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Systemic Loss: A Measure of Financial Stability*

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Abstract
The literature on modeling defaults in individual financial institutions has expanded dramatically. However, the links between defaults in individual institutions and system-wide crises remain inadequately understood, despite some recent attempts to transpose the existing indicators of the probability of default in individual institutions to the systemic level. The paper argues that any measure of systemic stability should incorporate three elements: probabilities of failure in individual financial institutions, loss given default in financial institutions, and correlation of defaults across institutions. It contains a review of existing measures of financial stability and finds that they generally fall short of this standard. The author demonstrates that looking at the distribution of systemic loss can lead to a clearer differentiation of cases of stability and instability.

1. Introduction

One of the main challenges of stability analysis is the lack of an operational definition of its subject, i.e. financial stability. I propose to address this challenge by using *the distribution of systemic loss* as a measure of default risk in the system. The proposed measure combines three key elements: probabilities of default (PDs) in individual financial institutions, loss given default (LGD) in the institutions, and correlation of defaults across the institutions. The measure is built from the bottom up, i.e. from individual defaults to systemic loss. It covers the full distribution of systemic loss, not just a central tendency of the distribution.

Using systemic loss to measure stability is not completely new. In stress testing, for example, results can be presented in terms of capital injections needed in response to losses from an adverse scenario (e.g., Čihák, 2005). Also, some recently proposed indicators of stability, such as the expected number of defaults (Chan-Lau, Gravelle, 2005), provide a very rough approximation for systemic loss. However, the analysis of financial soundness is dominated by other indicators (in particular, capital adequacy and other basic ratios, and distance to default indicators), with only a loose relationship to systemic loss. I survey the various indicators and find that each has weaknesses in terms of the three elements mentioned above. Some capture PDs in individual institutions, but approach all institutions as having the same systemic impact, which leads to biased results. Others take into account loss given default, but do not reflect PDs or correlations of defaults. Also, most measures look at the central tendencies, disregarding potentially important information in the loss distribution.

The contribution of this article is in proposing the use of the distribution of systemic loss, based on individual institutions' failures, as a key measure of stability.

* The views expressed in this article are those of the author and do not represent those of the IMF or IMF policy.

The proposal attempts to bridge two areas of research: one on PDs in institutions and one on losses on a portfolio. I illustrate the proposed framework by studying a range of indicators in instances of instability, using Monte Carlo simulations and empirical analysis using actual data.

The structure of the article is as follows. Section 2 proposes a framework for measuring financial stability. Section 3 discusses how the various measures developed in the literature compare with this framework. Section 4 illustrates this general discussion with a simulation and an empirical analysis. Section 5 concludes the article.

2. Distribution of Systemic Loss as a Measure of Financial Stability

2.1 The Proposal

There is a number of definitions of financial stability (for a survey, see e.g. (Čihák, 2006)). Some authors (e.g., Goodhart, 2006) have complained about the plethora of definitions and the lack of a generally accepted definition of financial stability. However, most definitions agree on the basics, in particular that financial stability is about the absence of system-wide episodes in which the financial system fails to function (crises), and about resilience of financial systems to stress. The fact that there are differences in definitions is not unique to financial stability. Even in the area of price stability, for example, some rather basic issues (e.g., whether to include asset prices) are still subject to discussion.

The aspect where analysis of financial stability is much weaker than the analysis of price stability is its lack of a widely accepted *operational* definition, or a measure of financial stability.[1] The analysis of price stability has a relatively clear operational definition in the form of inflation.[2] In contrast, there is a wide range of indicators of financial stability, from accounting ratios (e.g., capital to assets) to measures of PD derived from market prices or from supervisory early warning systems, and to indicators derived from stress testing. How to summarize the various measures into an indicator of stability remains an open issue.

This section proposes a measure of financial stability that can be used in practice. To do so, we focus on the risk of systemic default. The general definitions of financial stability also encompass other issues, such as the smooth operation of the payment system and systemic liquidity. However, to treat those systematically is much more complicated.

I propose looking at the distribution of aggregate loss in the system as a measure of stability. Using the literature on losses on loan portfolios as motivation (e.g., (Saunders, Allen, 2002)), I suggest looking at the financial system as a portfolio of counterparty risks, the counterparties being the individual financial institutions, each of them having a small, but non-zero chance of causing a loss to the system. Such a portfolio can be thought of in similar terms as a bank loan portfolio, even though the nature of the risks raises specific issues (e.g., the portfolio effectively consists of the sum of the "tail" risks of individual institutions).

[1] Čihák (2006) makes this point based on a survey of financial stability reports issued by central banks.

[2] I say "relatively" because there are numerous practical issues with measuring inflation (e.g., index number problems, "core" vs. "headline" inflation, consumer vs. producer inflation, and inclusion of asset prices).

More specifically, let us consider a financial system consisting of n financial institutions.[3] From the viewpoint of financial stability, the state of each institution in a given period can be characterized by the systemic loss associated with this institution, with the value equal to 0 if the institution i is solvent at time t and the value L_i>0 (measured in percent of GDP) if the institution is in default. L_i is a random variable with a distribution from 0 to X_i, where X_i is the maximum loss, or the "exposure" of the system to this institution.

To rephrase this using terms of the loan portfolio theory, we can break down the loss from an institution into three parts: a default variable d_i with a value of 0 when the institution is solvent and 1 when it is insolvent; an exposure variable X_i, characterizing the institution's size ("exposure" of the system to institution i), and variable S_i that is the proportion of X_i actually lost at default ("severity" of the loss).[4] Both d_i and S_i are random variables, insolvency taking place with a probability PD_i, and severity with a distribution $f(\mu_s,\sigma_s)$.[5] The multiple of exposure and severity, i.e. the actual loss occurring when there is default, is the loss given default.[6]

The core of the proposal is to study the distribution of systemic loss, $L_s = \sum_{i=1}^{n} L_i$.

This includes, but is not limited to, analyzing key characteristics of the loss distribution, such as its mean (EL_s), variance ($VarL_s$), extreme values (e.g., max L_s) as well as changes in these characteristics as a result of changes in external factors. Several features are important for this approach:

1. This approach is derived from data on individual institutions (bottom-up), and takes into account differences in individual institutions' PDs.
2. The weight of individual defaults (LGD) plays a key role in the aggregation from the micro- to the macroprudential level. Probabilities of default are not additive, and giving the observations the same weight would risk biasing the results.
3. The approach also takes into account correlation of defaults across the institutions. In systemic stress, defaults are likely to be highly correlated, so assuming away correlation could yield misleading results.
4. The central tendency of the loss distribution ("expected loss") is the starting point of the analysis. However, it is also important to look at the variability of losses across the states of the world ("unexpected loss"), and at the extreme losses that can materialize. It is also important to see how the distribution of

[3] Defining the boundaries of the "system" is straightforward if there is little cross-border activity (the system is constituted by institutions incorporated and operating in a given jurisdiction). However, if there are important cross-border financial activities, it may be important to define a "system" using financial institutions activities instead of country boundaries. For example, the system can be defined as a portfolio of institutions active in a region.

[4] ($1-S_i$) is the recovery rate (RR), a term used in *BOX 1*.

[5] In the portfolio risk literature, S_i is often taken to be a draw from a beta distribution. The portfolio literature often assumes that the distribution of severity is the same for all loans. That assumption may need to be relaxed when we deal with financial systems. For example, it is possible that there is a positive correlation between S_i and X_i because of the "too large to fail" argument.

[6] A part of the credit portfolio risk literature uses the term "loss given default" for severity. In this article, however, we follow the part of the literature that reserves the term for severity times exposure.

losses changes if there is a shock to an external factor shifting the distribution of losses (stress testing).[7]

5. Stability needs to be measured over a period of time. In this case, it is defined over one time unit. Generally, the longer the period, the more likely a crisis is to occur.
6. The losses are expressed in percent of GDP, allowing the illustration of the macroeconomic relevance of the observed (in)stability.

2.2 Linking Individual Losses and Systemic Loss

This section shows how the measure proposed here links individual defaults and systemic stability. The approach uses the basic insights from the credit portfolio risk theory (e.g.,(Saunders, Allen, 2002)), but applies them to a portfolio of financial institutions.[8]

Let PD_i denote the probability of default of financial institution i over the next period.[9] Leaving out the time index to simplify notation, we can characterize the expected loss from the institution (i.e., the unconditional mean of its loss distribution) as

$$EL_i = PD_i X_i S_i \tag{1}$$

The systemic expected loss, EL_S, is a summation of individual institution EL's, just as the expected loss on a loan portfolio is a summation of losses on the individual loans:

$$EL_S = \sum_{i=1}^{n} EL_i \tag{2}$$

Default is a Bernoulli (0-1) random variable, with a standard deviation of $\sqrt{PD_i(1-PD_i)}$. If we make the common assumption of portfolio risk literature of no correlation between PD_i, S_i, and X_i, we obtain the following formulation for standard deviation of loss, sometimes also called unexpected loss (UL_i) in the portfolio loss literature:

$$UL_i = \sqrt{(PD_i - PD_i^2)\mu_{s_i}^2 X_i^2 + PD_i X_i^2 \sigma_{s_i}^2} \tag{3}$$

Standard deviation of systemic loss ("unexpected loss" on the portfolio), UL_S, is:

$$UL_S = \sqrt{\sum_{i=1}^{n} UL_i^2 + \sum_{i=1}^{n}\sum_{j=1}^{n} \rho_{ij} UL_i UL_j} \tag{4}$$

[7] Goodhart (2006) argues that while analysis of price stability focuses on forecasting central tendencies, analysis of financial stability is about simulating extreme events. This distinction is exaggerated, because the former should also test resilience of prices to external shocks, and the latter should start from a baseline scenario.

[8] Kuritzkes, Schuermann, and Weiner (2005) use a very similar portfolio approach to model deposit insurance. However, they look at the issue from a narrow perspective of measuring losses to the deposit protection scheme. From a systemic perspective, loss to the protection scheme is only a part of losses from financial instability.

[9] In the literature on credit portfolio risk, probability of default is sometimes called "expected default frequency." A one-year horizon is typically referred to in the literature, but other time horizons are possible.

which can also be written as the sum of *contributory* unexpected losses, ULC_i, from each of the institutions in the system, $UL_S = \sum_{i=1}^{n} ULC_i$, where $ULC_i = \frac{\partial UL_p}{\partial X_i} X_i$.

The systemic risk depends on the contribution of the *i*-th institution to systemic volatility, ULC_i, which is driven by two factors: the volatility of *i*'s losses, which in turn is driven by its *PD* and exposure, and its correlation with the rest of the system.

Just as with a loss distribution on a loan portfolio, the cumulative loss distribution for systemic loss will reflect the expected loss of the individual institutions in the system, the size of individual exposures, and the correlation of losses within the system. The distribution will likely be heavily skewed and characterized by "lumpiness," reflecting the contribution of individual large financial institutions, each imposing a discrete, non-zero probability of a sizeable systemic loss.

The loss distribution is really a characterization of the loss experience in all states of the world. We have so far only focused on the state of the system, but the state of the system is likely to be correlated with other variables, outside the financial system. We need a way to link default (and loss) to changes in states of the world. Consider, therefore, the probability of default, PD_i, as determined by a function of systemic ("macro") variables **M**, shared by all institutions, and an institution-specific idiosyncratic stochastic component ε_i,

$$PD_i = f(\mathbf{M}, \varepsilon_i) \tag{5}$$

Thus default correlation enters via **M**, but not all elements of **M** affect all institutions in the same way. All credit portfolio models share this linkage of systematic risk factors to default and loss. They differ in how specifically they are linked. For brevity, we will follow the most popular approach, derived from the options pricing model by Merton (1974); however, using the other approaches is also possible under the proposed framework.[10]

We consider a simple structural approach to modeling changes in the credit quality of a firm. The basic premise is that the underlying asset value evolves over time (e.g. through a simple diffusion process), and that default is triggered by a drop in a firm's asset value below the value of its callable liabilities. Following Merton (1974), the shareholders effectively hold a put option on the firm, while the debtholders hold a call option. If the value of the firm falls below a certain threshold, the shareholders will put the firm to the debtholders.

The Merton model defines default as when the value of an institution's assets declines to below the value of its liabilities. Employing the empirically estimated probability of default (*PD*), the asset return threshold for default is given by

$$\begin{aligned} PD &= \Phi(Z_D) \\ Z_D &= \Phi^{-1}(PD) \end{aligned} \tag{6}$$

[10] This approach is used by industry models such as by CreditMetrics or KMV's PortfolioManager. Other approaches include an econometric approach where PD_i is estimated via logit with macro-variables entering the regression directly (Wilson, 1997), and an actuarial approach employed by CSFB's CreditRisk+, where the key risk driver is the variable mean default rate in the economy (see, e.g., (Saunders, Allen, 2002)).

where $\Phi(.)$ denotes the cumulative distribution of losses, typically assumed to be normal distribution in implementations of the Merton (1974) model. Building up the loss distribution is done by integrating the state-conditional losses over all states of the world. Recall that an individual loan will default when its asset return z_i is less than the critical value Z_D:

$$z_i \leq Z_D = \Phi^{-1}(PD) \tag{7}$$

Following (5), asset returns can be decomposed into a set of k orthogonal systematic factors, $\mathbf{M} = (m_1, m_2, ..., m_k)$, and an idiosyncratic shock ε_i

$$z_i = \sum_{j=1}^{k} \beta_{i,j} m_j + \varepsilon_i \sqrt{1 - \sum_{j=1}^{k} \beta_{i,j}^2} \tag{8}$$

where $\beta_{i,j}$ are the factor loadings. The sensitivity to the common factor reflects the asset correlations. If there is one systematic factor, m (say, GDP growth), (8) collapses into

$$z_i = m\sqrt{\rho} + \varepsilon_i \sqrt{1-\rho} \tag{9}$$

where $\rho = \sum_{j=1}^{k} \beta_j^2$.

Institution i will be in default when

$$m\sqrt{\rho} + \varepsilon_i \sqrt{1-\rho} \leq \Phi^{-1}(PD) \tag{10}$$

$$\varepsilon_i \leq \frac{\Phi^{-1}(PD) - m\sqrt{\rho}}{\sqrt{1-\rho}} \tag{11}$$

This means for a given value of m the probability that an individual institution will default is:

$$PD_i \left| m \leq \Phi \left[\frac{\Phi^{-1}(PD_i) - m\sqrt{\rho}}{\sqrt{1-\rho}} \right] \right. \tag{12}$$

Conditional on m, we draw a standard normal variable ε_i, and check whether the institution defaults or not. This is characterized by an indicator function:

$$I\left\{ \varepsilon_i \leq \frac{\Phi^{-1}(PD_i) - m\sqrt{\rho}}{\sqrt{1-\rho}} \right\} = \begin{cases} 1 \text{ if true} \\ 0 \text{ if false} \end{cases} \tag{13}$$

Then, for a given draw from state m, $m(r)$, and draw ε_i, $\varepsilon_i(r)$, the loss to i is

$$Loss_i \Big|_{m(r)} = I\left\{ \varepsilon_i(r) \leq \frac{\Phi^{-1}(PD_i) - m\sqrt{\rho}}{\sqrt{1-\rho}} \right\} X_i S_i \tag{14}$$

its expected loss is

$$E\Big|_{m}(Loss)=\frac{1}{R}\sum_{i=1}^{R}\left(I\left\{\varepsilon_i(r)\le\frac{\Phi^{-1}(PD_i)-m\sqrt{\rho}}{\sqrt{1-\rho}}\right\}X_iS_i\right) \tag{15}$$

and the portfolio loss conditional on the state draw $m(r)$ is

$$Loss_P\Big|_{m(r)}=\sum_{i=1}^{N}Loss_i\Big|_{m(r)} \tag{16}$$

2.3 What Do We Mean by Loss?

An important part of the proposed approach is the concept of loss. What is meant by losses? The macroprudential literature makes clear that it is concerned with *systemic loss* (see, e.g., the survey in (Čihák, 2006)). However, it is not very clear what *types* of losses (to whom) are considered. That has important implications for the analysis. Based on the literature, one can identify the following losses that may be relevant when monitoring systemic stability:

1. *Losses to creditors (depositors).* One of the reasons for government intervention in the financial sector is the potential for losses to depositors in banks. A natural approach to calculating losses would therefore seem to be losses for depositors. A practical issue in most banking systems is a large portion of depositors (in terms of their number) are a part of a deposit protection scheme, which substantially limits their losses. In terms of volume, a large part of losses to depositors consists of losses to the unprotected part of the deposit pool. On a macroprudential level, it is questionable whether one should be guided by losses to large depositors (or bondholders).
2. *Losses to a deposit protection agency*. Studies such as (Kuritzkes, Schuermann, Weiner, 2005) analyzed losses to the deposit protection scheme resulting from the payouts to protected depositors. This is very useful, but it may be too narrow a definition of systemic loss. For example, low losses to the deposit protection scheme do not mean low losses to depositors (in fact, it often means the opposite).
3. *Losses to owners*. Studies that use prices of stocks to estimate probabilities of failure implicitly refer to losses to shareholders of the financial institutions. On a macroprudential level, it is questionable to what extent one should be guided by losses to financial institutions' owners when measuring financial stability: the financial sector is not a government undertaking, but in most countries it is dominated by privately-owned profit-making firms. Nonetheless, it is rather common for results of systemic stress tests to be expressed in terms of capital injections needed to bring all banks in the system to the regulatory minimum (e.g., (Čihák, 2005)).
4. *Losses to the public sector/fiscal accounts*. This is a generalization of the previous concept. It would include losses to the deposit protection agency, losses to the public sector as owner or creditor of financial institutions, and possibly losses resulting from public sector guarantees (explicit or implicit) for financial institutions.

5. *Losses on assets*. Several studies define losses as the difference between the book value of an institution's assets at the time of its closure and the value of the assets in a receivership by the deposit protection agency or the value of the assets to an acquirer (e.g., (James, 1991)). These losses include expenses incurred in the liquidation and sale of assets, losses associated with forced liquidation, and past unrealized losses (those that occur before a failure but are not reported at the time of the failure).
6. *Macroeconomic losses*. This is a more general concept of losses, including those in terms of gross domestic product, employment, and other macroeconomic variables. This is an important concept, but in practice it may be extremely cumbersome to implement because these losses depend on factors such as the responses to stress by financial institutions' owners, other market players, and public authorities – factors that are difficult to address in a comprehensive model.

None of these definitions is without drawbacks. Ideally, one would like to model the macroeconomic losses, but that can be extremely complicated. Modeling losses to the deposit protection agency is easier (although not trivial), but it tells little about the systemic loss. In the empirical part of this paper, we opt for defining losses in terms of assets. It is a relatively broad measure (which can be seen as an advantage, since financial stability is a broad concept as well), and also one on which data are available relatively easily.

3. How Is the Systemic Loss Distribution Captured by Existing Measures?

We will now use the general framework introduced in Section 2 to discuss the pros and cons of the various measures of financial stability (Table 1 summarizes the discussion).

3.1 Individual Probabilities of Default Derived from Fundamental Data

A number of studies focus on individual institutions' probabilities of default, with limited attention to the exposure and loss given default for those institutions. For a long time, the literature on financial institutions' defaults has been built on supervisory early warning systems (e.g., (Sahajwala, van den Bergh, 2000)), which try to cluster financial institutions into groups by soundness, using a range of financial ratios and other indicators.

The models can be classified into three broad main groups. The first group is comprised of macroeconomic-based models, which attempt to assess how default probabilities are affected by the state of the economy. Macroeconomic-based models are usually employed for estimating sectoral or industry-level default rates or default probabilities. The second group is comprised of accounting-based or credit scoring models, which generate default probabilities or credit ratings for individual firms using accounting information. The third group consists of ratings-based models, which can be used to infer default probabilities when ratings information is available. Finally, there are hybrid models that generate default probabilities using as explanatory variables a combination of economic variables, financial ratios, and ratings data.

Recently, one indicator that has been gaining attention as a measure of individual financial institutions' soundness is the z-score (e.g., (Boyd, Runkle, 1993), (Demirgüç-Kunt, Detragiache, Tressel, 2006), and (Hesse, Čihák, 2007)). The z-score is defined as $z \equiv (k+\mu)/\sigma$, where k is equity capital as percent of assets, μ is return as percent of assets, and σ is standard deviation of return on assets as a proxy for return volatility. The popularity of the z-score stems from the fact that it is inversely related to the probability of a financial institution's insolvency, i.e. the probability that the value of its assets becomes lower than the value of its debt. The probability of default is given by $p(\mu < k) = \int_{-\infty}^{k} \phi(\mu) d\mu$. If μ is normally distributed, then $p(\mu < k) = \int_{-\infty}^{z} N(0,1)\, d\mu$ where z is the z-score. In other words, if returns are normally distributed, the z-score measures the number of standard deviations a return realization has to fall in order to deplete equity. Even if μ is not normally distributed, z is the lower bound on the probability of default (by Tchebycheff inequality). A higher z-score therefore implies a lower probability of insolvency.

The z-scores have several limitations, perhaps the most important being that they are based purely on accounting data. They are thus only as good as the underlying accounting and auditing framework. If financial institutions are able to smooth out the reported data, the z-score may provide an overly positive assessment of the financial institutions' stability. Also, the z-score looks at each financial institution separately, potentially overlooking the risk that a default in one financial institution may cause loss to other financial institutions in the system.

An advantage of the z-score is that it can be also used for institutions for which more sophisticated, market based data are not available. Also, the z-scores allow comparing the risk of default in different groups of institutions, which may differ in their ownership or objectives, but face the risk of insolvency. For example, Hesse and Čihák (2007) use z-scores to analyze the stability of commercial, cooperative, and savings banks in respect to financial stability.

3.2 Individual Probabilities of Default Derived from Market Data

A number of indicators have been developed to calculate probabilities of default of individual institutions based on prices of financial instruments. These indicators include distance to default (DD), bond prices, and credit default swaps.

An advantage of using market prices is that they are generally available at high frequency, providing more observations and shorter lags than balance-sheet data. Also, while the accounting measures of risk (such as nonperforming loans) are backward-looking, market-based indicators promise to incorporate market participants' forward-looking assessment. Finally, confidentiality is generally not an issue with market data, which makes it easier for data and results to be publicly shared and verified.

The market-based indicators also have limitations. In particular, for them to contain useful information, the markets need to be liquid, transparent, and robust. Their usefulness is limited if securities are not publicly traded or their trading is limited (as may be the case, for instance, for government-owned or family-owned institutions). Also, if relevant information is not publicly disclosed (e.g., loan classification data in some countries), but it is collected by supervisors, prudential data can be superior to market-based indicators in measuring financial sector soundness. Moreover, securities prices reflect potential losses to the security holders (bank owners for equity-based measures and bondholders for bond prices), which may be quite different from losses to banks' depositors. Finally, the market based indicators are based on a number of strong assumptions. For example, the basic DD measures are constructed assuming that asset values follow a lognormal process, which does not capture extreme events adequately.[11]

Despite these potential limitations, empirical studies show that the market-based indicators can be helpful in forecasting distress in individual financial institutions, and in some cases outperform more traditional measures of soundness. The market-based indicators have been shown to predict supervisory ratings, bond spreads, and rating agencies' downgrades in both developed and developing economies, performing generally better than "reduced form" statistical models of default intensities or measures relying on financial statements (e.g., (Arora, Bohn, Zhu, 2005)). More specifically:

a) For data on the United States, Flannery (1998), Gunther, Levonian, and Moore (2001) and Krainer and Lopez (2003) find that securities prices are a leading indicator of changes in supervisory ratings of large, publicly traded U.S. banks. Berger, Davies, and Flannery (2000) conclude that supervisory assessments are generally worse than equity and bond market indicators in predicting future changes in the performance of large U.S. bank holding companies, even though supervisors may be more accurate when inspections are recent.
b) For a sample of European banks, Gropp, Vesala and Vulpes (2006) find that distance to default and subordinated bond spreads predict bank defaults and rating downgrades up to 18 months in advance, and that these indicators can marginally, but not insignificantly, improve performance of models based on banking ratios. They also find that implicit safety nets weaken the predictive power of spreads.
c) For U.K. financial institutions, Tudela and Young (2003) find that adding Merton-type market-based indicators to a model based on financial ratios significantly improves the performance of that model.
d) For banks in East Asia, Bongini, Laeven, and Majnoni (2002) find that during the 1996–98 crisis, the information contained in stock prices and credit ratings did not outpace balance-sheet indicators, even though stock markets responded more quickly to changing financial conditions than ratings of credit risk agencies.
e) For 14 emerging market countries, Chan-Lau, Arnaud, and Kong (2004) find that DD can predict a bank's credit deterioration up to nine months in advance.

3.3 Portfolio Distance to Default and Related Indicators

Given the favorable empirical results on the micro level, market-based indicators have become popular not only in the literature on defaults in individual institutions, but increasingly also on the macro level, in reports on systemic financial

[11] Additionally, the market-based estimates of PDs typically define default as a situation when the market value of a firm's assets falls below the value of its debts. However, in financial institutions, prudential supervisors typically act before equity capital is exhausted. Measures such as DD may therefore overstate the likelihood that the institution would have to take corrective measures as its capital ratio falls. Chan-Lau and Sy (2006) and Danmarks Nationalbank (2004) present alternative risk measures, distance-to-capital and distance-to-insolvency, which take into account the fact that supervisors typically intervene before capital is exhausted.

BOX 1 Market Based Indicators of Individual Institutions' Probability of Default: A Primer

The idea of using ***equity prices*** for assessment of financial institutions' soundness comes from the insight that corporate securities are contingent claims on the asset value of the issuing firm. This insight, first highlighted by Black and Scholes (1973) and Merton (1974), can be illustrated in the case of a firm issuing one unit of equity and one unit of a zero-coupon bond with face value D and maturity T. At expiration, the value of debt, B_T, and equity, E_T, are given by $B_T = \min(A_T, D) = D - \max(D - A_T, 0)$ and $E_T = \max(A_T - D, 0)$, where A_T is the asset value of the firm at expiration. These two equations say that (i) bondholders only get paid in full if the firm's assets exceed the face value of its debt, otherwise the firm is liquidated and assets are used to partially compensate bondholders; and (ii) equity holders only get paid after bondholders. These equations can also be interpreted in terms of European options: the first one states that the bond value is equivalent to a long position on a risk-free bond and a short position on a put option with strike price equal to the face value of debt. The second one states that equity value is equivalent to a long position on a call option with strike price equal to the face value of debt. Using the standard assumptions underlying the derivation of the Black-Scholes option pricing formulas, the default probability in period t for a horizon of T years is given by:

$$p_t = N\left\{-\left[\ln\frac{A_t}{D} + \left(r - \frac{\sigma_A^2}{2}\right)T\right] / \left[\sigma_A\sqrt{T}\right]\right\}$$

where N is the cumulative normal distribution, A_t is the value of assets in period t, r is the risk-free rate, and σ_A is the asset volatility. The numerator is the distance to default (DD), defined as the difference between the expected value of the assets at maturity and the default threshold, which is a function of the value of the liabilities. DD illustrates the probability that the market value of a financial institution's assets will become lower than the value of its debt.

Bond prices can be used to provide information about default probabilities. Under risk neutrality, the price of a one-period zero-coupon bond (B) paying one unit of value at maturity is given by: $B = \frac{(1-p) + pRR}{1+r}$, where p is the default probability, RR is the recovery rate, and r is the risk-free discount rate. The default probability is then given by: $p = \frac{1-(1+r)B}{1-RR}$.

The intuition derived from this example was generalized by Fons (1987), under the assumption of risk neutrality, for a bond with a larger number of periods to redemption.

Perhaps the most direct way of obtaining probabilities of default is from ***credit default swaps*** (CDS). These contracts are analogous to insurance against default: the buyer of the CDS pays a quarterly fee (CDS spread) in exchange for protection against the default of a reference obligor during the life of the contract. If the obligor defaults, the protection buyer delivers a bond or loan of the reference obligor to the protection seller in exchange for the face value of the bond or loan. In the absence of market frictions, the probability of default can be calculated from the market price of the CDS spread (S), the risk-free interest rate (r), and the recovery rate (RR) as: $p = \frac{S(1+r)}{(1-RR)}$.

The above measures calculate the risk-neutral (or risk-adjusted) default probabilities, which may differ from real-world default probabilities (those reflecting investors' risk aversion). Chan-Lau (2006) reviews the literature on relationships between the risk-neutral and real-world probabilities of default.

stability by central banks and international institutions (Čihák, 2006). Transposing these indicators to the systemic level poses important aggregation challenges which are not always addressed in the literature. I will illustrate this in the example of studies using distance to default (DD).

Some of the studies use a simple or weighted average of the DDs or PDs for individual firms or banks (e.g., (Tudela, Young, 2003)). Taking a simple average can lead to very misleading results, because it does not take into account the differences in the size of institutions (and therefore loss given default). The use of weighted averages of DDs or PDs addresses this issue to some extent, but still does not address the issue of correlation of defaults among institutions. Because of the correlation, DDs or PDs for individual institutions are not simply additive. Using the weighted average may be a reasonable proxy when default correlations are low. However, when default correlations are high, the average DDs or PDs do not capture swings in systemic risk, as illustrated, e.g., by Chan-Lau and Gravelle (2005) for several East Asian countries during 1998–99.

Other studies (e.g., De Nicolò et al., 2005) measure systemic risk using "portfolio DD," defined as

$$DD_t = \frac{\ln(A_t^P / L_t^P) + (\mu_p - 0.5\sigma_P^2)}{\sigma_P} \tag{18}$$

where $A^P = \sum_i A_t^i$ and $L^P = \sum_i L_t^i$ are the total values of assets and liabilities, respectively. The mean and variance of the portfolio are given respectively by $\mu_P = \sum_i w_t^i \mu^i$ and $\sigma_P^2 = \sum_i \sum_j w_t^i w_t^j \sigma_{ij}$, where $w_t^i = A_t^i / \sum_i A_t^i$ and σ_{ij} is the asset return covariance of financial institutions i and j. Thus, the "portfolio" DD to some extent embeds the structure of risk interdependencies among the financial institutions. "Default" at date $t + 1$ occurs if $A_t^P <: L_t^P$. Thus, the DD indicates how many standard deviations $\ln(A_t^P / L_b^P)$ has to deviate from its mean for default to occur. Since $A_t^P = L_b^P + E_b^P$, declines in A_t^P / L_b^P are equivalent to declines in capitalization E_t^P / L_b^P. The proponents of the "portfolio DD" suggest that it can be viewed as a risk profile measure tracking the evolution of the joint risks of failure of the firms composing a portfolio. Lower (higher) levels of the DD imply a higher (lower) probability of firms' joint failure. Since variations in the individual firms' DD are allowed to offset each other, the DD of a portfolio is always higher than the (weighted) sum of the DDs of the individual firms. As a result, the probability of "failure" associated with the portfolio DD is always lower than that associated with the actual probability of joint failures of sets of firms in the portfolio. Thus, the "portfolio" DD tracks the lower bound to the joint probabilities of failure.

This approach to some extent overcomes the lack of additivity for DDs in individual institutions and partly takes into account the different sizes of the institutions. However, it is based on a number of simplifying assumptions, resulting in a potentially biased indicator. In particular, it just adds all the assets and liabilities in the system, creating a single fictitious "mega-institution". As a result, this approach understates the risk of failures in the system and the risk that such failures will grow into a systemic problem. For example, if the value of assets in i goes below the value of its liabilities, $A_t^i < L_t^i$, the institution fails and can potentially trigger failures in other institutions through their exposures to i, even if they would not fail in the first place. In the case of portfolio DD, the impact in the decline of A_t^i can be offset by an increase in the asset value of another institution, A_t^j. This approach therefore underestimates not only the risk of failures in individual institutions, but also the risk of contagion within the system. That is an important omission from the viewpoint of financial stability analysis.[12]

Similarly to "portfolio DD," one can define "portfolio z-score," defined as $z \equiv (k+\mu)/\sigma$, where k is total equity capital in the system as percent of total assets in the system, μ is total return as percent of total assets, and σ is standard deviation of the aggregate return on aggregate assets as a proxy for return volatility. The "portfolio z-score" is a direct analogue of the "portfolio DD" for accounting data. Section 4 of this article shows values of the "portfolio z-score" in a range of countries. Similarly to the portfolio DD, the portfolio z-score is always higher than the sum of z-scores for the individual institutions. As with the portfolio DD, an important weakness of the portfolio z-score from the viewpoint of the framework introduced in Section 2 is that it does not take into account contagion among institutions.

Related to the portfolio DD is also the contingent claims approach, which integrates option-based analysis along the lines of Merton (1974) within a macroeconomic framework with explicit linkages between contingent liabilities in the corporate, banking, and government sectors (e.g., (Gapen et al., 2004). Because the modeling of contingent liabilities is based on Merton (1974) and risk measures at the financial and non-financial sectoral level are obtained using aggregate data, the same caveats as discussed above apply.

3.4 First and *N*th to Default

The First-to-Default (FTD) probability, or the probability of observing one default among a number of institutions, has been proposed as a measure of systemic risk for large and complex financial institutions (IMF, 2005); (Avesani, 2005). This measure is constructed using risk-neutral default probabilities implied from credit default swap spreads. The FTD probability addresses one of the shortcomings of the DD measures, namely, the possibility that defaults among a number of institutions can be correlated. However, the major shortcoming of the FTD probability is its poor performance at capturing changes in the common component across institutions. For example, Chan-Lau and Gravelle (2005) illustrate that the FTD probability for the Korean corporate sector actually declined during the Asian crisis period. This result follows from the fact that a systemic crisis is the observable outcome of a common negative shock. Thus, for any time horizon, the likelihood of observing exactly one default among a number of institutions diminishes, while the probability of observing more defaults increases.

[12] To illustrate the issue with this aggregation, one can also look at the extreme example of a system consisting of two banks of equal size, with capital to asset ratios of 0 and 100 percent, respectively. The default risk of the "mega-institution," with a 50 percent capital to asset ratio, is not representative of the default risk in the system.

TABLE 1 Indicators of Systemic Stability: Overview of Pros and Cons

Indicator	Advantages	Disadvantages
Average DD or *z*-score (or probability of default)	* Easy to calculate from individual institutions' DDs, *z*-scores, or PDs.	* Does not reflect contagion (correlation across failures). * Does not reflect differences in loss given default in institutions, even though that can be partially addressed by weighting. * DD requires liquid market in financial institutions' stocks; liquid bond or CDS markets required if those markets are used to estimate PDs.
Portfolio DD or portfolio *z*-score	* Easy to calculate. * Unlike simple averaging, reflects to some extent the differences in institution sizes and correlation across institutions.	* Does not fully reflect contagion, correlation across failures. * Does not fully reflect differences in loss given default in institutions.
First-to-default and *n*th-to-default indicator	* Clear theoretical underpinnings for the *n*th--to-default indicator.	* Do not fully reflect different LGDs in institutions. * FTD does not measure systemic risk.
Expected number of defaults (END) indicator	* Relatively easy to interpret.	* Does not reflect different LGDs in institutions. * Difficult to calculate, not a closed-form expression. * Focuses only on central tendency of the distribution. * Depends on total number of institutions.
Financial soundness ratios (capital adequacy, nonperforming loans to total loans)	* Relatively easy to calculate.	* No clear link to probabilities of default found yet. * No clear link to systemic stability found yet.
Stress test results	* Takes into account differences in loss given default in institutions. * Takes into account extreme situations.	* Methodology not yet settled. * Sensitivity to assumptions. * Focus on extreme situations.
"Stress Index" of Swiss National Bank	* Clear definition.	* Unclear relationship to probabilities of default and systemic stability.
Distribution of systemic loss	* Captures differences in loss given default in institutions. * Captures correlation across institutions failures. * Focuses only on central tendencies.	* May be difficult to calculate in some cases; no closed-form expression.

In a recent study, Avesani, García Pascual, and Li (2006) propose using a *n*th-to-default credit-default-swap (CDS) basket of large complex financial institutions to determine PDs. This approach addresses the problems of using the first-to-

-default CDS data. However, it does not address differences in institutions' sizes (LGDs). In principle, it may be possible to bypass this issue by grouping financial institutions into baskets of similar size; however, the creation of *n*th-to-default baskets has been driven by market participants' needs and not necessarily by financial stability considerations. This criticism does not mean that *n*th-to default baskets are not a potentially useful approach to measuring stability. If the baskets are defined properly and if there are liquid markets, this is a very promising approach that offers a direct way to measure financial stability.

3.5 Expected Number of Defaults (END)

Chan-Lau and Gravelle (2005) propose measuring systemic default risk using the expected number of defaults (END), based on the joint occurrence of defaults among a number of institutions.[13] Using equity prices and balance-sheet data, they calculate the END to assess systemic risk in the corporate sector in Korea, Malaysia, and Thailand.

The END has advantages compared to indicators such as the portfolio DD. First, it relaxes some of the underlying assumptions of the DD calculations, such as the assumption that asset prices are continuous and the level of liabilities is constant; this makes the calculation more realistic and can yield non-negligible default probabilities even over short time horizons. Second, and more important, the END takes a less ad-hoc approach to aggregating the PDs in individual institutions than the "portfolio DD" or average PD or DD measures.

Two main problems with the END relate to the fact that it is focused on the *number* of defaults. First, unlike the systemic loss (which is expressed as a percentage of GDP), the END is difficult to compare across financial systems with different numbers of institutions. Second, the END treats all the financial institutions the same, irrespective of their systemic importance. The first issue is relatively easy to fix: one can present the END as a ratio to the total number of institutions in the system. The second problem is more difficult to address. The END indicator is derived by taking the Vasicek (2002) model of distribution of loan portfolio values and applying it to a portfolio of banks. However, the model assumes that all items in the portfolio are the same. The model therefore works well only if the portfolio is not dominated by a few exposures much larger than the rest – a condition that is not satisfied in most financial systems.

3.6 Other Approaches

Numerous studies have used cross-section or panel data on soundness or defaults in individual institutions to model systemic issues. For example, they have tried to regress DDs or *z*-scores for individual institutions on a number of institution-level and country-level explanatory variables (e.g., (Krainer, Lopez, 2003); (Hesse, Čihák, 2007)). These approaches can yield interesting results; however, institution-

[13] In terms of the notation employed in Section 2, the END can be expressed as $E\sum_{i=1}^{n} d_i$.

-by-institution regressions typically do not allow effective measuring of contagion among financial institutions and differences in sizes.[14]

A large body of statistics has also been developed on the macroprudential level, using practical consideration and expert assessment. These include basic system-level ratios, such as capital to risk-weighted assets or gross nonperforming loans to total gross loans (IMF, 2004). Emerging empirical analysis shows that these variables are correlated with macroeconomic variables (e.g., (IMF, 2003)) and with the presence of systemic crises (Čihák, Schaeck, 2007). However useful, these indicators generally do not have a clear micro-level link to PDs or LGDs (e.g., a high capital-adequacy ratio or a lower nonperforming-loan ratio does not necessarily mean a more stable institution if there are offsetting risks). Empirical research into how these variables can be combined into a composite indicator is ongoing. Recently, the Swiss National Bank started publishing a "stress index" (Swiss National Bank, 2006), which combines a set of accounting, market-based, and other indicators into a single number. However, the link between this indicator and systemic stability is unclear.

4. Empirical Illustration

4.1 How Sensitive Are "Systemic" Measures to Aggregation?

To illustrate the point that concentration of losses has important implications for systemic stability, let us assume that LGDs are correlated with total assets of an institution, A_i, and that the institution's asset size and rank in terms of assets, R_i, are related by $A_i = c \cdot R_i^{-\alpha}$.[15] Let us consider, for example, a system with 50 banks and $\alpha = 1$. If the expected number of defaults is five, it is important to know whether the failures affect the five largest institutions (more than 50 percent of the system's assets) or the five smallest institutions (about two percent of the assets). Analyzing the number of defaults of the average bank can yield misleading results.

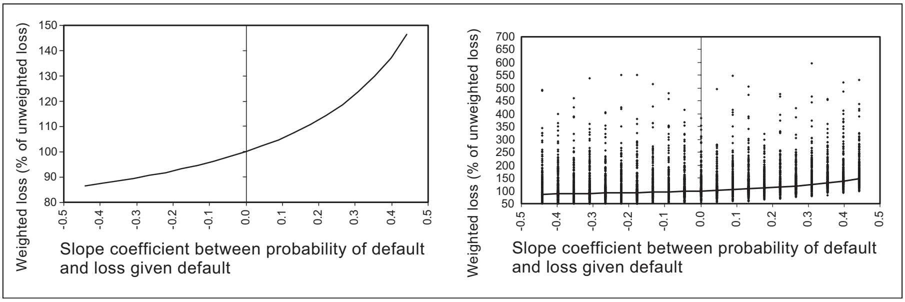
Figure 1 illustrates this point by using a Monte Carlo simulation. We focus on financial systems where the institution-by-institution LGDs are characterized by the above distribution with $\alpha = 1$. To illustrate the impact of concentration of losses, we allow there to be a correlation between PDs and LGDs and change the correlation of the two in a number of steps from positive to negative, and running 1,000 iterations for each of the steps. The figure illustrates that if PDs and LGDs are positively correlated (i.e., if larger institutions tend to be more likely to fail), the expected systemic loss is generally higher. The figure, however, also illustrates that focusing on expected systemic loss is not sufficient, since the actual loss can reach multiples of the expected value.

Table 2 reinforces this point using actual data from the 25 banking systems in the European Union. The table illustrates that if END = 5, the expected share of affected

[14] Differences in financial institution size can be addressed by including size as an explanatory variable or, preferably, as weight in a weighted regression. However, contagion among financial institutions is more difficult to address in a regression.

[15] This is not an unrealistic assumption. Empirical evidence shows that the distribution of firm sizes in various sectors follows this relationship (Stanley et al., 1995). Alegria and Schaeck (2006) find the same distribution for asset sizes in banks, with slope coefficients in individual countries from 0.25 to 1.

FIGURE 1 Size and Systemic Stability: Monte Carlo Simulations



Source: author's simulations

banks can be from 0.2 percent (the Netherlands) to 9.5 percent (Malta). However, if the actual share can be seven to 440 times bigger, it can reach even 98 percent (Estonia). Therefore, if failures are concentrated in large institutions, using the number of failures can lead to a misjudgment on the order of several hundred.[16]

4.2 What Do the Systemic Stability Indicators Measure?

The literature says relatively little about whether systemic stability indicators actually indicate observed instances of systemic problems. One of the exceptions is Čihák and Schaeck (2007), analyzing how well basic aggregate ratios identify banking problems. For market-based indicators (which generally perform better on the level of individual institutions), the available studies that focus on the systemic level (e.g., De Nicolò et al., 2005) analyze correlations of these indicators with macroeconomic and other variables, but not how well these indicators actually measure observed situations of distress. An exception is the study by Chan-Lau and Gravelle (2005), discussing the path of the END indicator during the 1997 Asian crisis. However, I am not aware of a study that would examine market-based indicators and systemic failures systematically.

This section looks at the behavior of a range of indicators in periods of crises. As in Čihák and Schaeck (2007), I follow the listing of crises since the 1970s provided by Caprio and Klingebiel (2003), which has become a standard in the literature on early warning models for banking problems. It defines systemic banking crises as episodes during which most or all bank capital was exhausted, identifying 117 such crises in 95 countries since the early 1970s.

Table 3 summarizes the results of an analysis of DD, *z*-score, and systemic loss in a number of crisis countries. For DD and systemic loss, the analysis is based on daily equity price data in 1990–2004; for the *z*-score, it uses annual data from financial reports from 1994–2004. It covers 29 countries, including 12 in which a systemic banking crisis started during this period according to Caprio and Klingebiel (2003). For the DD and the *z*-score, we present the unweighted and weighted

[16] Similar issues relating to adjustment of differences in size arise also in other areas of economics. For example, in the literature on economic growth, Sala-i-Martin (2002) obtains different conclusions on global income inequality depending on whether or not he weights country-level data by the size of the country.

TABLE 2 Concentration of Banking Systems in the EU

	Number of banks	Share of 5 largest banks [a]	Share of 5 random banks [b]	Share of 5 largest banks divided by share of 5 random banks
Austria	880	45.0	0.57	79
Belgium	100	85.2	0.78	109
Cyprus	391	59.8	0.52	115
Czech Republic	56	65.5	3.38	19
Denmark	197	66.3	0.88	76
Estonia	11	98.1	1.58	62
Finland	363	83.1	0.24	352
France	854	53.5	0.27	195
Germany	2,089	21.6	0.19	115
Greece	62	65.6	3.02	22
Hungary	215	53.2	1.11	48
Ireland	78	46.0	3.70	12
Italy	792	26.7	0.47	57
Latvia	23	67.3	9.08	7
Lithuania	78	80.6	1.33	61
Luxembourg	155	30.7	2.31	13
Malta	18	75.3	9.50	8
Netherlands	401	84.8	0.19	442
Poland	739	48.6	0.35	139
Portugal	186	68.8	0.86	80
Slovakia	23	67.7	8.97	8
Slovenia	25	63.0	9.25	7
Spain	348	42.0	0.85	50
Sweden	200	57.3	1.09	52
UK	400	36.3	0.81	45
Euro Area	6,308	43.0	0.05	951
EU-25	8,684	42.3	0.03	1,273

Notes: [a] Share in terms of total assets, measured in percent.
[b] Sum of squared market shares (in terms of total assets, in percent).

Source: The author's calculations based on data from the European Central Bank.

averages across institutions (using total assets as the weight), and the portfolio DD and *z*-score. For the systemic loss calculation, I use the framework described in Section 2. To be able to implement it on such a relatively wide sample, I approximate the exposure to an institution, X_i, by its total assets, and the loss given default by 0.3 X_i.[17] We then use (2) and (4) to calculate the expected and unexpected loss given default, using the Merton (1974) approach to calculate the PDs. In keeping with the framework in Section 2, it would be interesting to analyze also other moments of the loss distribution, but to keep the comparison simple, we focus on these two moments.[18]

The preliminary conclusion one can draw from Table 3 is that (i) the indicators indeed indicate increased instability; and (ii) taking the LGDs and correlations across failures into account improves the measurement. Specifically,

TABLE 3 Distance to Default, z-Scores, and Expected Loss in Crises [a]

Indicator	Crisis			Non-crisis			Signal to noise ratio [d]
	Obs.[b]	Mean	Std.[c]	Obs.[b]	Mean	Std [c]	
Distance to default							
Unweighted	62,188	58	24	43,848	128	56	0.9
Weighted	62,188	62	26	43,848	116	27	1.0
Portfolio	62,188	51	25	43,848	118	26	1.3
z-score							
Unweighted	255	34	15	180	63	25	0.7
Weighted	255	35	9	180	55	13	0.9
Portfolio	255	32	22	180	89	28	1.1
Systemic loss (% GDP)							
Expected	62,188	2.2	0.8	43,848	0.1	0.7	1.4
Unexpected	62,188	2.8	1.0	43,848	0.2	0.7	1.5

Notes: [a] Included are observations for Argentina*, Australia, Austria, Belgium, Brazil*, Canada, Chile, Denmark, France, Germany, Greece, Hungary*, Ireland, Israel, Italy, Japan*, Korea*, Malaysia*, the Netherlands, Norway*, the Philippines*, Poland*, Portugal, Spain, Sweden*, Thailand*, Turkey*, the United Kingdom, and the United States (asterisks denote systems for which Caprio and Klingebiel (2003) identify a crisis starting between 1990 and 2003).

[b] Number of system-level observations (the number of individual bank observations on which these system-level observations are based) is a multiple of this number.

[c] Standard deviation across the crisis (or non-crisis) observations.

[d] Absolute value of the difference of the two means (for crisis and non-crisis observations), divided by the sum of the two standard deviations. If crises are identified properly, better indicators should show a higher signal-to-noise ratio (assuming that the signal is correct, i.e. the difference of the two means has the expected sign).

Source: Author's calculations based on data from BankScope, DataStream, and Bloomberg.

the difference between the average crisis observations and average non-crisis observations has the expected sign (negative for DD and z-score and negative for systemic loss). The signal-to-noise ratio (the difference between the means of crisis and non-crisis observations, divided by the two standard deviations) is higher for weighted averages than for simple averages, and even higher for "portfolio" measures, indicating the importance of institutions' sizes (and LGDs). The signal-to--noise ratio improves further when using the systemic loss, i.e. when we more explicitly reflect both the effect of LGDs and the correlation of defaults. A more detailed analysis of the indicators would go beyond the scope of this article, which only attempts to illustrate the usefulness of systemic losses when analyzing stability.

[17] The assumed severity of 0.3 is based on the existing empirical work on losses in failures. In particular, analyzing about 800 bank failures, James (1991) finds that losses on assets (defined as the difference between book value and recovery value net of direct expenses) average at 30 percent. The calculation of systemic loss could be improved by allowing LGD to be a random variable (e.g., following the distribution estimated in (James, 1991)). However, that turned out to be too computationally complex for this sample.

[18] The expected loss calculation is similar to that for the END indicator, but with institutions weighted by the LGDs. Table 3 does not show the END because it is correlated with the total number of institutions, making cross-country comparisons difficult. It also does not show the nth-to default indicator, because of a lack of data.

5. Conclusion

The key point of this article is that it is useful to look at the financial system as a portfolio of counterparty exposures, the counterparties being financial institutions, and analyze the distribution of loss on that portfolio. This approach combines probabilities of default, losses given default, and correlations of defaults in the system.

We have evaluated the existing measures of financial stability and found that they generally come up short. Studies focusing on probabilities of default tend to overlook the fact that "size matters", i.e. financial institutions are not all the same. Other studies do not appropriately reflect the institutions' probabilities of default or correlations of defaults. Also, most measures look at the central tendencies of the loss distribution, potentially disregarding important information in the rest of the loss distribution.

The empirical analysis in this article illustrates this point. I find that the results of some of the market-based indicators of financial sector stability proposed in the literature can be altered substantially if one takes into account the differences in loss given default. I also find some evidence suggesting that accounting for the distribution of losses can lead to a clearer distinction between financial stability and situations of instability.

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