Modeling Systemic Risk to the Financial System

A Review of Additional Literature

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Introduction

The recent financial crisis has focused attention on systemic risk to the financial system and led to an explosion of research in the field. The data displayed in Figure 1 evince this. Figure 1 shows the annual output of research publications, as measured by searching on Google Scholar in the Business, Administration, Finance, and Economics subject areas for documents containing both the terms "systemic risk" and "financial system". These data suggest that the literature in the field is growing at a rate on the order of thousands of publications per annum. Although it is not possible for us to keep abreast of all new developments, we have reviewed some of the recent literature and present this report as a sequel to our previous literature review (Markeloff et al, 2011).

In the sections that follow, we summarize recent publications that we have found particularly interesting. We begin with an article by Darrell Duffie, Dean Witter Distinguished Professor of Finance at the Graduate School of Business, Stanford University, and follow with an article by two equally illustrious authors: Andrew Haldane, Executive Director for Financial Stability at the Bank of England, and Robert M. May, a renowned theoretical ecologist. Neither of these articles describes a specific systemic risk model, although their subject matter is certainly germane to the field. We go on to delineate seven models and summarize a valuable study that rigorously evaluates the performance of various systemic risk models.

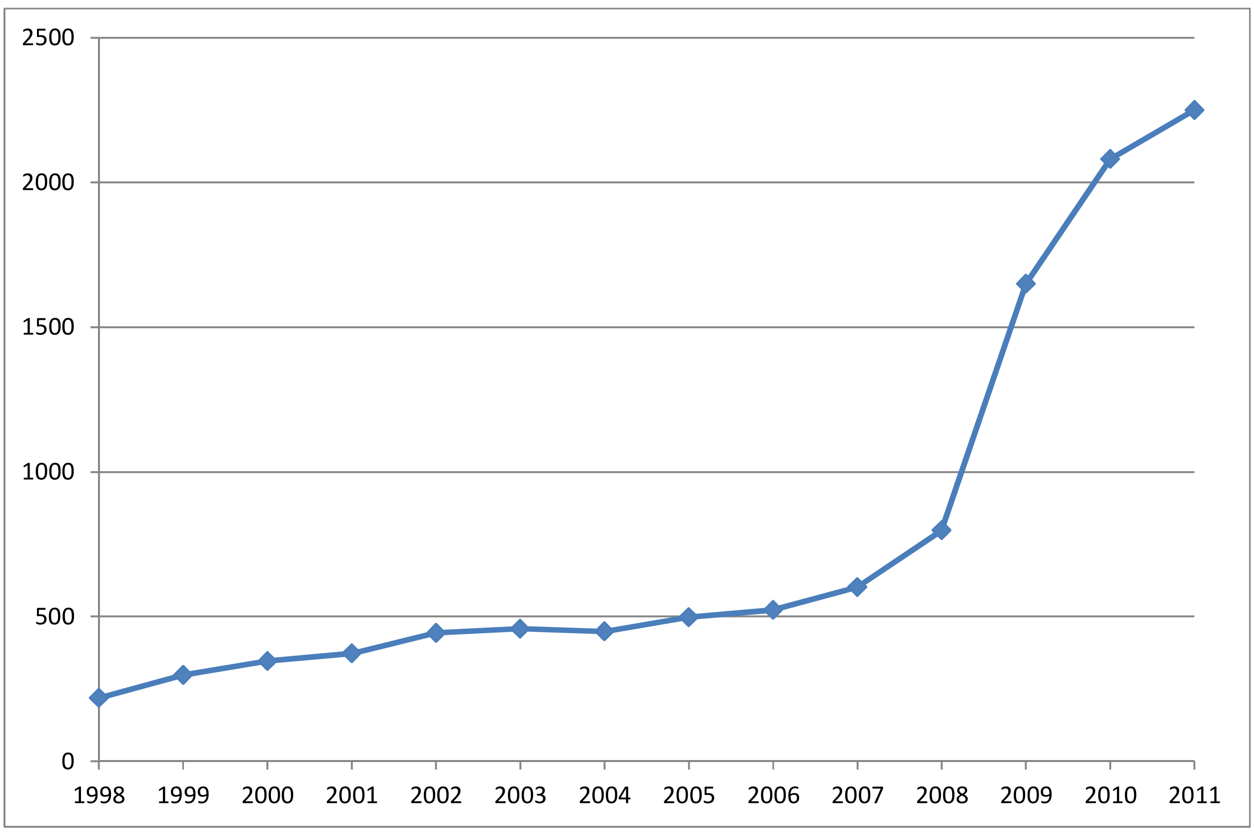

Figure 1. The annual output of publications in the field of systemic risk to the financial system for the period 1998-2011.

The 10 × 10 × 10 Approach

Duffie has proposed (2011) a new method for assessing systemic risk from stress test results. While not strictly a systemic risk model, this method is described in a recent publication from the Office of Financial Research (OFR) (Bisias et al, 2012), and an earlier version of Duffie's paper was included in a bibliography published in 2011 by the OFR. Clearly this is of interest to government regulators.

In Duffie's method, more properly called the $N \times M \times K$ approach, a regulator identifies N financial institutions deemed systemically important and applies M stress tests to each. These institutions then report their total gain or loss for each test, together with their K largest (in magnitude) gains and losses with respect to particular counterparties, which they must name. He suggests a number of potential stress tests, as quoted below:

- The default of a single entity
- A 4% simultaneous change in all credit yield spreads
- A 4% shift of the U.S. dollar yield curve
- A 25% change in the value of the dollar relative to a basket of major currencies
- A 25% change in the value of the Euro relative to a basket of major currencies
- A 25% change in a major real estate index
- A 50% simultaneous change in the prices of all energy-related commodities
- A 50% change in a global equities index

The N entities would be required to report the results of these tests periodically, perhaps quarterly, to a designated systemic risk regulator. Such reports might help identify new entities of systemic importance, since they will likely be significant counterparties to the N identified institutions. The public dissemination of such information, in summary form designed to protect proprietary interests, could help to curb systemic risk by encouraging firms to adjust their portfolios and re-price assets.

Although Duffie acknowledges that his monitoring system has some drawbacks, he claims that it would provide regulators with valuable knowledge about concentrations of stress within the financial system. The information contained in the reports could also be used to construct network models for evaluating contagion risk.

Systemic Risk in Banking Ecosystems

Haldane and May have recently published their insights into the stability of financial networks (2011). Haldane has written extensively on the topic of systemic risk (for example, Haldane, 2009). May's seminal work on ecological networks (1972, 1974) showed that ecosystems tend to become increasingly unstable as their complexity increases; the authors claim that financial networks can exhibit analogous instabilities. This has also been hypothesized by other systemic risk researchers (e.g., Markose et al, 2010).

Haldane and May assert that the growth in derivatives markets that preceded the recent financial crisis destabilized the financial system, and cite a mathematical analysis by Caccioli, Marsili, and Vivo (2009) to support this contention. They also review the work of Nier et al (2009) and Gai and Kapadia (2010), both of whom studied the properties of simple, idealized network representations of banking systems. Haldane and May claim that the relationships between system stability and network properties revealed by these models have important implications for public policy.

In a commentary on Haldane and May's paper, Johnson (2011) argues that toy network models are too simplistic to be useful in formulating public policy. In another commentary, Lux (2011) maintains that such models are a promising initial step towards a rigorous understanding of modern financial systems.

Financial Fragility Indices

Tymoigne (2011) proffers a set of indicators for the level of macroprudential risk in the financial system. The economic theories of Hyman Minsky (Minsky, 1986) form the basis for Tymoigne's model. In Minsky's view, financial crises arise from financial imbalances driven by, and feeding off, unsustainable economic expansion. The concept of *financial fragility*, broadly defined as the propensity of financial problems to generate financial instability, is key to Minsky's framework. Financial fragility reaches high levels when what Minsky refers to as *Ponzi finance* becomes prevalent in the economy. Economic units use Ponzi finance when they borrow using assets (e.g., real estate) as collateral with the expectation that the rising value of the assets will enable them to meet debt commitments. The relevance of this concept to the recent financial crisis, particularly to the housing bubble that precipitated it, should be obvious.

Tymoigne's Financial Fragility Indices are designed to capture the intensity of the growth of financial fragility. They are constructed using data from the Federal Reserve, the Bureau of Economic Analysis (BEA), and the Federal Housing Finance Agency (FHFA). Indices are defined for three sectors: Household, Financial Business, and Nonfinancial Nonfarm Corporation. We describe the Household index as an example. The purpose of this index is to indicate the rates at which the aggregate value of household assets and the level of household indebtedness are changing. A high value for the index signals that households are enjoying rising asset values and are increasing their borrowing, and warns of growing financial fragility in the household sector.

The Household index is comprised from the following components:

- Outstanding total liabilities (L)
- Net worth (NW)
- Debt-service ratio (DSR)
- Monetary instruments relative to outstanding liabilities (MLR). Monetary instruments include dollar-denominated currency, demand and time deposits, and money-market mutual funds shares.
- Proportion of cash-out refinancing mortgage loans in mortgage refinancing loans (COR)
- Proportion of revolving consumer debts (RCD)

For each component $X \in \{\text{L, NW, DSR,}\ldots\}$, with the exception of MLR, a dummy variable D_X is defined as

$$
D_X = \begin{cases} 1 & \text{if} \quad g_{X_t} > g_{X_{t-1}} > 0 \\ 0.9 & \text{if} \quad g_{X_t} > 0 \\ 0 & \text{if} \quad g_{X_t} = 0 \\ -0.9 & \text{if} \quad g_{X_t} < 0 \\ -1 & \text{if} \quad g_{X_t} < g_{X_{t-1}} < 0 \end{cases}
$$

where g_{X_t} denotes the growth rate for component *X* at time *t*. The dummy variable D_{MLR} is defined in the same way, except it has the opposite sign. The index is a linear combination of the dummy variables:

$$
I_H = 0.1D_L + 0.1D_{NW} + 0.25D_{DSR} + 0.25D_{MLR} + 0.15D_{COR} + 0.15D_{RCD}
$$

The coefficients of the dummy variables reflect Tymoigne's subjective evaluation of the relative weight that should be accorded to each component in the index. Tymoigne calculates the indices at quarterly intervals for the period Q1 1992 to Q3 2010. The results for the Household index are shown in Figure 2, reproduced from (Tymoigne, 2011).

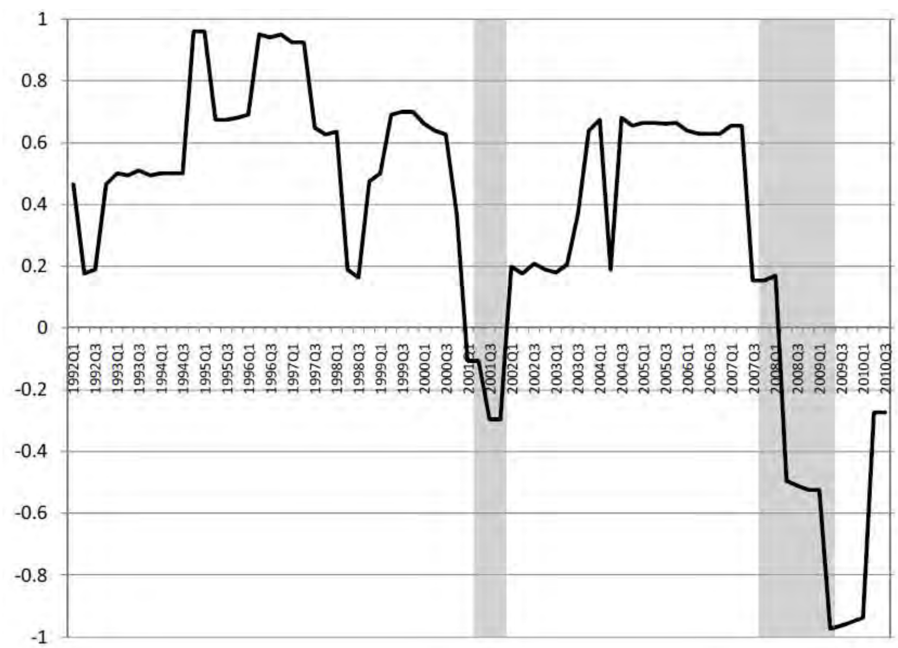

Figure 2. The Household index I_H for the period Q1 1992 – Q3 2010, reproduced from (Tymoigne, 2011). Shaded intervals indicate recessions.

Figure 2 shows that I_H was a relatively high level for an extended period leading up the recent financial crisis. Tymoigne attributes the high values for I_H observed for the 1990s and 2000, at least in part, to a credit-based consumption boom encouraged by rising stock prices.

Early Warning Indicators for Banking Crises

Borio and coauthors (Borio & Lowe, 2004; Borio & Drehmann 2009) have developed a model to provide early warning indicators for banking crises. Their model extracts a forecast signal from noisy data through statistical analysis of observed historical correlations. Borio and Lowe's 2004 analysis is based on a sample of 15 episodes of severe banking distress in 20 advanced economies for the period 1980-1997, assembled by Bordo et al (2001). Borio and Drehmann's 2009 paper refines the model and presents preliminary results for the recent financial crisis. In 2011, Drehmann, Borio, and Tsatsaronis published a new analysis encompassing 49 banking crises in 37 countries (not limited to advanced economies) for the period 1980-2008. The sample is taken from a database of banking crises assembled by Laeven and Valencia (2010).

These analyses are inspired by Minsky's theories and the history of financial crises as written by Kindleberger (2000). They seek to detect increases in asset prices and credit that often presage financial crises. Borio and Drehmann (2009) achieve their best results using a combination of three indicators representing real estate prices, equity prices, and private sector credit. A signal is indicated when the deviations between these quantities and their recursive trends exceed given thresholds. Recursive trends are calculated using a Hodrick-Prescott filter (Hodrick & Prescott, 1997). Drehmann et al (2011), however, favor the use of single indicators and claim that multivariate approaches offer only marginal improvements. They find that the best performing indicator is the gap between the ratio of credit to GDP and its long-term trend (also calculated using a Hodrick-Prescott filter).

Figure 3 shows Receiver Operating Characteristic (ROC) curves for Borio and Lowe's 2009 model and Drehmann et al's 2011 model. The curves show the true positive rate (i.e. detection probability) versus the false positive rate (i.e. Type II error rate) for various values of the real estate price gap threshold for Borio and Lowe's model and the credit to GDP gap threshold for Drehmann et al's model. The time horizon for both models is three years. The data are taken from the respective publications. Note that a direct comparison between the two models is not possible due to the differences in their data samples.

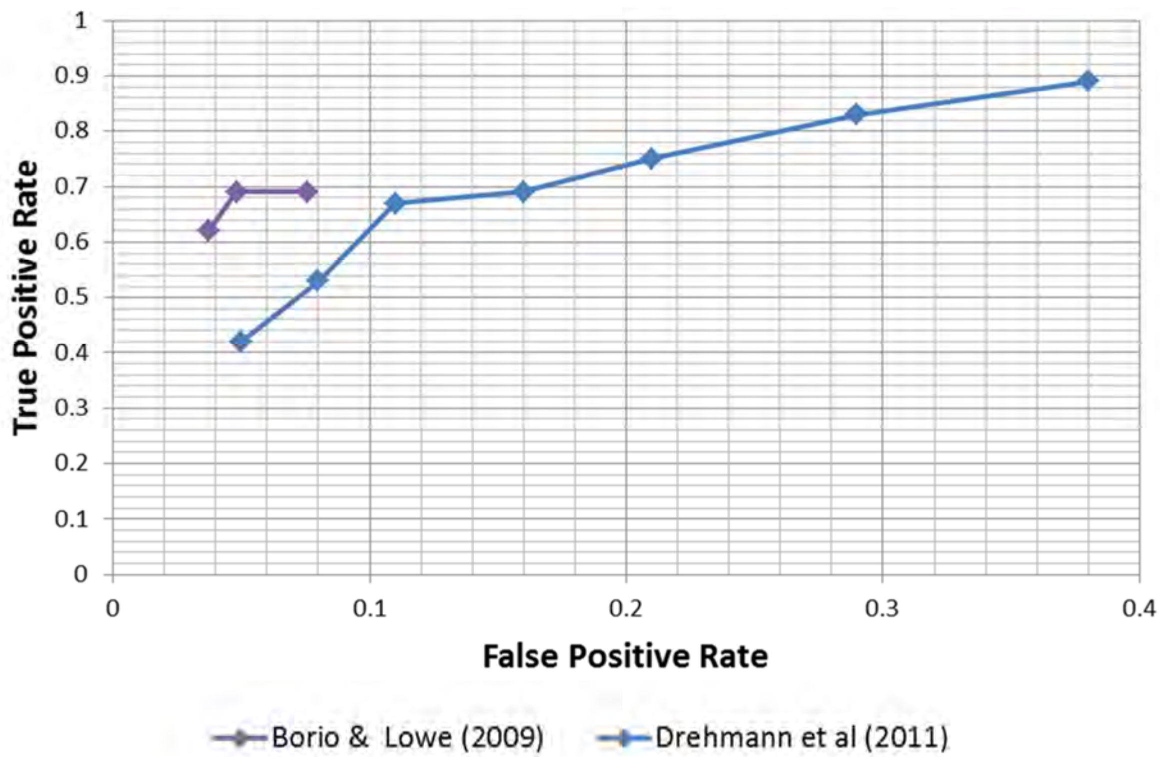

Figure 3. ROC curves for banking crises early warning indicators.

The SRISK Index

Acharya, Pedersen, Philippon, and Richardson (2010) have developed a model, described in our previous report, which estimates the potential losses and capital shortfalls of individual banks in the event of a systemic crisis. The authors define a systemic crisis as the situation arising when the aggregate equity capital of the banking system falls below some fraction of aggregate assets. Their model is based on the concept of expected shortfall (ES), a standard risk measure employed by many financial firms. For each bank in the system, the model predicts the marginal expected shortfall (MES), which captures the expected loss in a bank's equity in the event of a of a systemic crisis (as defined by their criterion), and the systemic expected shortfall (SES), defined as the shortfall in the bank's capital requirement should such an event occur. Acharya et al propose a method for estimating MES based on a firm's equity returns and derive an expression for SES in terms of MES and other variables, but they do not offer a means for estimating SES from empirical data. Beginning with the same definitions for a systemic crisis and MES, Brownlees and Engle (2011) formulate a capital shortfall measure equivalent to SES which they call they the SRISK index. The major advance of the SRISK index over SES is that Brownlees and Engle describe how it can be calculated. We present below a brief outline of this calculation.

Let CS_{i0} denote the value for the capital shortfall for firm *i* at $t=1$ expected at $t=0$. If *k* is the prudential ratio of asset value to equity, b_{it} is the of the firm's debt at time *t*, and w_{it} is the firm's net worth at time *t*, then CS_{i0} is given by $\mathrm{CS}_{i0} = k(b_{i0}+w_{i1}) - w_{i1}$. Here we assume that the firm incurs no additional debt between $t=0$ and $t=1$. In the event of a systemic crisis, defined as the case where the arithmetic market return R_{mt} at time *t* drops below some threshold *C*, the expected capital shortfall CS_{i0} is given by

$$\begin{aligned}\mathrm{CS}_{i0} &= E_0\left((k(b_{i0}+w_{i1})-w_{i1}) \mid \mathrm{Crisis}\right)\\ &= kb_{i0}-(1-k)E_0\left(w_{i1} \mid \mathrm{Crisis}\right)\\ &= kb_{i0}-(1-k)w_{i0}E_0\left(R_{i1} \mid R_{m1}<C\right)\end{aligned}$$

where R_{it} is the return of firm *i* at time *t*. The expectation value is recognized as the definition of MES, leading to

$$\mathrm{CS}_{i0} = kb_{i0}-(1-k)w_{i0}E_0\mathrm{MES}_{i0}.$$

Brownlees and Engle define systemic risk, as Acharya et al do, as the risk of an aggregate capital shortfall across the banking system. The quantity SRISK_i represents firm *i*'s contribution to this risk and is given by

$$\mathrm{SRISK}_i = \min\left(0, \mathrm{CS}_{i0}\right).$$

Estimating SRISK hinges upon estimating MES. Brownlees and Engle's approach for estimating MES begins with assuming that the log returns r_{it} and r_{mt} for firm *i* and the overall market, respectively, are governed by stochastic processes that can be cast in the following forms:

$$r_{mt} = \sigma_{mt}\varepsilon_{mt}$$
$$r_{it} = \sigma_{it}\rho_{it}\varepsilon_{mt} + \sigma_{it}\sqrt{1-\rho_{it}^2}\xi_{it}$$

Here σ_{it} and σ_{mt} are the standard deviations for the returns for non-crisis periods. The quantities ε_{mt} and ξ_{it} are random variables drawn from distributions with zero mean and unit variance. The correlation coefficient between the firm and market returns is denoted by ρ_{it}. These processes have the following interpretation. The random variables ε_{mt} and ξ_{it} describe the time variations in the returns, including infrequent deviations far from the usual range. These are scaled by the spread in returns typically observed. Firm-level returns are decomposed into a component correlated with the market and an uncorrelated component. Brownlees and Engle make the additional assumption that ε_{mt} and ξ_{it} are identically distributed:

$$(\varepsilon_{it}, \xi_{it}) \sim F .$$

The form of F is left unspecified.

The authors then invoke the definition of MES, $\mathrm{MES}_{it-1} = E_{t-1}\left(r_{it} \mid r_{mt} < C\right)$, to derive the expression

$$\mathrm{MES}_{it-1}^{1} = \sigma_{it}\sqrt{1-\rho_{it}^2}\,E_{t-1}\left(\xi_{it} \mid \varepsilon_{mt} < \frac{C}{\sigma_{mt}}\right).$$

The superscript 1 indicates that the expectation value is for the next time period, i.e., one day in advance. The authors acknowledge that the use of log rather than arithmetic returns introduces a relatively small error in this expression, but do not correct for it.

Brownlees and Engle estimate σ_{mt} and σ_{it} using a threshold autoregressive conditional heteroskedasticity (TARCH) model (Rabemananjara & Zakoïan, 1993; Glosten et al, 1993). The correlations between the firm and market returns are modeled using the dynamic conditional correlation (DCC) approach (Engle, 2002; 2009). They estimate these quantitites on a weekly basis using daily returns from CRSP for U.S. financial firms with market capitalization greather than $5B for the 2000-2010 time period.

To calculate MES^{1}, the tail expectation $E_{t-1}\left(\xi_{it} \mid \varepsilon_{mt} < C / \sigma_{mt}\right)$ is estimated from events in the data sample where the market returns for the financial sector drop 2% or more. However, MES^{1} is not used in calculating SRISK values. For this purpose, the authors use what they refer to as the *long-term* MES, denoted by MES^{h}, where the expectation value is for a six month period and the market drop threshold is 40% . Values for MES^{h} are obtained from Monte Carlo simulations based on the output from the TARCH and DCC models. Figure 4, reproduced from (Brownlees & Engle, 2011), shows the SRISK index summed over all the financial institutions in the sample for the 2006-2010 time frame. Here SRISK is calculated from MES^{h} values obtained from Monte Carlo simulations, market capitalizations from CRSP, and the quarterly book values of equity from COMPUSTAT. The peak SRISK in Figure 4 coincides with the Lehmann Brothers bankruptcy.

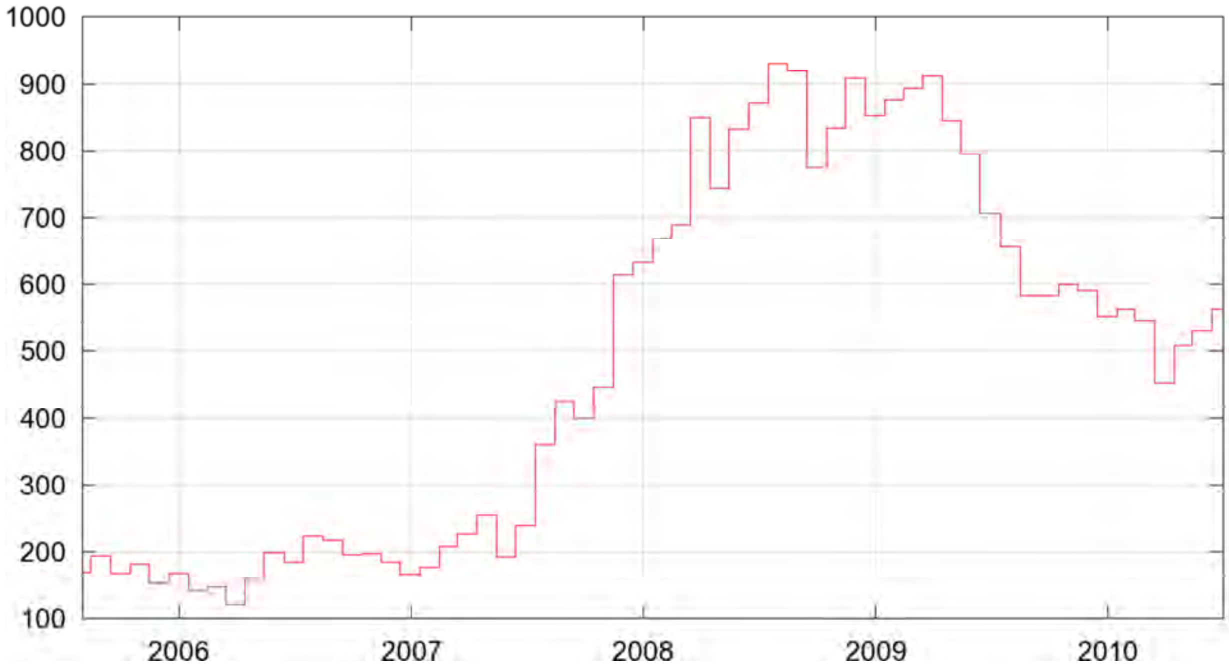

Figure 4. Aggregate SRISK for U.S. financial institutions with market capitalization greater than $5B. Reproduced from (Brownlees & Engle, 2011).

Brownlee and Engle maintain a web site, vlab.stern.nyu.edu/welcome/risk, where they present their SRISK calculations for major financial institutions, updated on a weekly basis.

Mahalanobis Distance

Mahalanobis Distance refers to a mathematical measure originally developed by Prasanta Chandra Mahalanobis in 1927 to classify human skulls. Kritzman and Li (2010) have applied this concept to measure turbulence in financial markets. Kritzman and Li define the turbulence index d_t as

$$d_t = (\mathbf{y_t} - \boldsymbol{\mu})\Sigma^{-1}(\mathbf{y_t} - \boldsymbol{\mu})^T$$

where $\mathbf{y_t}$ denotes a vector of asset returns for time period t, $\boldsymbol{\mu}$ denotes a vector of historical average returns, and Σ is the covariance matrix of historical returns. The turbulence index has a simple interpretation: it measures the propensity for the asset returns to deviate from their historical averages, relative to the observed variances in the returns. Figure 5 shows the turbulence index calculated using monthly returns of six asset-class indices: U.S. stocks, non-U.S. stocks, U.S. bonds, non-U.S. bonds, commodities, and U.S. real estate. The average vector $\boldsymbol{\mu}$ and covariance matrix Σ were calculated for the full sample from January1980 to January 2009. There is an obvious coincidence between spikes in d_t and events that roiled financial markets. Although Kritzman and Li devote the bulk of their paper to discussing the application of the Mahalanobis Distance to equity investing, it is clearly applicable as a systemic risk measure as well.

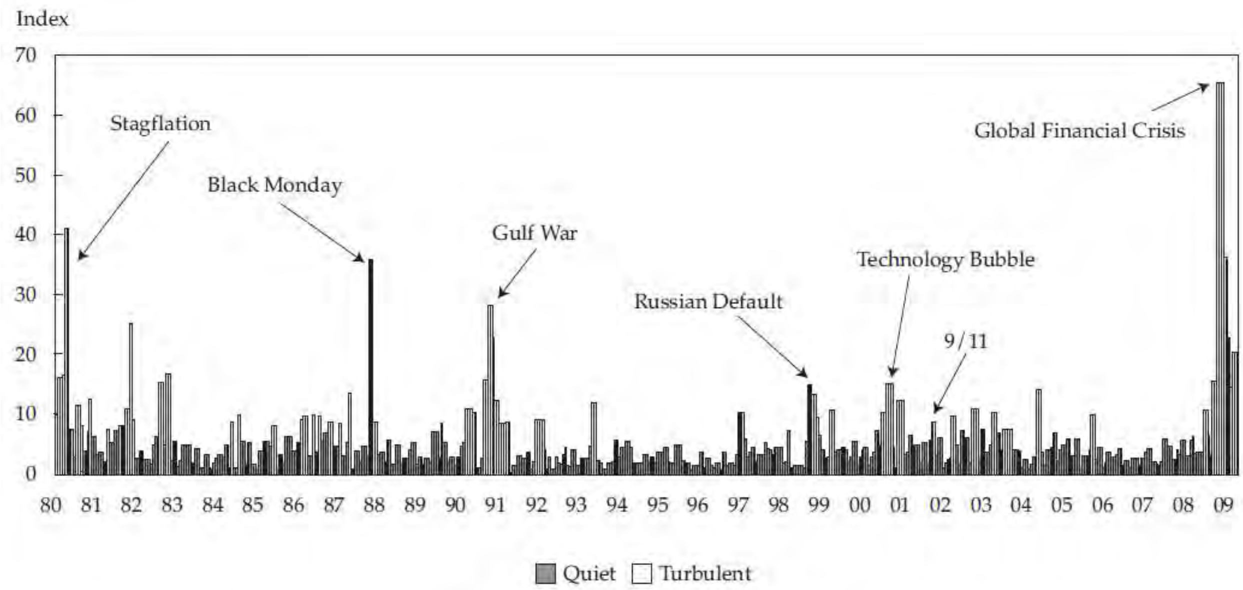

Figure 5. Historical turbulence index calculated from monthly returns of six global indices, 1980-2009. From (Kritzman & Li, 2010).

Absorption Ratio

In an additional paper published in 2010, Kritzman and Li, joined by Page and Rigobon, develop another simple but powerful statistical tool for understand market turbulence and systemic risk. Their approach utilizes principal components analysis (PCA), a statistical procedure for analyzing covariance between time series. PCA was introduced in our previous report in the context of the work published by Billio, Getmansky, Lo and Pelizzon in 2010. PCA is based on eigenvalue decomposition of the covariance matrix for a set of data in the form of time series. The eigenvalues represent the share of the total variance that is taken up by the each eigenvector. If a relatively small number of the eigenvalues are disproportionally large, the implication is that the time series are tightly coupled and tend to vary in unison.

Kritzman et al introduce a measure of the coupling between time series that they refer to as the *absorption ratio* (AR). AR is defined as the fraction of the total variance of a set of time series explained or “absorbed” by a fixed number of eigenvectors, which they set at one-fifth of the rank of the covariance matrix (rounded to the nearest integer):

$$\mathrm{AR}=\frac{\sum_{i=1}^{N/5}\sigma_i^2}{\sum_{j=1}^{N}\sigma_j^2}$$

where $\sigma_1^2, \sigma_2^2, \ldots, \sigma_N^2$ are the eigenvalues of the covariance matrix in order of decreasing magnitude, and N is the rank of the matrix.

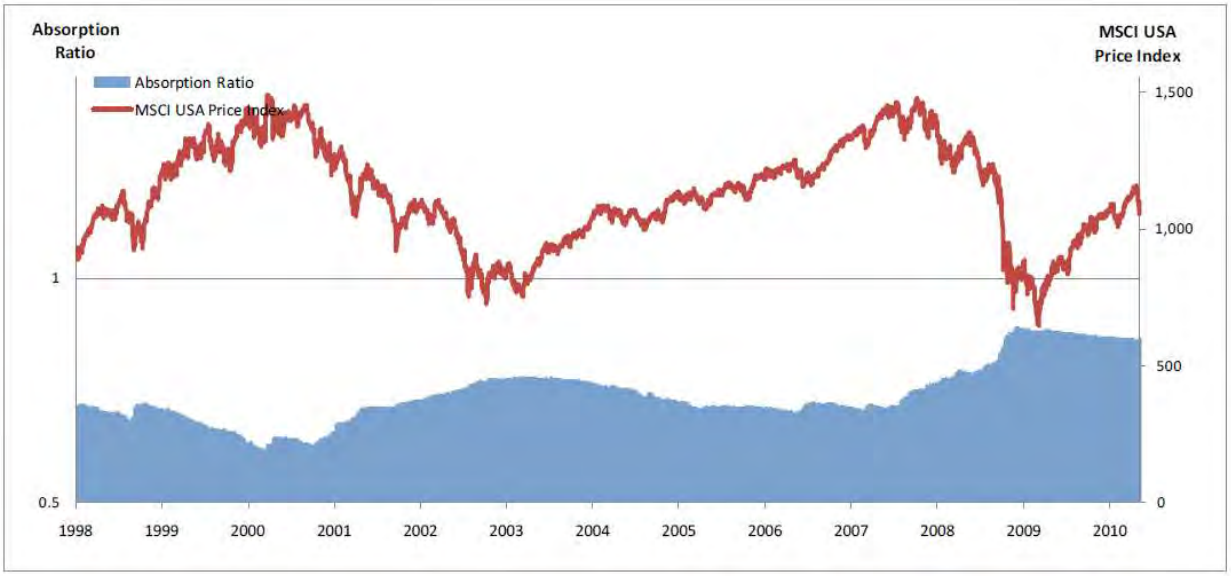

Figure 6. AR calculated from the equity returns for the 51 U.S. industries in the MSCI USA index, along with the value of the MSCI USA index, for the period 1998 to 2010. Reproduced from (Kritzman et al, 2010).

Kritzman et al calculate the AR for time series of U.S. equity returns, global equity returns, and the U.S. housing market. Figure 6 (reproduced from (Kritzman et al, 2010)) shows the AR calculated from trailing 500 day overlapping time series of equity returns for the 51 industries that comprise the MSCI USA index for the period January 1, 1998 to January 31, 2010. The AR is equal the fraction of the variance attributed to the top ten eignvectors. Also shown in Figure 6 is the value of the MSCI USA index. Figure 6 shows a clear inverse relationship between the AR and stock prices. Also noticeable is a ramping up of the AR that begins around the onset of the recent financial crisis, with the AR reaching its highest value in late 2008 when the crisis was at its peak. This suggests that a rapid rise in AR could be a warning signal of increasing systemic risk.

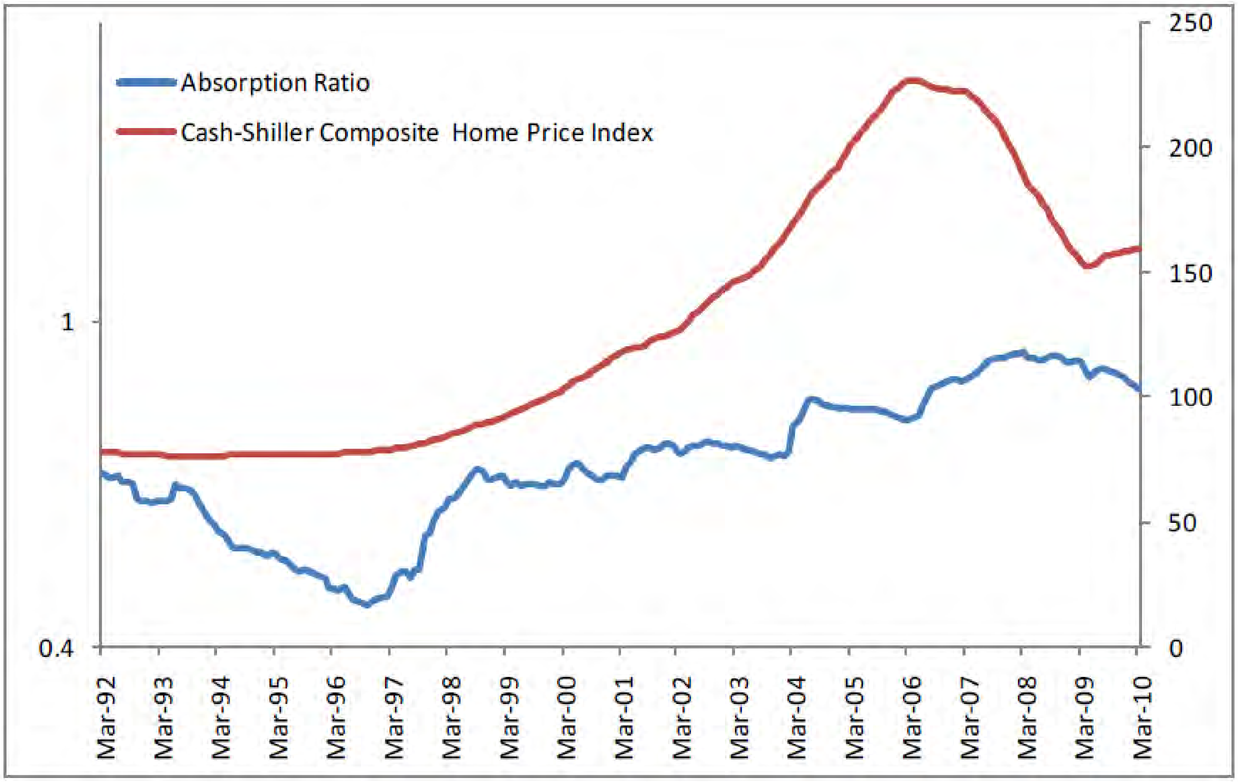

Figure 7. The AR for 14 major metropolitan U.S. housing markets, along with the Case-Schiller Home Price Index, for the period 1992 to 2010. Reproduced from (Kritzman et al, 2010).

Figure 7, reproduced from (ibid.), shows how the AR measure can be applied to the U.S. housing market. Here the AR is calculated from five year rolling time series of monthly returns for 14 major metropolitan housing markets for the period January, 1987 to March, 2010. The Case-Schiller index for the same period is shown for comparison. As in the case of equity returns, a rising AR signals danger as the housing bubble inflates. The increasing coupling between the housing markets shown in Figure 7 belies the assumption, prevalent during the period leading up the financial crisis, that residential mortgage-backed securities were of relatively low risk because prices in regional housing markets could be expected to vary independently.

To explore whether upward shifts in the AR can be used as a measure of systemic risk, Kritzman et al define a quantity $\Delta\mathrm{AR}$ that they refer to as the standardized shift in the absorption ratio:

$$\Delta\mathrm{AR} = \frac{\mathrm{AR}_{15\mathrm{day}} - \mathrm{AR}_{1\mathrm{year}}}{\sigma}$$

where $\mathrm{AR}_{15\mathrm{day}}$ and $\mathrm{AR}_{1\mathrm{year}}$ are the 15-day and 1-year moving averages of AR respectively, and σ is the standard deviation in AR over the previous year. They show that precipitous declines in U.S. stock prices are nearly always preceded by a one-sigma spike in AR one month in advance. Figure 8, also reproduced from (ibid.), suggests that $\Delta\mathrm{AR}$ for global equities could be used as a systemic risk indicator. In Figure 8 we see the AR calculated from stock returns for 42 countries, along with some regional indices, for the period February 1995 to December 2009. A sharp rise in AR accompanies the major systemic events indicated in the figure.

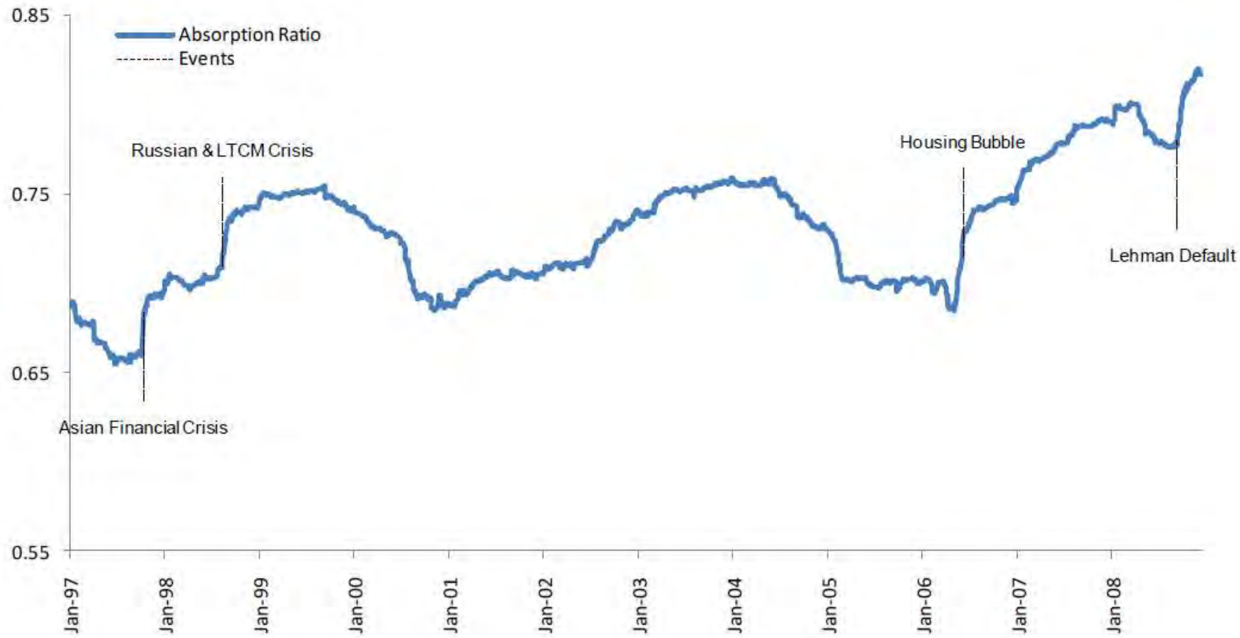

Figure 8. The AR calculated from stock market returns from 42 countries and some regional indices for the period 1995 to 2009. Reproduced from (Kritzman et al, 2010).

Kritzman et al provide further evidence that the global AR is useful as a measure of systemic risk by showing that it is closely correlated with a measure of global contagion risk proposed by Pavlova and Rigobon (2008).

Advances in Network Modeling

Two major studies that use network models to analyze the resilience of the global financial system were published in 2011. These are the papers by Hale and Minoiu and Ryes. Hale constructs a global banking network of 7938 banking institutions from 141 countries using interbank lending data from a database of international syndicated bank loans. Hale claims that this is the first global banking network constructed at the bank level; other studies (for example, the work of Espinosa-Vega and Solé (2010) discussed in our previous report) use country-level aggregate data. Such a network can potentially offer insights into global contagion risk.

Hale calculates a variety of network statistics. An example is shown Figure 9. Note the steep drop off in network size during the recent financial crisis. Hale analyzes the effects of shocks, such as recessions (both local and global), on global interbank lending.

Minoiu and Ryes construct a global banking network using cross-border banking data for 184 countries for the period 1978-2010. Minoiu and Ryes calculate network statistics with the goal of understanding how the flow of global capital changes over time. They find that the network is unstable and subject to marked changes in response to shocks.

Minoiu and Ryes divide their network into two parts: the core and periphery. The core consists of 15 countries with advanced economies for which information on bilateral positions are available. The periphery comprises an additional 169 emerging and developing countries for which only data on borrowing is available. Minoiu and Ryes observe that the flow of capital within the core network is roughly ten times the flow from the core to the periphery. Figure 10 shows the network constructed for 2007. This is reminiscent of the networks constructed by Haldane (2009), mentioned in our previous report.

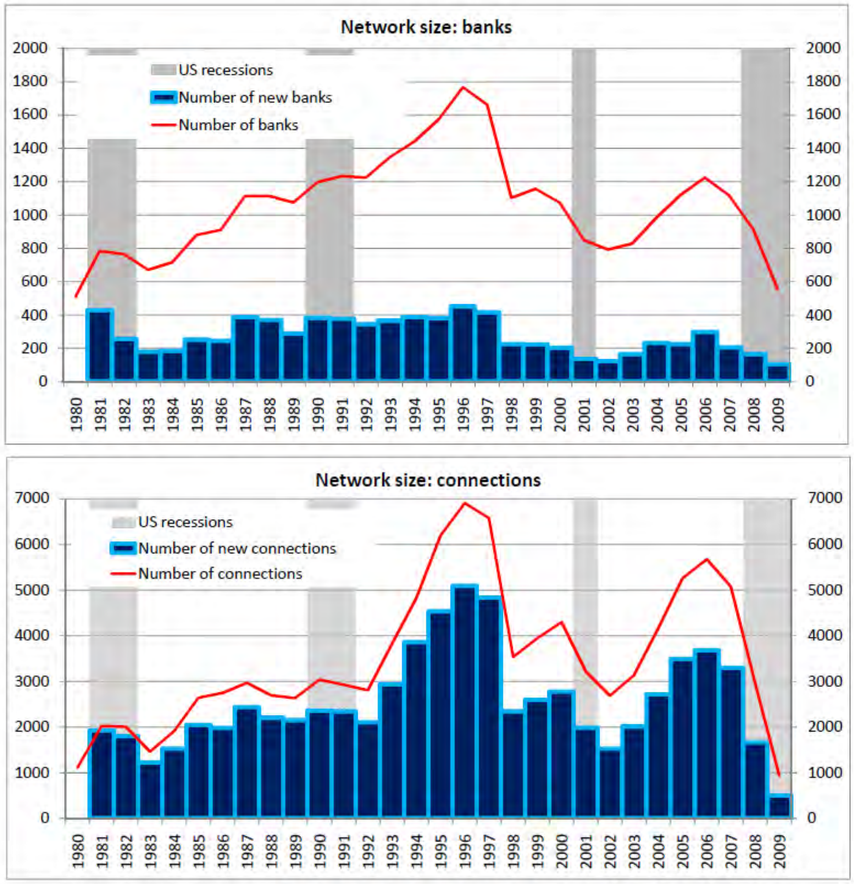

Figure 9. Number of nodes (top) and edges (bottom) for the global banking network, 1980-2009. From (Hale, 2011).

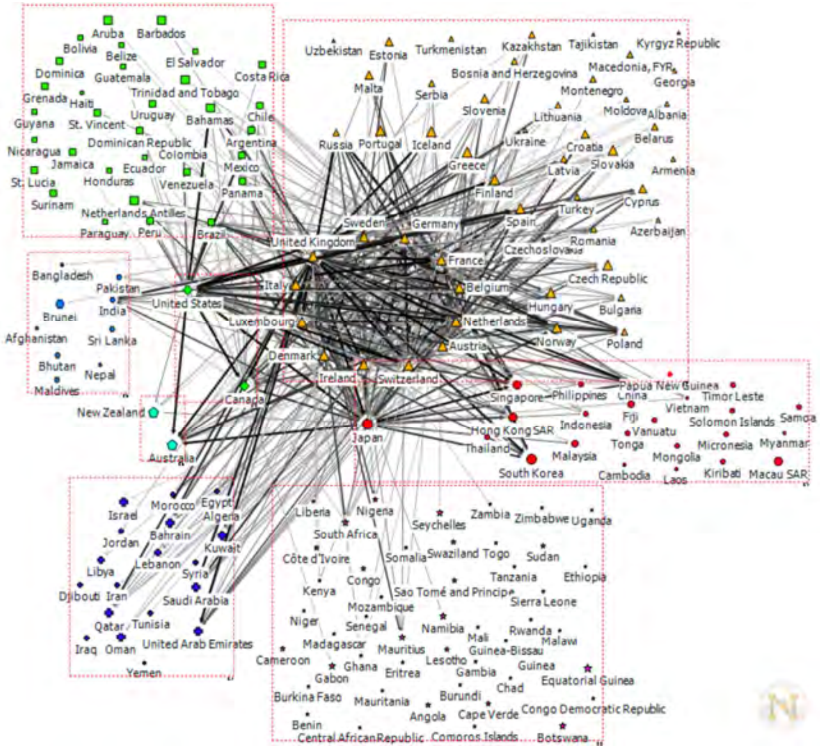

Figure 10. The global banking network, 2007. From (Minoiu & Ryes, 2011).

Comparing Systemic Risk Models

There is a dearth of studies in the literature that compare systemic risk models and attempt to determine their value to policymakers, but one such study can be found in a recent report from the International Monetary Fund (IMF) (IMF, 2011b). The goal of this report is to provide policymakers with guidance on the use of systemic risk models in executing macroprudential policy.

The authors of the IMF report draw a distinction between slow-moving leading indicators and high-frequency market-based indicators. The former signal the buildup of risks in the financial system months or years before the occurrence of a crisis, while the latter predict an imminent crisis and potentially provide information on its extent and possible consequences.

Examples of models based on slow-moving leading indicators include the models of Borio, Drehmann, and their coauthors, described above, and the work of Alessi and Detken (2009) presented in our previous report. The IMF study examines the potential for various macroeconomic statistics to serve as warning signals for financial crises, with the help of a dynamic stochastic general equilibrium (DSGE) economic model that more accurately models the linkages between the financial sector and the real economy than most such models. One of the key findings is that increases in the credit-to-GDP ratio can serve as an effective signal of financial imbalances. This is consistent with the analyses of both Drehmann et al (2011) and Alessi and Detken.

The IMF study also measured the performance of ten near-coincident indicators of financial system stress. Performance was defined as the ability to predict the value of a quantity the authors refer to as Systemic Financial Stress (SFS) index. The SFS index is the proportion of financial institutions, out of a set of 17 US financial institutions, that exhibit large negative abnormal equity returns. The SFS index was calculated on a weekly basis for the period 12/30/2002-4/11/2011. Various statistical tests were used to score each indicator's performance on three tasks:

- Predicting SFS at a reasonable horizon. The authors do not quantify "reasonable". This is measured using Granger-causality.
- Predicting extreme SFS values with reasonable likelihood (again, no definition of "reasonable" is provided). This measurement is based on logit regressions with extreme SFS as the dependent variable.
- Predicting structural breaks (i.e., sudden shifts, aka early turning points) in the SFS time series. This is done using the Qaundt-Andrews breakpoint test, a standard practice in econometrics.

The ten indicators used for comparison were:

- Yield curve: The difference between the 10-year and 3-month Treasure yields.
- Time-varying CoVaR: The CoVaR model (Adrian and Brunnermeier 2010) is described in our previous report.
- Rolling CoVaR: CoVaR based on 200-week rolling quantile regressions of equity returns.
- Joint Probability of Distress (JPoD): This comes from the distress dependency model of Segoviano and Goodhart (2009), also described in our previous report.
- Credit Suisse Fear Barometer (CSFB): The CSFB essentially tracks the willingness of equity investors to pay for downside protection with collar trades on the Standard & Poor's 500 index.
- Distance to Default (DD) of banks: A measure of how much the assets of the banking system exceed its liabilities (De Nicolò & Kwast, 2002).
- Diebold-Yilmaz: A measure of volatility spillovers for financial systems weekly CDS spread returns (Diebold & Yilmaz, 2009).
- VIX: The Chicago Board Options Exchange Volatility Index.
- LIBOR-OIS Spread: The difference between LIBOR and the overnight indexed swap (OIS) rates.
- Systemic Liquidity Risk Indicator (SLRI): A global indicator of liquidity stress (IMF, 2011a).

Figure 11, reproduced from (IMF, 2011b), shows the scores on the three tests for each indicator for the three tests as well as their overall scores. The time varying CoVaR takes first place. It is interesting to note how well the simple yield curve measure performs in comparison to complex and sophisticated models.

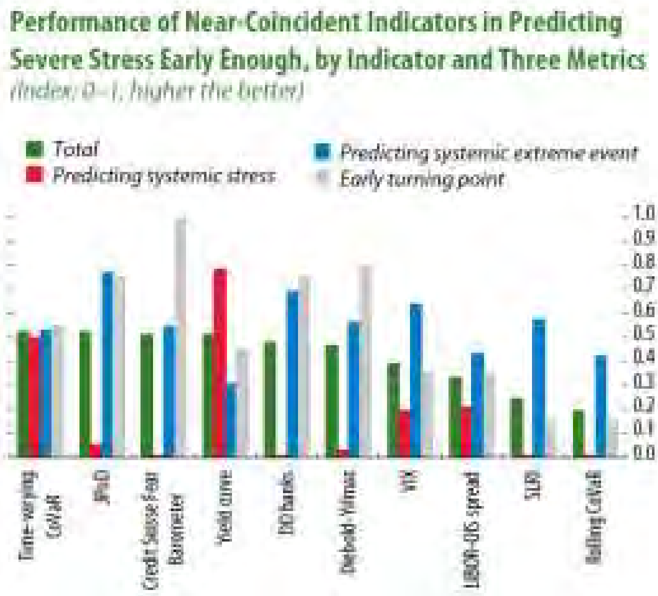

Figure 11. Comparison of near-coincident systemic risk indicators, from (IMF, 2011b).

Additional Literature

With this report and predecessor, we have striven to review literature in the field of modeling systemic risk to the financial system that we believe is consequential and informative. However, there are many worthwhile publications we were unfortunately forced to omit. A few of these that we have read are:

- Geanakoplos' seminal work on the leverage cycle (Geanakoplos, 2009)
- Brunnermeier, Gorton, and Krishnamurthy's effort to design a data acquisition and dissemination process for systemic risk (Brunnermeier et al, 2011)
- IMF publications that discuss the serious issue of systemic liquidity risk (IMF, 2010 and 2011a).

We hope that the reader will find in our work a useful introduction to this crucial and fast-growing field.

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