the calibration of required capital. Second, the SCAP was applied to each participating institution individually, assembling the macroprudential outcome from its microprudential parts. Third, the process included a detailed "bottom-up" analysis of the risk profile of individual portfolios and positions, using the firms' own data, models, and estimation techniques. This implies mapping from scenarios defined in terms of macroeconomic variables to the concrete inputs required by the analytics packages.

Duffie's (2011) "10-by-10-by-10" policy proposal goes a step further. Here, a regulator would analyze the exposures of N important institutions to M scenarios. For each stress scenario, each institution would report its total gain or loss against its K largest counterparty exposures for that scenario (as a rule of thumb, he suggests setting $N = M = K = 10$). This would help clarify the joint exposure of the system to specific shocks, and could help identify additional important institutions via counterparty relationships to the original set of N firms. He recommends considering severe but plausible stress scenarios that are not covered by delta-based hedging and are conjectured to have potential systemic importance. He offers the following examples, chosen to highlight broad-scope scenarios that would likely incorporate: default of a large counterparty; a 4% shift in the yield curve or credit spreads; a 25% shift in currency values or housing prices; or a 50% change in a commodities or equity-market index. As a caveat, note that many financial exposures are hedged to basis risk, which have nonlinear and non-monotonic sensitivities to risk factors, so that the magnitude of the shocks may not correlate simply with the severity of losses for a particular firm. A shortcoming of a focus on a handful of "important" institutions is the possibility of missing widely dispersed events, such as the U.S. savings and loan crisis of the 1980s.

Systemic fragility metrics supporting stress testing include Acharya, Pedersen, Philippon, and Richardson's (2010) systemic expected shortfall (SES) measure and Duffie's (2011)10 × 10 × 10 model. Chan-Lau, Espinosa, and Sole (2009) simulate their model, due to the lack of firm-level data.

2.5.3 Contemporaneous Measures: Fragility

Measuring financial fragility is not simply a matter of obtaining advance warning of impending dangers; crisis response is an important role for policymakers charged with systemic risk monitoring. Supervisory responsibilities intensify when a systemic event occurs. These tasks include ongoing monitoring of the state of the system, identification of fragile or failing institutions, markets, or sectors, the development and implementation of regulatory interventions, and clear and regular communication with the media and the public. All of this will likely need to occur within compressed timeframes.

Forecasting measures that are updated on a daily or intradaily basis can be valuable as real-time signals of fragility in an emerging crisis. For example, they may clarify the possible ramifications and side effects of various interventions. A number of the models we consider can be updated frequently, including the contingent claims analysis of Gray and Jobst (2010), Adrian and Brunnermeier's (2010) CoVaR model, Adrian and Brunnermeier's (2010) and the International Monetary Fund's (2009a) related Co-Risk measures, the SES measure of Acharya, Pedersen, Philippon, and Richardson (2010), and the iPoD measures of Capuano (2008) and Segoviano and Goodhart (2009).2.5.4 Contemporaneous Measures: Crisis Monitoring

Regardless of forecast power, some measures may still be useful in tracking a crisis as it unfolds, to aid in the allocation of staff and other resources and in the crafting of policy responses. These include the liquidity measures of Khandani and Lo (2011) and Hu, Pan, and Wang (2010), the Mahalanobis distance metric of Kritzman and Li (2010), and the absorption ratio of Kritzman, Li, Page, and Rigobon (2010). In addition, a number of the models cited above as short-horizon forecasting or fragility measures might also be deployed as contemporaneous monitoring tools; these include Adrian and Brunnermeier (2010), International Monetary Fund (2009b), Segoviano and Goodhart (2009), Capuano (2008), and Duffie (2011).

2.5.5 Ex Post Measures: Forensic Analysis

For policy purposes, measurement of the system continues to occur even after a systemic event or regulatory intervention. Publication of “flash” reports in the immediate aftermath (i.e., within hours or days) can help inform and coordinate the responses of other regulators and market participants. Such “immediate” transparency may have special significance in situations where panic or herd behavior is a factor. For example, the CFTC and SEC (2010a, 2010b) published a detailed analysis of the May 6, 2010 Flash Crash on September 30, 2010, which largely resolved the fear and uncertainty created by the unusual events surrounding that market dislocation. Imagine the market reaction if the report had been a half-hearted effort with inconsistent and inconclusive findings.

Understanding what went wrong can help in the redesign of market and regulatory practices and institutions. Borio (2010) emphasizes the critical role that measurement plays in maintaining accountability. Regulation is a repeated game, and monitoring performance can help enforce diligent behavior. In some cases, civil and/or criminal legal remedies may require thorough and unbiased explication of the sequence of events. Any of the models described above as tools for *ex ante* or contemporaneous analysis would have value as tools for *expost* analysis. For example, Khandani, Lo, and Merton (2009) use their risk-ratcheting methodology in a historical analysis of the housing market; Getmansky, Lo, and Makarov (2004) is an *ex post* analysis of serial correlation and illiquidity in hedge fund returns.2.5.6 Ex Post Measures: Orderly Resolution

Systemic risk analytics also have a role to play in the orderly resolution of failed institutions. This is particularly true of network models, such as Duffie (2011) or Brunnermeier, Gorton, and Krishnamurthy (2010), where a detailed understanding of the web of contractual connections can assist in the unwinding of a complex portfolio.

3. Research Perspective

In contrast to the supervisory perspective of Section 2 that involves practical challenges of implementation and policy issues, the research perspective is focused primarily on theoretical underpinnings and econometric methods. We define researchers as those skilled in developing and applying analytical techniques to economic and financial questions. As a result, the researcher's taxonomy of the systemic risk analytics surveyed in this paper is quite different from those in Tables 1–3. However, before describing this new taxonomy in more detail, we first propose a simple conceptual framework for organizing our measures of systemic risk in Section 3.1, and raise the important econometric issue of nonstationarity in Section 3.2 which is particularly relevant to systemic risk measurement. In Section 3.3, we provide a brief discussion of other research directions that are not included in this survey, but which may prove useful and bear further investigation. We then present the research taxonomy in Section 3.4.

3.1 Conceptual Framework and Econometric Issues

Denote by R_t the vector of asset returns of all systemically relevant entities and/or securities at date *t*, and let X_t denote the vector of state variables that capture the date-*t* economic and business conditions. If we define E_t to be a 0/1 indicator variable indicating the occurrence of a systemic event at date *t*, then the objective of any systemic risk measure is to shed light on one or more of the following three probability distributions:

$$\text{Prob}(E_t \mid R_{t-1}, X_{t-1}, R_{t-2}, X_{t-2}, \ldots) \equiv \text{Pre-Event Distribution} \quad (1)$$

$$\text{Prob}(R_t, X_t \mid E_{t-1}) \equiv \text{Post-Event Distribution} \quad (2)$$

$$\text{Prob}(R_t, X_t, E_t) \equiv \text{Contemporaneous Distribution.} \quad (3)$$

The first distribution is the most relevant from the regulatory perspective: what can we say about the likelihood of a future systemic event given current and past conditions? The second is critical for determining the appropriate responses to systemic shocks. And the third is relevant for evaluating and refining our understanding of what a systemic event is.[18]

At this level of generality, (1)–(3) is nearly vacuous, but it does serve the useful purpose of motivating the need for additional structure—theoretical and econometric specifications and constraints—to narrow the parameter space of these highly nonlinear high-dimensional multivariate distributions. In particular, we must first identify the relevant institutions and securities to study (R_t), then narrow our field of vision to a specific set of state variables (X_t) that are relevant to the particular notion of systemic risk we wish to capture (E_t), decide on the appropriate time horizon and sampling frequency for these variables, and then formulate a suitable parametrization of the appropriate probability distribution in (1)–(3)— presumably guided by theory and practice—that is amenable to parameter estimation and statistical inference.

When described in this formulaic way, it becomes obvious that we are unlikely to ever develop a single measure of systemic risk; the dimensionality and complexity of (1)–(3) imply that multiple measures must be used to piece together a coherent, albeit incomplete, view of possible threats to financial stability. For example, if we specify the returns of publicly traded financial institutions for R_t, and define a systemic event as simultaneous losses among multiple financial institutions, then Adrian and Brunnermeier's (2010) CoVaR, the International Monetary Fund's (2009b) Co-Risk, and Acharya, Pedersen, Philippon, and Richardson's (2010) systemic expected shortfall measures are the result. However, if our focus is on the network topology of the asset returns of the financial system, then the Granger-causality network measure of Billio, Getmansky, Lo, and Pelizzon (2010) and the absorption ratio of Kritzman, Li, Page, and Rigobon (2010) are more relevant. By narrowing the set of possible free parameters for the distributions in (1)–(3), we are able to infer more precise information regarding specific aspects of systemic risk.

3.2 Nonstationarity

Even after doing the hard work of narrowing down the parameter space in (1)–(3) to yield a tractable specification that can be estimated, there is still the remaining question of how to conduct the estimation and statistical inference. Virtually all methods of estimation and inference rely on the assumption of stationarity:

$$\forall t_1, t_2, t_3, k: \quad \text{Prob}(R_{t1}, X_{t2}, E_{t3}) = \text{Prob}(R_{t1+k}, X_{t2+k}, E_{t3+k}). \quad (4)$$

In other words, the joint distribution of the relevant variables is stable over time. The motivation for such an assumption is clear: we are attempting to use historical data to infer something about the structure of systemic risk, and if that structure is not stable over time, historical data may not be an accurate guide to what the future holds. The well-known mutual-fund disclaimer that "past performance is no guarantee of future returns" can take hold with a vengeance in such circumstances.

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[18] *We note two key assumptions implicit in this framework. First, since the expectations and conditioning revolve around past asset returns, we implicitly restrict attention away from data and methodologies that are not traditional financial econometrics. While financial econometrics should predominate, there are other sources of information and other techniques may warrant attention. For example, there are accounting measures (including the flow of funds data), surveys of experts and industry insiders, visual analytics, linguistic analyses (e.g., sentiment analyses of news reports), etc. Second, there is the reification of a "systemic event", which occurs at a point in time, t, since that is how systemic threats typically manifest their damage. Such a focus may discourage the analysis of threats that do not play out abruptly in calendar time. Although abrupt discontinuities are important, these are not the only outcomes to worry about. For example, Reinhart and Rogoff (2009) point to "post-event" episodes that play out in historical time (i.e., over months and years).*

Nonstationarity is not a new challenge to econometrics, and a large literature has developed to address specific types of nonstationarities such as deterministic and stochastic trends, and cointegration relationships.[19] However, these are very specific types of nonstationarity, whereas the kind of nonstationarity that affects systemic risk may be less easily parametrized, e.g., political, institutional, and cultural changes. In fact, the very notion of systemic risk is a good illustration of nonstationarity. Two decades ago, credit default swaps, collateralized debt obligations, ETFs, strategic mortgage defaults, and high-frequency trading would not have been part of any theoretical or empirical analysis of systemic risk. Today, they are systemically relevant markets and activities that must be carefully monitored.

The very nature of systemic risk implies a certain degree of nonstationarity that may not always be consistent with the econometric framework in which risk measures are typically estimated. While financial innovation can be useful in facing immediate challenges, it can have unintended consequences by reducing transparency and increasing complexity in the system. Significant innovations can disrupt empirical relationships, rendering reliable statistical estimation difficult or impossible. Accordingly, the amount of data available for addressing systemic risk may be intrinsically more limited than other areas of econometric analysis.

One concrete illustration of this limitation is the default probability estimates of mortgage-backed securities during the years immediately preceding the recent problems in the U.S. subprime mortgage market. A key parameter of those default probability estimates was the correlation of defaults of individual mortgages in a geographically diversified pool. Because there had been no significant national decline in the value of residential real estate in the trailing 20-year history of U.S. housing prices, the estimated default correlations were extremely low, leading to even lower default-probability estimates for the diversified pool of mortgages and higher credit ratings.

However, spotting the danger of nonstationarity is considerably easier than addressing it satisfactorily. Because nonstationarity is a vastly broader set of outcomes than its complement, the curse of dimensionality suggests that there are no easy fixes. One common approach among financial industry practitioners is to use rolling windows of data in estimating models and parameters, in some cases with exponentially declining weights to give more emphasis to current observations and less to older ones. While this practice does capture simple nonstationarities, it does so in a very crude manner that can yield other types of misleading inferences. For example, Lo and Newey (2011) show that if a time series is indeed stationary, then an exponentially weighted mean is an inconsistent estimator of the population expectation, implying that even as the sample size increases without bound, the estimator will not converge in probability but will continue fluctuating randomly. This suggests that even when economic conditions are stable, systemic risk measures estimated with exponential weights can yield “false positives” on a regular basis.

These considerations underscore the importance of incorporating realistic institutional features and constraints in modeling and measuring systemic risk, and also highlights the need for new econometric methods that are able to address nonstationarity in more sophisticated ways.

3.3 Other Research Directions

Several other research directions that we did not include in this survey may yield additional insights into systemic risk, and bear further investigation. One of the most intriguing of these “non-standard” approaches is agent-based modeling (ABM) techniques, in which economic agents with relatively simple behavioral rules are allowed to interact freely in a computer simulation, with the objective of studying the dynamic properties of these interactions over the course of the simulation. ABM has deep intellectual roots that go back to the 1940s with John von Neumann's creation of “cellular automata”.[20] The motivation is compelling: because the dynamics of realistic interactions between a large population of economic agents are far too complicated to compute analytically, simulation is a natural and efficient alternative, especially given the tremendous increase in computing power in recent years. Axelrod (1997) provides a useful introduction to this literature, and there are many online resources to help the uninitiated get started.[21] Farmer and Foley (2009) have made a compelling case for using ABM techniques in studying the financial crisis, and Farmer and colleagues have received several large grants to develop new computational models for this purpose. In addition, ABM is a topic that has engaged the interest of FSOC and OFR staff.

[19] *See, for example, Hamilton (1994).*

[20] *Cellular automata are mathematical constructions involving a simple grid of "cells" that have two states, "on" and "off", with rules for how these states evolve over time. From a relatively spare set of assumptions, these cellular automata can generate a surprisingly rich spectrum of patterns.*

[21] *See, in particular, http://www2.econ.iastate.edu/tesfatsi/abmread.htm.*

Another potentially relevant research area is the empirical properties of extreme returns of financial assets, i.e., “tail probabilities”. Although a number of techniques in this survey do involve tail probabilities and extreme events (see, for example, Sections C.2, C.4, E.1, E.3, and E.4 of the Appendix), the “econophysics” literature—a discipline that, curiously, has been defined not so much by its focus but more by the techniques (scaling arguments, power laws, and statistical mechanics) and occupations (physicists) of its practitioners—has taken a very different tack. By carefully measuring the mathematical properties of tail probabilities of financial data, econophysicists have documented power laws that provide more accurate descriptions of how the senon-Gaussian probabilities decay for more extreme scenarios. These findings have important implications for traditional risk measures such as value-at-risk and expected-loss statistics, but also imply slowly decaying autocorrelations, long-range dependence, and non-normal asymptotic distributions for most standard econometric estimators. Mantegna and Stanley (2000, 2009) provide an excellent summary of this literature, and Bouchaud, Farmer, and Lillo (2009) present a fascinating market-micro structure application of these techniques that may be particularly relevant for high-frequency trading contexts.

A third research direction that may be useful is behavioral economics and finance. This may seem contrary to the quantitative focus of systemic risk measurement, but two considerations should give even the most skeptical readers pause in dismissing this literature.

The first is the observation that among the many nonstationarities that characterize financial markets and their regulatory environment, the one constant throughout is human behavior—*Homosapiens* has changed relatively little over the past 60,000 years. In fact, it can be argued that the ultimate source of systemic risk is the inherent incompatibility of human behavior (which has been adapted to the environment of the Neolithic ice age) with the many technological innovations of modern civilization. For example, for the first time in human history, at the click of a mouse button, we are now able to wipe out a substantial portion of our life savings with one bad trade.

The second observation is that the behavioral literature has progressed far beyond the less analytical and more phenomenological approach of the early experimental studies of behavioral biases and anomalies. Recent advances in the cognitive neurosciences have provided more formal and specific underpinnings of human behavior and their implications for financial decision making,[22]and the implications for systemic risk measurement may be significant.

For example, in reviewing the financial crisis from a cognitive neurosciences perspective, Lo (2011) observes that risk perception may differ from risk reality, and because the former drives behavior, not the latter, financial crises may be an inevitable outcome of free enterprise. In particular, he cites the example of the so-called “Peltzman effect” (Peltzman, 1975) in which regulations mandating the installation of various automobile safety devices may have the unintended consequence of encouraging people to drive more recklessly because they feel safer. While this effect has been challenged by a number of subsequent studies that control for various confounding factors such as enforcement practices, driver age, rural vs. urban roads, and vehicle weight, in the more narrowly defined context of NASCAR drivers, the Peltzman effect has been confirmed. This behavioral version of the Lucas critique is an ironic twist of fate in which the cognitive neurosciences are now providing neurophysiological micro-foundations for economic ideas such as rational expectations.[23] By developing a better understanding of the cognitive foundations of such patterns of behavior—including the subtleties of their context dependence—we may be able to construct more informative measures of systemic risk, as well as more responsive policies for promoting financial stability.

3.4 Research Taxonomy

Although no single classification scheme can encompass all of the relevant characteristics of all of our systemic risk measures, and there is inevitable overlap among them, from the research perspective, the taxonomy proposed in Table 4 may be more user-friendly to researchers in allowing them to identify common themes, algorithms, and data structures quickly within each category. The main differences between this taxonomy and those of Tables 1–3 stem from the fact that the origin of systemic events throughout history seem to be the four “L's” of financial crisis: liquidity, leverage, losses, and linkages. When leverage is used to boost returns, losses are also magnified, and when too much leverage is applied, a small loss can easily turn into a broader liquidity crunch via the negative feedback loop of forced liquidations of illiquid positions cascading through the network of linkages within the financial system. From this stylized narrative of financial crisis, we can categorize our systemic

[22] *See, for example, Bossaerts (2009).*

[23] *In fact, the “theory of mind” literature in psychology is intimately related to the formation of expectations and what economists consider to be rational behavior. See Lo (2011)for further discussion.*

risk measures into five groups organized by the particular aspect of the four L's they capture and the techniques used: probabilities of loss, default likelihood, illiquidity, network effects, and macroeconomic conditions.

3.4.1 Probability Distribution Measures

Perhaps the most direct measure of systemic risk is simply the joint distribution of negative outcomes of a collection of systemically important financial institutions. The financial turbulence model of Kritzman and Li (2010), the banking system's multivariate density (BSMD) function of Segoviano and Goodhart (2009), and the co-dependence measures of Adrian and Brunnermeier (2010) (CoVaR), International Monetary Fund (2009a) (Co-Risk), and Acharya, Pedersen, Philippon, and Richardson (2010) (SES) are all examples based on the joint distribution of asset returns. These measures are largely atheoretical, but some may interpret this as a virtue rather than a vice; regardless of one's theoretical priors, these measures can still provide informative estimates of correlated losses. Moreover, the probability distributions on which these measures are based often serve as inputs to other measures with more structure. For example, Segoviano and Goodhart's (2009) BSMD is used to produce the joint probability of default (JPoD); banking stability index (BSI); distress dependence matrix (DDM); and the probability of cascade effects (PCE).

Systemic Risk Measure	Section
Probability Distribution Measures:	
Mahalanobis Distance	C.2
Multivariate Density Estimators	C.4
CoVaR	E.1
Co-Risk	E.3
Marginal and Systemic Expected Shortfall	E.4
Contingent-Claims and Default Measures:	
The Default Intensity Model	B.1
Contingent Claims Analysis	C.1
The Option iPoD	C.3
Simulating the Housing Sector	C.5
Consumer Credit	C.6
Distressed Insurance Premium	E.2
Illiquidity Measures:	
Mark-to-Market Accounting and Liquidity Pricing	B.7
Noise as Information for Illiquidity	F.3
Crowded Trades in Currency Funds	F.4
Equity Market Illiquidity	F.5
Serial Correlation and Illiquidity in Hedge Fund Returns	F.6
Broader Hedge-Fund-Based Systemic Risk Measures	F.7
Network Analysis Measures:	
Network Analysis and Systemic Financial Linkages	B.2
Granger-Causality Networks	B.5
Bank Funding Risk and Shock Transmission	B.6
Principal Components Analysis	C.7

Systemic Risk Measure	Section
Macroeconomic Measures:	
Costly Asset-Price Boom/Bust Cycles	A.1
Property-Price, Equity-Price, and Credit-Gap Indicators	A.2
Macroprudential Regulation	A.3
Simulating a Credit Scenario	B.3
Simulating a Credit-and-Funding-Shock Scenario	B.4
GDP Stress Tests	D.1
Lessons from the SCAP	D.2
A10-by-10-by-10Approach	D.3
Risk Topography	F.1
The Leverage Cycle	F.2

Table 4: Taxonomy of systemic risk measures by research method.

3.4.2 Contingent-Claims and Default Measures

With additional structure regarding an institution's assets and liabilities, it is possible to construct measures of default likelihood for each institution and then link them either directly or indirectly through their joint distribution, as in the International Monetary Fund (2009b) default intensity model. Using a nonparametric estimation technique known as "machine learning" applied to bank transactions and credit-bureau data for customers of a major U.S. commercial bank, Khandani, Kim, and Lo (2010) construct nonlinear, non-parametric, out-of-sample forecasts of consumer credit risk that significantly improve the classification rates of credit-card delinquencies and defaults.

For a more structural approach to modeling default, Merton (1973) shows that equity can be viewed as a call option on a firm's assets, and once a stochastic process for the asset's value is chosen, equity and debt contracts on those assets, and implied default probabilities, can easily be valued using contingent-claims analysis (i.e., derivatives pricing models). This is the approach taken by Capuano (2008), Gray and Jobst (2010), and Huang, Zhou, and Zhu (2009a).

Contingent claims analysis can also be applied to measuring the implicit cost of guarantees, as in Khandani, Lo, and Merton's (2009) simulation of the magnitude of cumulative losses borne by mortgage lenders through the implicit put option in non-recourse mortgages.

3.4.3 Illiquidity Measures

Illiquidity is an example of a highly specific measure of systemic risk that often requires considerable structure. Because of their role in providing maturity transformation as a valuable service, banks are vulnerable to funding illiquidity. This fragility forms the rationale for some of the main weapons in the macroprudential arsenal, including deposit insurance and the lender of last resort. These issues appear repeatedly in the literature, including recent papers by Kapadia, Drehmann, Elliott, and Sterne (2009) and Brunnermeier and Pedersen (2009). The Bank of England has developed its risk assessment model for systemic institutions (RAMSI) to simulate the possibilities (Aikman, Alessandri, Eklund, Gai, Kapadia, Martin, Mora, Sterne, and Willison, 2010). Ricks (2010) and Pozsar, Adrian, Ashcraft, and Boesky (2010) point out that funding troubles can apply to both traditional intermediaries as well as shadow banks.

Liquidity also affects the other side of the ledger. A key aspect of asset liquidity is the valuation methods used to mark positions, either to model or to market. Sapra (2008) considers the trade-offs in the choice between these two valuation regimes, and shows benefits and costs to both. Hu, Pan, and Wang (2010) propose a measure of illiquidity by computing the deviation of observed market yields on Treasury bonds from their model-based yields derived from a daily estimate of the zero-coupon curve, and find that deviations are typically quite low (and liquidity correspondingly high), but spike during crises as arbitrage capital exits the marketplace. Pojarliev and Levich (2011) use a proprietary high-frequency dataset of currency funds' returns to capture the "crowded trade" phenomenon in currency markets. From a systemic perspective, the most interesting results arise when funding illiquidity and asset illiquidity interact to generate self-reinforcing feedback of funding shortfalls and asset fire sales, which propagate to additional funding shortfalls elsewhere. Examples include Kapadia, Drehmann, Elliott, and Sterne (2009) and Brunnermeier and Pedersen (2009).

Among the approaches described below, Khandani and Lo (2011) propose two distinct measures of equity market liquidity, one of which is the profitability of an equity mean- reversion strategy, and the other is a more direct measure of price impact based on Kyle (1985). For assets that are not publicly traded such as hedge-fund and private-equity returns, Getmansky, Lo, and Makarov (2004) propose using serial correlation as a proxy for illiquidity. By definition, current prices in illiquid markets are frequently unavailable or unreliable, forcing funds to report mark-to-model estimates that often rely on linear extrapolation pricing methods. Serial correlation in observed returns is an artifact of this autoregressive smoothing, thus providing an indication of illiquidity.

3.4.4 Network Analysis Measures

Like probability distribution measures, measures of connectedness are largely atheoretical, but they do offer more direct indications of linkages between firms, and are easily aggregated to produce overall measures of “tight coupling”. One approach is to use principal components analysis to gauge the degree of commonality among a vector of asset returns. When the asset returns of a collection of entities are jointly driven by a small number of highly significant factors, fewer principal components are needed to explain the variation in the vector of returns, hence sharp increases in the proportion of variability explained by the first *n* principal components is a natural indication of systemic risk. The absorption ratio of Kritzman, Li, Page, and Rigobon (2010) and the PCAS measure of Billio, Getmansky, Lo, and Pelizzon (2010) are based on this property.

More explicit measures of financial networks may be derived from graph theory, a branch of discrete mathematics in which abstract “nodes” are connected to each other by “edges” that represent a particular type of relationship. Such networks have been popularized through social networking websites and degree-of-separation games, but there is a rich set of analytics that have been developed for networks which can be drawn upon to measure systemic risk. Chan-Lau, Espinosa, and Sole (2009) and the International Monetary Fund (2009b) contain two network models of interbank exposures to assess the network externalities of a bank failure using institutional data. Using Granger-causality test statistics for asset returns to define the edges of a network of hedge funds, banks, broker/dealers, and insurance companies, Billio, Getmansky, Lo, and Pelizzon (2010) show that Granger-causality networks are highly dynamic and become densely interconnected prior to systemic shocks.

And the funding gap model of Fender and McGuire (2010a) reveals important linkages within multinational banks that have many geographically dispersed offices. While aggregate balance sheet data at the banking-group level may not show much risk, a network map of the exposures between offices within a banking group may yield a very different picture, especially for large banking organizations that fund their local foreign currency (especially USD) positions through their internal (i.e., within the banking group) and external networks.

3.4.5 Macroeconomic Measures

The diametric opposite of the atheoretical probability-distribution measures of Section 3.4.1 are the macroeconomic models of systemic risk. Because the macroeconomy is so complex, it is virtually impossible to derive useful information from basic macro data without significant structural hypotheses. Accordingly, there are a multitude of macroeconomic measures of systemic risk, corresponding to the many macro models of business and credit cycles, unemployment, inflation, and growth.

The comprehensive volume by Reinhart and Rogoff (2009) provides useful comparisons of broad macroeconomic aggregates such as asset price indices (equities, housing, etc.), GDP growth rates, and public debt over many financial crises, and find a number of common patterns. Alfaro and Drehmann (2009) use the Reinhart and Rogoff episodes as their starting point for generating GDP stress tests.

A natural complement to systemic risk measurement is macroprudential regulation, which Borio (2010) defines as calibrating supervision from the top down, rather than building it up from supervision of individual institutions. Caruana (2010b) makes the case for countercyclical regulation, arguing that if Basel III had existed at the time of the crisis, banks would have had much stronger capital bases so that the negative feedback from credit losses to credit supply—i.e., procyclical aggravation of the business cycle from financial distress— would have been milder, and the required bailouts much smaller.

Alessi and Detken (2009) construct simple early-warning indicators from a broad range of real and financial indicators—including GDP and its components, inflation, interest rates, and monetary aggregates—for 18 OECD countries between 1970 and 2007. Extreme values of these aggregates are taken as indications of pending booms or busts over the following 6- quarter horizon. Borio and Drehmann (2009b) propose a related approach, but with signals defined by simultaneous extreme values for pairs of property prices, equity prices, and credit spreads, again drawn from 18 industrialized countries between 1970 and 2007.

4. Data Issues

While this survey covers a diverse range of models of threats to financial stability, they all have one feature in common: significant new data requirements. Although there is still considerable controversy over the root causes of the Financial Crisis of 2007–2009, there is little dispute that regulators, policymakers, and the financial industry did not have ready access to information to generate early warning signals or implement rapid resolution plans. For example, prior to the Dodd Frank Act, even systemically important financial institutions such as AIG and Lehman Brothers were not obligated to report their amount of financial leverage, asset illiquidity, counterparty risk exposures, market share, and other critical risk data to any regulatory agency. If aggregated over the entire financial industry, such data could have played a crucial role in providing regulators with advance notice of AIG's unusually concentrated position in credit default swaps, and the broad exposure of money market funds to Lehman bonds.

The Dodd Frank Act mandates central reporting of large swaths of the over-the-counter (OTC) derivatives market, and has assigned to the OFR and FSOC the responsibility for coordinating data collection, data sharing, and supervision of financial firms. Similar efforts are underway in Europe, with the creation of the European Systemic Risk Board (ESRB). The Financial Stability Board (FSB) and International Monetary Fund (IMF) are spearheading an effort for the G-20 finance ministers and central bank governors to address information gaps at the international level (see Financial Stability Board and International Monetary Fund (2010)). These efforts will undoubtedly raise many new issues surrounding data acquisition, archiving, and management. In this section, we provide a brief introduction to some of these issues by summarizing in Section 4.1 the data required by the risk analytics in this survey, reviewing the issues surrounding the standardization of legal entity identifiers (LEIs) in Section 4.2, and discussing recent advances in computer science that have significant implications for the trade-off between transparency and privacy in Section 4.3.

4.1 Data Requirements

To be able to implement the statistical models and algorithms for calculating various systemic risk measures described in this paper, risk regulators will have to collect, archive, and access data on a regular basis, while addressing security and privacy concerns of all stakeholders. To provide a concrete illustration of the scope of this effort, we provide in Table 5 a detailed list of the data sources used by the measures in this survey.

4.2 Legal Entity Identifier Standards

Separately, the OFR and FSB are coordinating the development of a standardized legal entity identifier (LEI) registry, which would, for the first time, provide consistent global identification of obligors in financial transactions. The LEI has special significance for systemic risk measurement because it facilitates the implementation of many of the network measures described in this survey.

The need for a standardized method of identification is easiest to see within—but not limited to—the context of network or graph-theoretic measures such as Chan-Lau, Espinosa, and Sole (2009) and Duffie (2011), where the nodes in the graph represent legal entities, and edges represent individual or aggregated contractual relationships. In practical implementations of such models, especially with systemic scope, both entities and relationships will be first-class objects with persistent state. This fact implies a need for an efficient, consistent, globally unique identification scheme for both entities and relationships. An LEI is simply a systematically maintained tag or code that uniquely identifies an entity in the system. Bottegaand Powell (2010) describe LEIs in detail, noting that they are “a critical component in measuring and monitoring systemic risk”, because they enable the construction of the counterparty network graph of linkages and interrelationships in the system.

Table 5: Data Requirements

Replicable Studies Covered in this Document					
Source	**Asset**	**Type**	**Frequency**	**Start**	**Stop**
Asset Price Boom/Bust Cycle Alessi and Detken (2009)					
IMF International Financial Statistics	Credit	Price	Quarterly	Q1:1970	Q4:2007
OECD Econ Outlook, Main Econ Indicators	Macro	Macro	Annual	Q1:1970	Q4:2007
OECD Econ Outlook, Main Econ Indicators	Macro	Macro	Quarterly	Q1:1970	Q4:2007
BIS and ECB sources	Money Market	Return	Quarterly	Q1:1970	Q4:2007
BIS	Real Estate	Price	Quarterly	Q1:1970	Q4:2007
Bank Funding Risk and Shock Transmission Fender and McGuire (2010b)					
BIS locational banking statistics by nationality	Bank	Accounting	Quarterly	Q1:2000	Q1:2010
BIS locational statistics by residency	Bank	Accounting	Quarterly	Q1:2000	Q1:2010
Consumer Credit Khandani, Kim, and Lo (2010)					
Proprietary Commercial Bank data	Bank	Miscellaneous	Monthly	January 2005	April 2009
Contingent Claims Analysis Gray and Jobst (2010)					
Moody's KMV creditEdge	Bond	Price	Quarterly	January 1, 2007	January 1, 2010
Bloomberg	Option	Price	Daily	January 1, 2007	January 1, 2010
MarkIt	Swap	Spread	Daily	January 1, 2007	January 1, 2010
Co-Risk International Monetary Fund (2009a)					
FRB H15 Release	Bond	Return	Daily	July 1, 2003	September 12, 2008
CRSP	Equity	Return	Daily	July 1, 2003	September 12, 2008
Bloomberg	Money Market	Return	Daily	July 1, 2003	September 12, 2008
FRBNY Website	Money Market	Return	Daily	July 1, 2003	September 12, 2008
CBOE Website	Option	Return	Daily	July 1, 2003	September 12, 2008
Bloomberg and Primark Datastream	Swap	Price	Daily	July 1, 2003	September 12, 2008

CoVAR Adrian and Brunnermeier (2010)					
FRBNY Website	Bond	Return	Weekly	Q1: 1986	Q1: 2010
CRSP	Equity	Price	Weekly	Q1: 1986	Q1: 2010
COMPUSTAT	Equity	Accounting	Quarterly	Q1: 1986	Q1: 2010
Bloomberg	Money Market	Return	Weekly	Q1: 1986	Q1: 2010
FRB H15 Release	Money Market	Return	Weekly	Q1: 1986	Q1: 2010
CBOE Website	Option	Return	Weekly	Q1: 1986	Q1: 2010
CRSP	Real Estate	Return	Weekly	Q1: 1986	Q1: 2010
Crowded Currency Trades Pojarliev and Levich (2011)					
DB Currency Harvest G10 Index	Currency	Return	Weekly	April 2005	June 2010
AFX Currency Mgmt. Index	Currency	Return	Weekly	April 2005	June 2010
DB Currency Volatility Index	Currency	Return	Weekly	April 2005	June 2010
DB G10 Valuation Index	Equity	Return	Weekly	April 2005	June 2010
Proprietary	Private Partnership	Return	Weekly	April 2005	June 2010
Default Intensity Giesecke and Kim (2009)					
Moody's Defaults Risk Services	Bond	Ratio	Static	January 1, 1970	December 31, 2008
Distressed Insurance Premium Huang, Zhou, and Zhu (2009a)					
Market Participants	Bond	Probability	Weekly	January 2001	December 2008
Moody's KMV	Bond	Probability	Weekly	January 2001	December 2008

FRB H15 Release	Bond	Spread	Weekly	January 2001	December 2008
TAQ Database	Equity	Price	Tick	January 2001	December 2008
Bloomberg	Equity	Return	Quarterly	January 2001	December 2008
FRB H15 Release	Money Market	Return	Weekly	January 2001	December 2008
Bloomberg	Option	Implied Vol	Weekly	January 2001	December 2008
MarkIt	Swap	Spread	Daily	January 2001	December 2008
Early Warning Macro Indicators Borio and Drehmann (2009b)					
BIS	Macro	Price	Annual	1970	2007
BIS	Macro	Miscellaneous	Static	1970	2007
Equity Market Liquidity Khandani and Lo (2011)					
NYSE Trade and Quote (TAQ)	Equity	Price	Tick	July 2, 2007	September 28, 2007

GDP Stress Tests Alfaro and Drehmann (2009) Authors' Estimates BIS	Macro Macro	Miscellaneous Return	Static Quarterly	1970:Q1 1970:Q1	2007:Q4 2007:Q4
Granger Causality Networks and PCA Billio, Getmansky, Lo, and Pelizzon (2010)					
CRSP	Equity	Return	Monthly	January 1994	December 2008
CRSP/Compustat Merged	Equity	Accounting	Quarterly	January 1994	December 2008
CS/Tremont hedge fund index	Private Partnership	Return	Monthly	January 1994	December 2008
TASS Database	Private Partnership	Return	Monthly	January 1994	December 2008
TASS Database	Private Partnership	Ratio	Monthly	January 1994	December 2008

Hedge Fund Based Systemic Risk Measures Chan, Getmansky, Haas, and Lo (2006b, 2006b)					
TASS Database	Private Partnership	Return	Monthly	January 1977	August 2004
TASS Database	Private Partnership	Return	Mixed	January 1994	August 2004
CSFB/Tremont Hedge Fund category indices	Private Partnership	Return	Monthly	January 1994	August 2004
Housing Sector Khandani, Lo, and Merton (2009)					
CRSP	Bond	Return	Monthly	February 1977	December 2008
Robert Shiller Website	Bond	Return	Annual	January 1919	January 1977
SandP/Case-Shiller Home Price Composite	Real Estate	Return	Monthly	January 1987	December 2008
FHFA national house price index	Real Estate	Return	Quarterly	Q1: 1975	Q4: 1986
Nominal home price index collected by R. Shiller	Real Estate	Return	Annual	1919	1974
U.S. Census Bureau	Real Estate	Number	Monthly	January 1963	December 2008
U.S. Census Bureau	Real Estate	Number	Quarterly	1974	December 2008
U.S. Census Bureau	Real Estate	Price	Monthly	January 1963	December 2008
Freddie Mac	Real Estate	Return	Monthly	April 1971	December 2008
Mahalanobis Distance Kritzman and Li (2010)					
Not Specified by Authors	Bond	Return	Monthly	January 1973	December 2009
Not Specified by Authors	Commodities	Return	Monthly	January 1973	December 2009
S&P 500	Equity	Return	Monthly	January 1973	December 2009
MSCI non-U.S. Index	Equity	Return	Monthly	January 1973	December 2009
Not Specified by Authors	Real Estate	Return	Monthly	January 1973	December 2009

Marginal and Systemic Expected Shortfall Acharya, Pedersen, Philippon, and Richardson (2010)					
CRSP	Equity	Return	Daily	June 2006	June 2007
CRSP/Compustat Merged	Equity	Accounting	Static	June 2007	June 2007
MarkIt	Swap	Spread	Daily	June 2006	June 2007
Multivariate Density Estimator Segoviano and Goodhart (2009)					
MarkIt	Swap	Spread	Daily	January 2005	October 2008
Network Analysis of Linkages International Monetary Fund (2009b)					
BIS Intl. Banking Statistics	Mixed	Price	Static	March 2008	March 2008
Noise as Information for Illiquidity Hu, Pan, and Wang (2010)					
CRSP Daily Treasury Database	Bond	Price, Return	Daily	January 1987	December 2009
Option iPoD Capuano (2008)					
Bloomberg	Option	Price	Daily	February 12, 2008	June 21, 2008
Principal Components Kritzman, Li, Page, and Rigobon (2010)					
MSCI U.S. Index and 51 Subindices	Equity	Return	Daily	January 1, 1998	January 31, 2010
For each country, the MSCI Index and all subindices	Equity	Return	Daily	January 1, 1998	January 31, 2010
Case-Shiller U.S. Housing Price Index	Real Estate	Return	Monthly	January 1987	December 2009

Serial Correlation and Illiquidity in Hedge Fund Returns Getmansky, Lo, and Makarov (2004)					
CRSP	Equity	Price, Return	Monthly	November 1977	January 2001
TASS Database	Private Partnership	Return	Monthly	November 1977	January 2001
CSFB/Tremont Hedge Fund category indices	Private Partnership	Price, Return	Monthly	November 1977	January 2001
10-by-10-by-10 Duffie (2011)					
Bank Executive Survey	Mixed	Text	Quarterly	N/A	N/A

This is the foundation of network analysis, as described in Section B, and allows for efficient and accurate aggregation when searching for concentrated exposures and patterns of activity.

A move toward a globally standardized LEI is already underway, and the OFR is helping to coordinate an international agreement around a standardized global registry of LEIs.[24] A registry of globally unique LEIs has ancillary benefits for the financial industry, which currently replicates this costly function at each firm to support internal trading, compliance, and risk management functions.[25]

The set of instrument types defines the available contractual relationships within the system—the attributes of the edges between nodes in a counterparty network graph. By extension, the full set of instrument types establishes the universe of possible portfolios for market participants. Because there are so many possible contracts, this universe is very large indeed. The portfolio for a given participant at a particular point in time can be represented by a vector of numbers, namely the amounts of each contract type contained in the portfolio. This vector will have many elements, i.e., it will be very high-dimensional. Moreover, for most participants, it will be very sparsely populated, i.e., it will have zeroes in most elements, since most participants have relatively specialized activities. Measuring financial contracts will require the capture of much more detail about those contracts than is the case under traditional firm-centric accounting systems.

To implement forward-looking risk metrics, the goals should be to capture and understand each contract's implied cash flow commitments between the counterparties to the contract, noting that, in many cases, these cash flows are contingent on other factors. The ability to work directly with the cash flows is crucial because, in practice, it is possible for two contracts or portfolios to generate substantially identical cash flow patterns, even when their legal or accounting representations differ widely.

Much of financial engineering is devoted to repackaging a fixed set of cash flow commitments into a different contractual configuration, perhaps to manage or lay off risk, avoid taxable events, reduce the market impact of a trade, or simply to obfuscate the activity.[26]

4.3 Privacy vs. Transparency

Historically, government policy has tread carefully on the financial industry's disclosure requirements because much of the industry's data are considered highly proprietary. Apart from the obvious privacy issues surrounding customer financial data, the majority of intellectual property in the financial industry consists of trade secrets. Unlike other industries in which intellectual property is protected by patents, the financial industry consists primarily of “business processes” that the U.S. Patent Office deems unpatentable, at least until recently.[27] Accordingly, trade secrecy is the preferred method by which financial institutions protect the vast majority of their intellectual property, hence their desire to limit disclosure of their business processes, methods, and data. Forcing a financial institution to publicly disclose its proprietary information—and without the quid pro quo of 17-year exclusivity that a patent affords—will obviously discourage innovation.

Nevertheless, the recent crisis, as well as the skepticism with which the financial industry has greeted current proposals for systemic-risk surcharges, provide even greater motivation for the OFR's mandate to collect data from SIFIs and conduct thorough empirical analysis on the efficacy of various analytics for capturing systemic risk.

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[24] *See Office of Financial Research (2011, 2010) for further details.*

[25] *In November 2010, the Office of Financial Research (2010) issued a policy statement to promote the development of a global LEI system. This included requirements for attributes of an LEI standard and associated reference data, as well as operational attributes for a system to issue and maintain LEIs. Simultaneously, the SEC and CFTC issued “Notices of Proposed Rule making” for reporting swap transactions to trade repositories, and expressed a preference for using an LEI for swap reporting. In January 2011, the International Organization for Standardization (ISO) launched a process to establish an LEI standard. It developed a draft specification for the standard and selected a registration authority to oversee assignment of LEIs: SWIFT, which is partnering with DTCC and its subsidiary Avox as facilities managers. The initial vote on the LEI standard (17442) being developed by ISO closed at the end of June. In September 2011, the Financial Stability Board (FSB) met in Basel to consider options for coordination around governance of a global LEI infrastructure.*

[26] *Note that the Dodd Frank Act (see especially section 153(c)(2)) mandates that the FSOC standardize data types and formats for reporting. Separately, the Committee on Payment and Settlement Systems (CPSS) and International Organization of Securities Commission (IOSCO), at the direction of the Financial Stability Board (FSB), established a task force to define requirements for reporting and aggregation of over-the-counter (OTC) derivative information.*

[27] *See, for example, Lerner (2002).*

These two seemingly irreconcilable objectives—protecting trade secrets while providing regulators with systemic risk transparency—are not as difficult to reconcile as they may appear. In particular, the banking industry already provides a significant amount of proprietary data to its regulator (the Office of the Comptroller of the Currency) without jeopardizing its intellectual property, hence some of these procedures may be applied to SIFIs not currently regulated as banks. However, an even more significant development for systemic risk management is the recent breakthroughs in cryptography that enable individuals to maintain the privacy of their data through encryption algorithms that allow third parties to compute aggregate statistics across multiple individuals while preserving the privacy of each individual.[28]

These algorithms will permit regulators to compute systemic risk exposures without ever requiring individual institutions to reveal their proprietary data; only encrypted information is used by the regulators. Although still in experimental stages of development, these so-called "secure multi-party computational" and "fully homomorphic encryption" algorithms will likely revolutionize the way in which systemic risk is measured and managed.

5. Conclusions

Regulators have been given a mandate by the Dodd Frank Act to measure and monitor systemic risk. Market participants have a complementary and immediate interest in better measurement and management of systemic risk. Although the impact of systemic events is widely felt, the burden for measuring and monitoring financial stability falls first and foremost on government regulators, given the unavoidable conflicts of interest faced the private sector. Because systemic risk is a multifaceted problem in an ever-changing financial environment, any single definition is likely to fall short, and may create a false sense of security as financial markets evolve in ways that escape the scrutiny of any one-dimensional perspective.

The scholarly literature is instructive in this regard. A wide variety of measurement techniques have been proposed and implemented, attempting to capture systemic risk from diverse perspectives. Ultimately, the specific measures regulators choose to deploy will become the *effective* operational definition of systemic risk, and these metrics should be chosen to tackle the problem from many different directions.

The data requirements to support these metrics are correspondingly wide-ranging. In many cases, academic researchers have made do with publicly available data, adjusting their modeling approaches accordingly. This is a constraint that regulators will not necessarily face, given the mandates and authorities granted to them by recent legislation. While the scholarly literature serves as a useful introduction to the scope of possible measurement approaches, it should be regarded only as a starting point, not a conclusion. We hope this survey will expedite the process of discovery and innovation in systemic risk measurement, and look forward to future editions as more stakeholders engage in this important research endeavor.

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[28] *See, for example, Abbe, Khandani, and Lo (2011).*

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