CHAPTER 3

DETECTING SYSTEMIC RISK

Summary

The current crisis demonstrates the need for tools to detect systemic risks. Given that there are many facets and causes of such risks, this chapter presents a range of measures that can be used to discern when events become systemic. The chapter first reviews the standard financial soundness indicators' ability to highlight those financial institutions (FIs) that proved to be vulnerable in the current crisis. For the sample of global FIs examined, leverage ratios and return-on-assets proved the most reliable indicators, while capital asset ratios and nonperforming loan data lacked predictive power.

The chapter then proceeds to examine several techniques to analyze forward-looking market data for groups of FIs in order to detect whether and when systemic risks became apparent. Market-based measures that are able to capture tail risks seem to have given forward indications of impending stress for the overall financial system. Chapter 2 provides a slightly different approach to systemic risk by examining interlinkages, both direct and indirect, between selected FIs.

Finally, proxies for "market conditions" that influence (and reflect) the risks facing FIs are examined to capture other key factors, such as investors' risk appetite. The signaling capacity of these indicators is examined by detecting whether and when they moved from low, to medium, and to high volatility states, with the high state associated with systemic crisis. Several measures signaled periods during which the financial system suffered a systemic crisis.

The various techniques clearly identify major stress events, such as those associated with the merger of Bear Stearns and the failure of Lehman Brothers, as systemic. Some indicators, as early as February 2007, also signaled rising systemic pressures. However, advance notice of systemic stress was relatively brief and the extent to which some markets remained in high volatility states was somewhat short-lived. Hence, the use of a number of market-based indicators provides a more holistic picture.

Being able to identify systemic events at an early stage enhances policymakers' ability to take necessary exceptional steps to contain the crisis. In this regard, the chapter suggests enhancing stress tests and capital requirements to take account of the build-up of systemic risks. Some of the analysis presented could be a starting point to calibrate the risk contribution of FIs to overall systemic risk, thereby prompting additional regulatory capital and enhanced supervision to discourage practices that increase systemic risk.

In sum, although systemic events are difficult to predict, and may only become apparent concurrently in some cases, policymakers should monitor a wide range of market indicators tuned to systemic risk, and have comprehensive crisis plans in place to be implemented quickly if needed.

Systemic events are intrinsically difficult to anticipate, though once they have occurred it is easier to look back and agree that a disruption was, in fact, systemic. Because of the severity and reach of the current crisis, renewed attention on what constitutes a systemic crisis and whether it can be uncovered, early or even concurrently, has come to the fore. The task of identifying warnings of impending systemic crises has become increasingly complex as global financial markets have become highly integrated and hence systemic shocks can arise from and extend to outside national borders. Analyzing systemic risks is further hampered because there have been so few modern episodes of global systemic crises, particularly involving a core group of advanced economies. Even so, this chapter attempts to make inroads into this area by seeking to shed light on what constitute systemic events and by providing policymakers with tools that can be used to recognize systemic risks. Instead of attempting to offer a single methodology, a range of empirical approaches is examined in order to provide a more robust way of detecting systemic risks.[1]

The chapter focuses on measures of overall systemic risk derived from higher frequency market data, rather than the identification of underlying macroeconomic vulnerabilities based on data at lower frequencies. While the latter models are helpful in identifying the buildup of macroeconomic vulnerabilities, they are usually not very successful in predicting the actual timing of crises or how they spill over across global markets.[2] Thus, this chapter is intended to complement the more traditional macro-oriented exercises attempting to predict financial crises. In particular, it focuses on the role of financial market signals as indicators of overall systemic risks.

Specifically, the chapter seeks to answer the following questions:

- What were common factors among the financial institutions (FIs) that have required public intervention? Did traditional financial soundness indicators (FSIs) provide meaningful warnings?
- How can one determine which FIs are systemically important? Can one shed light on whether allowing Lehman Brothers to go bankrupt was or was not a policy "mistake" ex ante?
- What are early, or concurrent, indicators of systemic risk? When might their reliability be compromised?
- Can one determine when policymakers should enter and exit policies designed to contain systemic risk?

The chapter presents a series of "modules" to examine systemic risk from various perspectives. The chapter first looks at the "fundamental" characteristics of FIs based on the balance sheet data that are typically used by supervisors and regulators. This analysis is further expanded to review individual FIs from the markets' perspective based on credit default swap (CDS) spreads and equity option prices. Then groups of institutions are analyzed jointly, building from simple tools such as cluster analysis to more elaborate methods that look at the joint probability of various outcomes. The role of global market conditions is then analyzed to shed light on whether certain factors, such as proxies for investors' risk appetite, affect the incidence of systemic

Note: This chapter was written by a team comprised of Brenda González-Hermosillo (team leader), Christian Capuano, Dale Gray, Heiko Hesse, Andreas Jobst, Paul Mills, Miguel Segoviano, and Tao Sun. Yoon Sook Kim provided research support. The chapter also benefited from comments from Andrew Lo and Kenneth Singleton.

[1]The use of multiple approaches is also present in Chapter 2, where the perspective is to examine linkages across institutions or groups of institutions.

[2]Indeed, financial shocks (e.g., sudden stops in capital flows, the bursting of asset bubbles, etc.) often serve to reveal the unsustainability of macroeconomic imbalances. Macroeconomic imbalances can last many years before they result in crisis. For example, while the peak of the U.S. housing market was reached in mid-2005, the subprime crisis was not revealed until 2007. Similarly, while many developing countries had sustained large current account deficits for several years, it was not until late 2008 that some of them began to face financing constraints and dramatic pressures on their currencies.

risk.[3] Global market conditions are important in determining the market value of the FIs and thus both influence and also echo the risks of individual FIs.[4]

Based on the sample of FIs examined, the results suggest that traditional balance sheet data are only partially able to detect, ex ante, institutions at risk of failing. Although market-based indicators are largely coincident with events that have been deemed of systemic importance, notably the collapse of Lehman Brothers on September 15, 2008, some indicators are able to give some advanced signals of risks. And although it would have been difficult to know ex ante that larger disruptions were coming, markets showed signs that a regime change, a generalized breakdown of financial system functioning, occurred as early as late February 2007, when the price on the ABX (BBB) index began to decline and there was a significant correction in the Shanghai stock market that reverberated across emerging markets.[5,6] The various indicators examined suggest that letting Lehman collapse aggravated what appeared to be a global systemic financial crisis already in the making because Lehman's potential effects on other FIs were observable in several indicators.

The techniques examined show some success in revealing when the financial system is in a systemically elevated regime, providing some guidance about when policymakers should use the "systemic crisis" toolkit rather than policy tools meant to deal with individual institutions or markets. Similarly, these techniques can be used to determine when systemic risks subside, and thus provide guidance as to when to unwind guarantees and other supportive policies introduced during the systemic phase.

What Constitutes "Systemic" Risk?

"Systemic risk" is a term that is widely used, but is difficult to define and quantify. Indeed, it is often viewed as a phenomenon that is there "when we see it," reflecting a sense of a broad-based breakdown in the functioning of the financial system, which is normally realized, ex post, by a large number of failures of FIs (usually banks). Similarly, a systemic episode may simply be seen as an extremely acute case of financial instability, even though the degree and severity of financial stress has proven difficult, if not impossible, to measure.[7] Systemic risk is also defined by the breadth of its reach across institutions, markets, and countries.

A natural starting point to begin to investigate systemic events is by examining individual FIs and their interlinkages (the latter is the focus of Chapter 2). However, during systemic events, channels over and above the normal fundamental mechanisms that link FIs and asset markets during noncrisis periods can be important sources of contagion.[8] Contagious events,

[3]Other elements not directly considered in this chapter, such as the "shadow banking system" (e.g., hedge funds and special-purpose vehicles) are also likely captured by the various variables used to proxy for global market conditions.

[4]For example, low interest rates reduce the default risk of loans. Similarly, the value of securities and other assets, including derivatives, depend on market conditions such as overall volatility and global liquidity.

[5]The ABX (BBB) is an index based on credit default swaps written on subprime mortgages, investment grade tranches.

[6]Rosenblum and others (2008), Gorton (2008), and González-Hermosillo (2008) also identify end-February 2007 as a period when early signs of stress began to emerge in global markets prior to the time when the subprime crisis was clearly revealed in mid-2007. This correction reflected a reappraisal of market risks (see IMF, 2007, Box 1.5).

[7]Some recent attempts to measure the degree of severity of financial stress in a given country include Illing and Liu (2006). As well, Huang, Zhou, and Zhu (2008) develop a framework to assess the systemic risk of large U.S. financial institutions. However, most empirical analyses of multi-country financial crises rely on a binomial notion whereby the dependent variable takes the value of 1 during the known, ex post, crisis period or zero otherwise with no information about the actual severity of the crises (e.g., Kaminsky and Reinhart, 1999; Hardy and Pazarbasioglu, 1999; Demirgüç-Kunt and Detragiache, 1998; Davis and Karim, 2008; and Weistroffer and Vallés, 2008).

[8]A body of literature on contagion examines these additional links. See, for example, Masson (1999); Dornbusch, Park, and Claessens (2000); and Dungey and

which can result from asymmetric information or uncertainty, generate changes in the normal behavior of prices and thus in the distribution of returns used for trading and risk management purposes, causing the distributions to be skewed and "fat-tailed" (that is, exhibit more downside than upside risk, the third moment or skewness; and more "risk" generally, the fourth moment or kurtosis). Also important in identifying systemic events are the underlying "market conditions" and the ability for events to further alter market conditions.[9] For example, when the level of market uncertainty (measured by the implicit volatility of assets) is high, then even a temporary shock can lead to defaults and generates significant aftershocks. Similarly when investors' risk appetite is low or global liquidity is tight, then even relatively small shocks can have large effects on global financial markets—and vice-versa.[10]

In this chapter, three basic concepts that underpin the measurement of systemic risk are used. First, several techniques apply the notion that interlinkages across institutions are important—including identifying groups of similarly exposed FIs and observing the effects of potential defaults of individual institutions on each other and the financial system as a whole.

Second, changes in the return distributions of FIs' assets and equity are examined during periods of stress to determine the additional risks in the "tails" of such distributions and how the "tails" of a multiple institution return distribution can provide more accurate measures of systemic risk.[11]

others (2005, 2006, 2007). Dungey and others (forthcoming) argue that the Long-Term Capital Management/Russian crisis in 1998 and the subprime crisis that began in mid-2007 have been the most contagious crises in the past decade, based on a sample of advanced and emerging economies in which credit and equity market daily data are modeled jointly across countries.

[9]For example, Brunnermeier and Pedersen (forthcoming) discuss liquidity spirals.

[10]Different measures of risk appetite are discussed in European Central Bank (2007) and González-Hermosillo (2008).

[11]These first two notions are also taken up in Chapter 2.

Lastly, the observation that general "market conditions" matter for the existence and propagation of risks through the financial system is used to examine periods of high vulnerability to shocks that may become systemic.

Since there are several concepts of systemic risk, it is natural to expect a collection of measures rather than a single all-encompassing index.[12] Moreover, by examining systemic risk with three complementary approaches, a more comprehensive and robust assessment can be made to guide policies, though not every method can be expected to signal the same intensity or nature of systemic risk.

"Fundamental" Characteristics of Intervened and Nonintervened Financial Institutions

Regulators and supervisors typically use a set of FSIs to assess the stability of their financial system. Indeed, the International Monetary Fund (IMF) has promoted their construction and collection over the last several years (see Annex 3.1).[13] As a starting point for the analysis of systemic risk, it is thus useful to examine whether traditional FSIs were able to discern institutions that would eventually require gov-

[12]Lo (2008), for example, considers that "systemic" risk should be measured by leverage, liquidity, correlation, concentration, sensitivities, and connectedness. The Group of Ten (2001) extends systemic events to include factors affecting the economy.

[13]Various studies have proposed early warning indicators of impending turmoil in banking systems (e.g., Demirgüç-Kunt and Detragiache, 1998, 1999, 2005; Hardy and Pazarbasioglu, 1999; González-Hermosillo, 1999; Hutchinson and McDill, 1999; Hutchinson; 2002; Rojas-Suarez, 2001; and European Central Bank, 2005). The IMF proposed sets of so-called "core" and "encouraged" FSIs (Sundararajan and others, 2002), encapsulated in the *Compilation Guide on Financial Soundness Indicators* (IMF, 2006), that have become essential for the macroprudential surveillance carried out by the IMF across countries. However, recent studies suggest that FSIs may not fully capture risks (e.g., Cihák and Schaeck, 2007; Poghosyan and Cihák, 2009; Bergo, 2002; and Sorge, 2004), suggesting that FSIs need to be complemented by other indicators, including market data.

Table 3.1. Selected Indicators on Fundamental Characteristics in Financial Institutions

	Nonintervened Banks		Intervened Commercial Banks		Intervened U.S. Investment Banks	
	1998:Q1–2008:Q1	2005:Q1–2007:Q2	1998:Q1–2008:Q1	2005:Q1–2007:Q2	1998:Q1–2008:Q1	2005:Q1–2007:Q2
Capital adequacy (in percent)						
Capital/assets	14.5	19.4	17.9***	20.3	17.3**	19.4
Common equity/assets	3.7	4.4	6.0***	5.7***	3.7	3.7**
Tier 1 capital/risk-weighted assets	4.9	10.8	8.1***	9.0	. . .	. . .
Tier 1 and 2 capital/risk-weighted assets	7.3	15.8	11.0***	12.5	. . .	. . .
Asset quality (in percent)						
Nonperforming loan ratio	2.3	2.3	1.4***	1.0**	n.a.	n.a.
Provision for loan losses/loans	0.1	0.1	0.2***	0.2***	n.a.	n.a.
Leverage						
Debt to common equity	7.5	7.6	8.1***	9.0***	13.3***	13.7***
Short-term debt[1]	0.4	0.5	0.7***	0.7***	0.7***	0.7***
Liquidity						
Loans/deposits	1.1	1.3	1.2	1.3	n.a.	n.a.
Loans/assets	0.6	0.5	0.5***	0.5***	n.a.	n.a.
Earning and profit (in percent)						
Return on assets	1.2	1.2	1.9***	1.6***	3.9***	4.3***
Return on equity	3.6	4.8	4.1	5.3	4.1	5.3
Stock market performance						
Price/earnings ratio	15.5	12.6	16.8	12.0	15.6	13.1
Earnings per share	0.6	1.0	0.6	0.9	1.3***	2.4***
Book value per share	14.8	21.7	14.1	18.3***	34.0***	50.5***

Sources: Thomson Reuters; and IMF staff estimates.

Note: A *t*-test is performed to determine whether two samples are likely to have come from the same two underlying populations that have the same mean. The intervened commercial banks and the U.S. investment banks are compared to the nonintervened banks. *, **, and *** represent the statistically significant differences at the 10, 5, and 1 percent levels, respectively.

[1]Short-term and other debt payable within one year.

ernment intervention from those that have not from a small sample of major institutions.[14]

The sample comprises 36 key commercial and investment banks across the world (Annex 3.2).[15] The advantage of focusing on FSIs is that they are readily available and some are widely used by financial regulators. However, these indicators are also reported at low frequencies, are generally static and backward-looking, and focus on an individual FI without much regard for the spillovers from other institutions. Table 3.1 divides the sample of FIs into nonintervened commercial banks, intervened commercial banks, and intervened investment banks during 1998:Q1–2008:Q1 (before the wave of government intervention) and 2005:Q1–2007:Q2 (before the start of current cycle and the beginning of the subprime crisis).

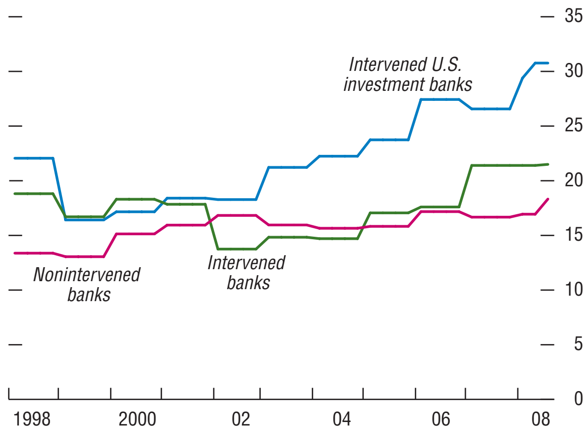
The results in Table 3.1 show the following:

- Capital adequacy ratios were unable to clearly identify institutions requiring intervention. In fact, contrary to the common belief that low capital adequacy ratios would signal weakness for a FI, all four capital adequacy ratios

[14]In this chapter, intervened institutions are assumed to be those that have gone bankrupt, or that have received government capital injections or loans, or that have had assets purchased by government, or that have received official loans to facilitate a merger or acquisition. Central bank temporary liquidity injections are not considered to be a type of intervention. Intervened institutions and periods of intervention are detailed in Annex 3.3.

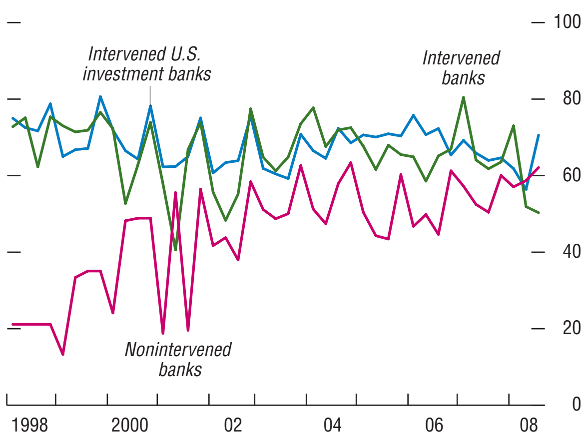
[15]The insurance companies were excluded from the analysis given their different business lines. The rationale for choosing these FIs is based on their systemic importance while keeping a balanced sample representative of the various regions around the world. Data constraints also played a role, as the sample chosen was limited to FIs for which balance sheet and market-based data were available.

Figure 3.1. Capital-to-Assets Ratio
(In percent)



Sources: Thomson Reuters; and IMF staff estimates.
Note: The ratios of nonintervened banks, intervened banks, and intervened U.S. investment banks are the average of all institutions in each category.

Figure 3.2. Ratio of Short-Term Debt to Total Debt[1]
(In percent)



Sources: Thomson Reuters; and IMF staff estimates.
Note: The ratios of nonintervened banks, intervened banks, and intervened U.S. investment banks are the average of all institutions in each category.
[1]Short-term and other debt payable within one year.

examined for intervened commercial banks were significantly higher than (or similar to) the nonintervened commercial banks as a whole (Figure 3.1). There are, of course, regional differences among nonintervened commercial banks. During 2005:Q1–2007:Q2, the capital-to-assets ratio for nonintervened commercial banks in Asia and the euro area were higher than for intervened commercial banks. However this was not the case for FIs in the noneuro area. This suggests that regional differences can make direct comparisons problematic.[16]

- Several basic indicators of leverage appear to be informative in identifying the differences in the institutions, although the reasons for this deserve further examination. The higher ratios of debt to common equity, and short-term debt to total debt in the intervened commercial banks and intervened investment banks, all indicate that these measures of leverage are especially informative about the differences (Figure 3.2).[17]
- Traditional liquidity ratios are not very indicative of the differences between intervened and nonintervened institutions. In part, this is because these liquidity ratios may not be able to fully measure wholesale funding risks.
- Asset quality indicators show a mixed picture. Similar to the capital adequacy ratios, the ratio of nonperforming loans (NPL) to total loans for the intervened commercial banks has been lower than for the nonintervened commercial banks, indicating that NPL ratios are not very reliable indicators of the deterioration in asset quality. However, the lower provisions for the loan-losses-to-total-loans ratio for the nonintervened commercial

[16]The reasons that capital adequacy ratios are not always useful indicators of distress may reflect (1) difficulties in determining the actual riskiness of assets; (2) deficiencies in mark-to-market accounting practices; and (3) locating assets and contingent claims (e.g., derivatives) in off-balance-sheet vehicles where they can receive lower risk-weights.

[17]Short-term and other debt payable within one year.

banks suggests that this is a better indicator than the NPL ratio.

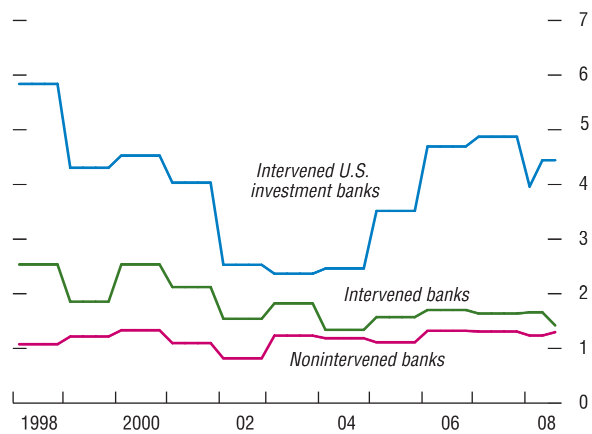
- The standard measures of earnings and profits show a mixed picture. While return on assets (ROA) for the intervened institutions are much higher than those in the nonintervened commercial banks, suggesting that elevated risks are associated with higher returns, return on equity (ROE) has not captured any major differences between the FIs that were intervened or not (Figure 3.3). This contrast between the effectiveness in ROA and ROE may reflect the high leverage ratio of intervened FIs, which typically rely on higher levels of debt to produce profits.
- Stock market indicators are able to capture some differences. The price-to-earnings ratios, earning per share, and book value per share of the intervened investment banks have been generally higher than those in the nonintervened commercial banks, which suggest that the higher equity prices and earnings do not necessarily reflect healthier institutions, but perhaps concomitant higher risks.

This section finds that (1) risk-weighted capital adequacy ratios have generally not been informative in discerning financial firms that eventually required intervention (in fact, the intervened institutions sometimes had higher capital adequacy ratios than the nonintervened institutions); and (2) several indicators, such as the debt-to-common-equity ratio, short-term-debt-to-total-debt ratio, ROA and stock market indicators have been better at discerning the differences between intervened and the nonintervened institutions.

In conclusion, based on the sample of institutions examined, which notably includes U.S. investment banks, it would be useful to include indicators on leverage and more on stock market performance on the regulatory radar screen, since they could provide a starting point for a deeper analysis of vulnerable institutions. Also, the center-stage focus on regulatory capital adequacy ratios may need to be redefined, especially if it can be shown that FIs were able to shift risks to off-balance-sheet vehicles, which

Figure 3.3. Return on Assets

(In percent)



Sources: Thomson Reuters; and IMF staff estimates.

Note: The ratios of nonintervened banks, intervened banks, and intervened U.S. investment banks are the average of all institutions in each category.

receive lower risk weights, and thus the risks on the balance sheet are underrepresenting those of the FI. Though the analysis here has been partial and cursory, others have found similar issues with the application of FSIs, calling for further improvements (see footnote 13). For less sophisticated institutions and general financial sector analysis, the FSIs can still be useful to signal risks.

Market Perceptions of Risk of Financial Institutions

Financial soundness indicators, especially those based on accounting balance sheet data, have certain limitations: they fail to anticipate changes in market conditions and spillovers from other FIs, and tend to be static and backward looking. In particular, investment positions and bank loans that are apparently profitable at a given time can turn into large losses if market conditions deteriorate going forward. Moreover, in addition to general market conditions, asset prices may reflect how other FIs value similar assets. By contrast, these and other issues, including business objectives and the management quality of firms, are continuously monitored by markets and are reflected in their equity prices and CDS spreads, perhaps providing more sensitive assessments of the institutions' future prospects and their interactions.[18] This section investigates how markets perceive FIs, attempting to discern whether such market-based measures gave any advanced knowledge of the impending difficulties, or if they can be used to determine when the disruptions become systemic. The analysis that follows relies on market perceptions of the FIs' risk and starts with simple measures using individual institutions before moving to more sophisticated measures that account for the interactions among a number of FIs.

Brief Taxonomy of Credit Risk and Tail-Risk Models

The different tools to assess systemic risks by examining FI risks, both individually and collectively, are summarized in Table 3.2. One family of tools includes the contingent claims approach (CCA), which explicitly accounts for the inherent uncertainty in balance sheet components, and links the value of equity, assets, and debt in an integrated way.[19] Generally, this set of models takes the volatility of equity prices as the starting point and derives other risk measures from it.[20] This approach has been widely applied in the analysis of credit risk, as it permits the estimation of asset values and asset volatility (that are otherwise not directly observable), which are used to provide an equity market-based assessment of default risk (Box 3.1). The incorporation of uncertainty and asset volatility are important elements in risk analysis since uncertain changes in future asset values relative to promised payments on debt obligations ultimately drive default risk and credit spreads—important elements of credit risk analysis and, further, systemic risk.

Another set of tools uses equity options prices (or equivalently, their implied volatility) as starting points. Examining higher moments of equity options is critical to account for nonlinearities of

[18]These spreads are quoted as a spread over the equivalent maturity U.S. treasury securities for U.S. institutions. For institutions in various countries, they are a spread over the comparable government security. Note that all market-traded prices (CDS spreads, equity, and equity options) also contain a liquidity risk component—the risk that an investor may or may not be able to trade at a price close to the last traded price. Such risks rise during periods of stress.

[19]CCA is a generalization of the option pricing theory pioneered by Black-Scholes (1973) and Merton (1974). The approach is based on three principles: (1) the values of liabilities are derived from the value of assets; (2) liabilities have different characteristics (i.e., senior and junior claims); and (3) the value of assets follows a stochastic process.

[20]These include risk exposures in risky debt, probabilities of default, distance-to-distress, the present value of the expected loss (i.e., the value of the implicit put option), spreads on debt, and the sensitivity of the implicit options to the change in the underlying asset and other sensitivity measures.

Table 3.2. Taxonomy of Credit Risk Models

	Univariate Measures					Multivariate Measures	
	Accounting balance sheet	Merton contingent claims approach model	Moody's KMV	*Option*-iPoD[1]	CDS-based PoD	Higher moments and multivariate dependence[2]	Time-varying multivariate density distress dependence and tail risk[3]
Calibrated using	Accounting data	Historical equity volatility[4]	Historical equity volatility	Equity option data	CDS and recovery rate	Equity option data	Individual CDS-PoDs and/or stock prices[5]
Outputs for individual institutions	(1) Financial soundness indicators; and (2) Other ratios	(1) Implied asset distribution; (2) Implicit put option; and (3) Credit spreads	EDF and EDF-implied CDS	(1) Univariate probability density function; (2) PoD; and (3) Probability of default hitting leverage threshold	PoD	n.a.	n.a.
Multiple institutions	n.a.	n.a.	n.a.	n.a.	n.a.	(1) Recovers multivariate density; and (2) Dependence measures between institutions	(1) Recovers multivariate density and thus common distress in the system: JPoD, bank stability index; (2) Distress dependence matrix; and (3) Probability of cascade effects triggered by particular financial institution.
Advantages	Widely available	Simple way to measure and analyze credit risk	(1) Time-varying volatility; and (2) Provides EDFs that can be mapped to ratings	Accounts for deviations from log-normality and has model-determined default barrier	Measures map to disruptions in markets	(1) Appears to lead CDS; and (2) Generates systemic risk measures	(1) Able to use other PoDs; (2) Multiple outputs; (3) Includes linear and nonlinear dependence; and (4) Endogenous time-varying distress dependence
Shortcomings	(1) Static backward looking; and (2) Accounting definitions can differ across countries	(1) Constant asset volatility unrealistic; and (2) Assumed default barrier	Assumed default barrier	Requires options quoted at a variety of strikes not directly comparable with one-year default probability estimates	Uncertain recovery rate	Potentially affected by government capital injections or dilution	Drawbacks attached to the inputs (e.g., PoDs) would affect the output
Estimated in this chapter	"Fundamental" Characteristics of Intervened and Nonintervened Financial Institutions	Box 3.1	Box 3.1	Box 3.2	n.a.	Box 3.3	Box 3.4

Source: IMF staff.

Note: CDS = credit default swap; EDF = expected default frequency; JPoD = joint probability of default; *option*-iPoD = option-implied probability of default; PoD = probability of default. The literature on credit-risk modeling is large; see Lando (2004) and Gray and Malone (2008), among others, for an overview of popular models. The table describes the features of the models presented in the chapter. Enhanced contingent claims approach models include extensions of the Merton model to include time-varying volatility (like MKMV) and other extensions. Some equity option-based credit risk models, such as Hull, Nelken, and White (2004), explicitly use two or more equity options to calibrate higher moments of the underlying asset distribution. Other equity-option-based credit risk models, such as Zou (2003), and *option*-iPoD, calibrate the entire probability density function of the underlying asset.

[1]Capuano (2008).

[2]Gray and Jobst (forthcoming).

[3]Segoviano and Goodhart (2009).

[4]Model can use implied volatility from options.

[5]Model can use PoDs estimated from alternative methods, not only CDS spreads.

changes of default risk and thus provides a tool to observe when FIs' defaults may become systemic. The option-implied probability of default (*option*-iPoD), featured below, uses equity option prices to infer default probabilities on individual FIs, with the advantage that determining when

Box 3.1. Modeling Risk-Adjusted Balance Sheets: The Contingent Claims Approach

Forward-looking equity market information can be combined with balance sheet information to estimate risk-adjusted balance sheets that provide useful and timely indicators of default probability and credit risk.

The contingent claims approach (CCA) is a risk-adjusted balance sheet framework where equity and risky debt of a firm or financial institution derive their value from assets, which are uncertain. The total market value of assets at any time is equal to the market value of the claims on the assets, which is represented by equity, and risky debt maturing at time *T*:

Assets = Equity + Risky Debt

Asset values are uncertain and in the future may decline below the point where debt payments on scheduled dates cannot be made. In the CCA, the equity can be modeled and calculated as an implicit call option on the assets, with an exercise price equal to the promised debt payments, *B*, maturing in *T-t* periods. The risky debt is equivalent in value to default-free debt minus a guarantee against default. This guarantee can be calculated as the value of a put on the assets with an exercise price equal to *B:*

Risky Debt = Default-Free Debt – Debt Guarantee

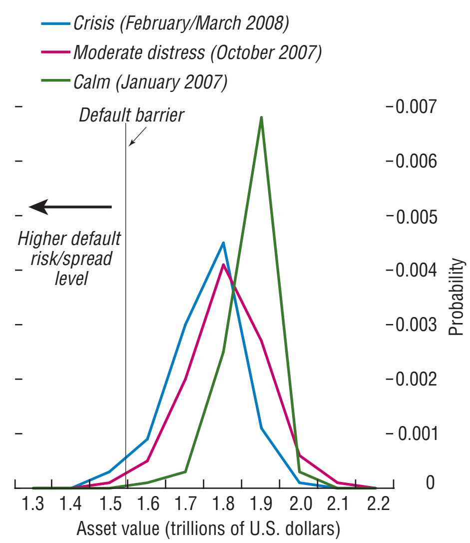
In the CCA framework, the value of the equity can be computed as the value of an implicit call option and the value of the debt guarantee can be modeled as an implicit put option. The balance sheet components can be calibrated by using the value of market capitalization, the volatility of equity, and information from the balance sheet to define the "distress" or "default barrier." Using two equations and two unknowns, the implied asset level and implied asset volatility can be calculated. The credit risk indicators can be calculated, i.e., default probabilities, spreads, distance-to-distress. Robert C. Merton proposed the CCA framework and the simple model is known as the Merton model, where a constant volatility of assets is assumed.

Example: Assuming that Assets = \$100, volatility σ = 0.40 (40 percent), distress barrier *B* = \$75, *T* = 1 (one year), then the value of the equity is \$32.36, the value of risky debt is \$67.63, and the credit spread is 534 basis points.

The Merton model has been extended in many directions, including models where the asset volatility is not constant. For example, information from equity options can be used. The figure shows the implied asset distribution (in billions of dollars) for Citigroup in January 2007 (calm period), October 2007 (moderate distress period), and February/March 2008 (crisis period). As can be seen, the left tail skew is very small in the calm period (credit default swap [CDS] spread was 12 bps), but it increases in the moderate distress period (CDS spread was 124 bps) and is even larger in the crisis period (CDS spread over 200 bps).

Moody's KMV is based on a CCA-type model.

Implied Asset Distribution: Citigroup



Sources: Bloomberg L.P.; Moody's KMV; and IMF staff estimates.

Note: Implied asset distribution from equity option prices from Bloomberg for three dates and the default barrier estimated by Moody's KMV.

Note: Dale Gray prepared this box.

the institution goes into default (the default barrier) is also derived within the model in line with the observation that the value of debt also moves with market conditions (Box 3.2). This is an advance over other models in which a default barrier is assumed to be fixed.

Two general methods are then employed to examine FI interdependence and thus the incidence of systemic risk. The first uses higher moments in equity and implied asset distributions calibrated from equity options. Equity option information can be used to calculate tail-risk indicators for individual institutions as well as between institutions. These tail risks encompass both the skewness and the kurtosis and thus adjust to stressful conditions. More accurate indicators of interdependence of FIs are obtained by "tail dependence" measures as compared to simple correlation measures (Box 3.3).[21]

The second method calculates a joint probability of distress (JPoD) among a group of FIs and then a banking stability index (BSI), which estimates the probability of default (PoD) of other FIs if one institution defaults. Instead of equity volatility or equity options, CDS spreads are used to calculate the PoD for individual institutions and as an input to the model, though the general technique could be applied using equity prices (Box 3.4). Once the JPoDs are estimated, there are three potential outputs: the BSI; a matrix of (pairwise) distress dependencies; and the probability of one or more FIs becoming distressed if a specific FI becomes distressed. Examples of the second application are discussed in Chapter 2, which presents a matrix of distress dependencies before the crisis and at different periods since the crisis began (Table 2.8). The third output, probability of cascade effects whereby the distress of a particular FI affects another, is presented below.

One disadvantage of using market data (CDS spreads and equity options) to infer PoDs (or other tail behavior) in the current period is the recent extension of government financial guarantees on FI debt, as this can transfer risk to the sovereign entity—thus sharing the credit risk of FIs with the other debt holders. For example, this alters the interpretation of CDS data for FIs.[22]

The use of several different tools and supervisory examinations to analyze similar FI risks is helpful because if the basic conclusions are the same, then policymakers will have more comfort in using the tools for their analysis of systemic risks. Moreover, since some tools may not be appropriate under certain conditions (e.g., when government guarantees are in place or when short-selling restrictions are imposed on equities), it is useful to know which techniques are still valid.

Measures of Risk Based on Individual Financial Institutions

Conditional Correlations and Cluster Analysis

A simple starting point for potential systemic connections among FIs is to use conditional correlations and cluster analysis. Observing how (or whether) these measures change over time may provide supervisors with information about which institutions' failures would affect others. Based on a sample of 45 individual FIs, equity returns are used to investigate the conditional correlations and clusters among them during various intervals beginning in January 2005.

[21]Although higher (Pearson) correlation coefficients are commonly used to measure potential spillover effects and systemic risks, these conventional correlations are inaccurate measures of dependence in the presence of skewed asset distributions and higher volatility. The standard correlation coefficient detects only linear dependence between two variables, making it ill-suited for the examination of systemic risk when extreme events occur jointly and in a nonlinear fashion.

[22]In principle, one reason to choose either equity-based information or CDS spreads to deduce PoDs would be if there were a lead-lag relationship showing one as providing default information earlier. Linear and nonlinear Granger causality tests suggest unidirectional Granger causality from stock returns to CDS changes, although there are no clear-cut dynamics in all sample cases (Baek and Brock, 1992; and Hiemstra and Jones, 1994).

The conditional correlation matrices are based on residual equity returns, which are free from world and local market effects and volatility.[23] Cluster analysis (also known as "look-alike groups") attempts to determine the natural grouping (a "class") that captures similarity or distance between observations. In particular, the analysis is used to determine groups of FIs where their residual equity returns behave in similar ways. These companies can then be considered to be "similar" institutions.[24] The drawback for both correlation and cluster analysis is that even after controlling for world and local market effects and volatility, the methodology may not fully capture nonlinear dependencies in the data.[25] Despite this (important) caveat, the conditional correlation and cluster analysis show a relatively higher degree of co-movements of most FIs during the stress periods than during normal periods.

Specifically, a comparison between different stress periods indicates the following:

Table 3.3. Correlations Among 45 Financial Institutions During Different Stress Periods

	Number of Coefficients within the Range	
Correlation coefficient values	0.5–0.6	>0.6
Post approval of the Troubled Assets Relief Program (October 3, 2008–December 31, 2008)	23	10
Lehman's collapse to the approval of the Troubled Assets Relief Program (September 15, 2008–October 2, 2008)	87	68
Rescue of Bear Stearns to Lehman's collapse (March 17, 2008–September 12, 2008)	73	52
Bankruptcy of two hedge funds of Bear Stearns to rescue of Bear Stearns (August 1, 2007–March 16, 2008)	41	19
Shanghai stock market correction to the bankruptcy of two hedge funds of Bear Stearns (February 27, 2005–July 31, 2007)	16	2
Before Shanghai stock market correction (January 3, 2005–February 26, 2007)	17	8

Sources: Bloomberg L.P.; and IMF staff estimates.

- The conditional correlations show that the highest correlations among FIs occurs in the period between Lehman's bankruptcy on September 15, 2008 and the approval of the Troubled Assets Relief Program (TARP) on October 2, 2008.[26] The period between the rescue of Bear Stearns and Lehman's collapse ranks second in the context of high correlations among institutions (Table 3.3).
- The average variance in three clusters or groupings of FIs rises from 1 in a normal period (before the Shanghai stock market correction) to 2.7 in the stress period (after the Lehman bankruptcy).
- The within-class variance in cluster 1, where most FIs are grouped together, is 86 percent higher during the stress period than during the normal period (Table 3.4).
- The tree diagrams in Figure 3.4 for the groups of FIs show the greater extent of cross-border co-movement and interconnections

[23]To concentrate on the extra correlation among these 45 institutions, three steps are taken to get residual returns. Specifically, first regress each institution's equity return on the return on the world equity index and the return on the relevant local equity index, respectively. Thus, the data is first purged by performing the following regression:

$$r_i = c + b_1 W_i + b_2 L_i + res_i$$

Where the dependent variable r is the equity return for each of the institutions at time t, W represents the return on the MSCI world equity index and L represents the return on the relevant local equity MSCI index. Second, GARCH(1,1) models are performed to account for excess kurtosis and volatility clustering, resulting in new residual returns. Third, conditional correlations are estimated conditioned on negative MSCI world equity returns to capture more directly systemic risks.

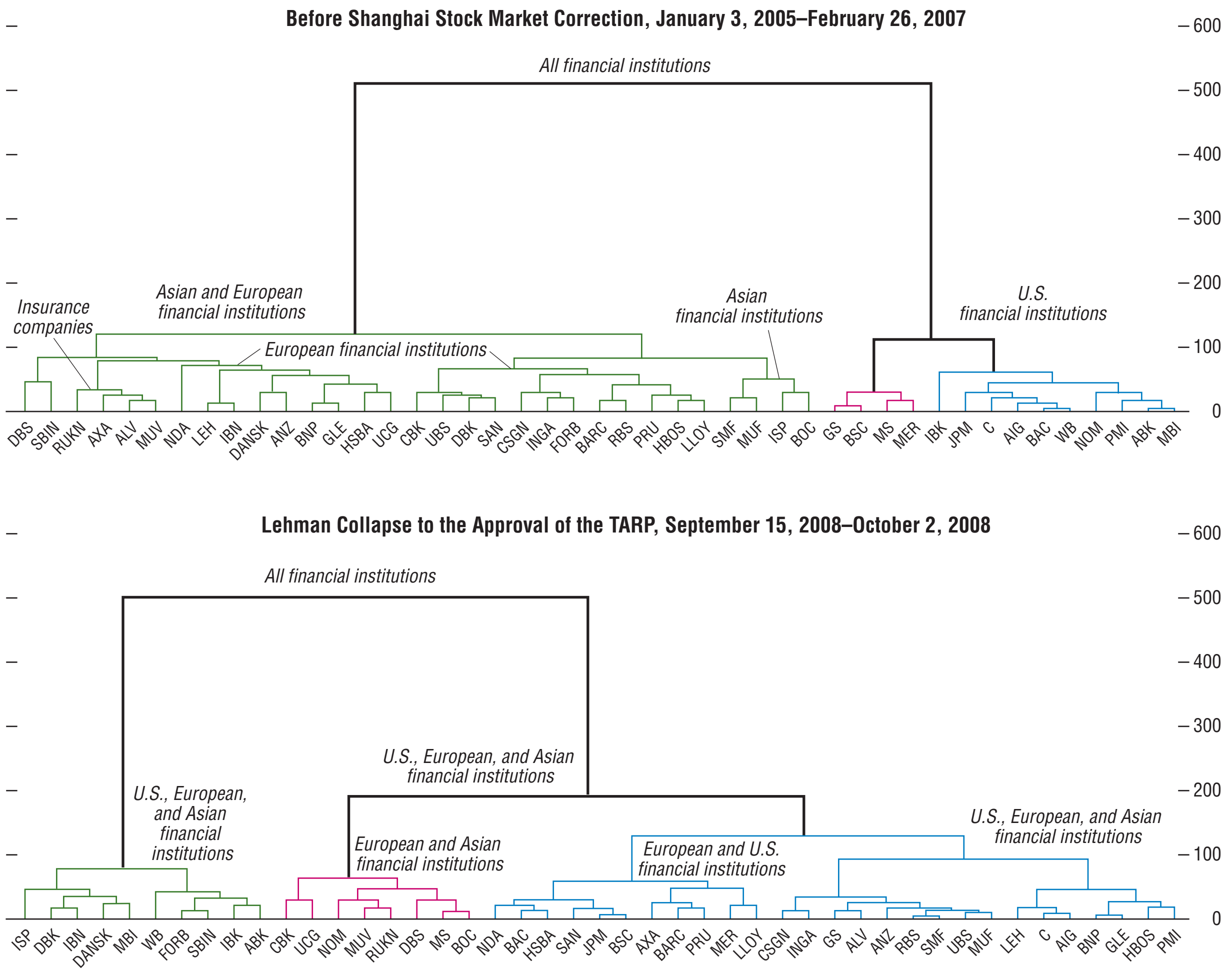
[24]Though many types of cluster analysis exist, the agglomerative hierarchical cluster analysis is the most popular. This approach combines FIs into groups of similar institutions. The algorithm initially views each observation as a separate group (giving N groups each of size 1). The closest two groups in terms of the Euclidean distance are then combined (giving N–2 groups of 1, and one group of 2). This process continues until all observations are combined into one group (of N financial institutions).

[25]As argued by Forbes and Rigobon (2002), correlation coefficient can be biased during periods of high volatility.

[26]The TARP is the U.S. government program to purchase assets and equity from financial institutions in order to strengthen the financial sector.

Figure 3.4. Dendogram

(Euclidean distance)



Sources: Bloomberg, L.P.; and IMF staff estimates.

Note: A dendogram (tree diagram) is used to illustrate the arrangement of the clusters and determine groups of financial institutions whose residual equity returns behave in similar ways. These companies are considered to be similar institutions. Sample of 45 institutions, see Annex 3.2.

among FIs during the stress period.[27] During the normal period, FIs are mainly clustered based on geography and their primary line of business, as indicated by obvious divisions between the U.S. FIs (which are further divided into U.S. investment banks in the middle of the tree in magenta and U.S. commercial banks and insurance on the right-hand side of the tree in blue) and a combination of the insurance, European-Asian FIs (on the left-hand side of the tree in green). During the stressful period, however, FIs are clustered based completely on cross-border groupings. In particular, the FIs cleanly divide into the European-Asian group (in the middle of the tree in magenta), a smaller group of U.S.-

[27]The tree diagram (dendrogram) is used to illustrate the arrangement of the clusters produced by a clustering algorithm. It is applied here to determine groups of financial institutions where their residual returns (based on the same data as the conditional correlation analysis) behave in similar ways.

Table 3.4. Cluster Analysis

	Before Shanghai Stock Market Correction (January 3, 2005–February 26, 2007)			Lehman's Collapse to the Approval of the Troubled Assets Relief Program (September 15, 2008–October 2, 2008)		
Cluster[1]	1	2	3	1	2	3
Number of institutions	31	4	10	27	10	8
Within-cluster variance of residual returns	1.31	0.77	0.89	2.45	3.04	2.60
Average variance across clusters		0.99			2.70	

Sources: Bloomberg L.P.; and IMF staff estimates.
[1]Three clusters are determined automatically by the clustering algorithm.

European-Asian FIs (on the left-hand side of the tree in green) and a larger combination of U.S.-European-Asian FIs (on the right-hand side of the tree in blue). In the latter group, the bloc contains subgroups made up of U.S.-European institutions and U.S.-European-Asian groups.

In sum, although these techniques are fairly basic and have a number of caveats, they can be used to judge whether certain groups of institutions' returns are perceived as being more similar during periods of stress, and thus to determine the prospects for spillovers to the group in the case of a single institution's distress. Moreover, the tree diagrams can be used to provide a rough idea of which institutions are viewed by markets as having similar return characteristics and can show how these relations may change over time.

Option-iPoD

As noted earlier, and despite their broad use, analyses based simply on correlations are less than ideal when dealing with extreme downside movements, as fat tails tend to develop. Several models provide a more general approach by looking at the characteristics of the entire distribution of asset returns. A number of those models do this univariately (one firm at the time). As described in Table 3.2, an important shortcoming of these models is that they require the modeler to assume a specific value of debt, below which the institution will fail. This assumption is relaxed in the *option*-iPoD model as the default-barrier is determined within the model of univariate probability distributions.

Applied to five institutions during the current crisis, the *option*-iPoD model would have had provided some early warning signals of distress for some of the key FIs (Box 3.2). On several occasions prior to their respective "default events," the *option*-iPoD jumped by a multiplicative factor for several of the institutions that have required intervention.[28] Ex post, the pattern of warning signals suggested that Bear Stearns, Merrill Lynch, and Wachovia were perceived by markets as having a heightened chance of default before their difficulties were announced, although these signals were less severe for Lehman and Citigroup. Although the model does not give definitive signals for all five institutions examined, an estimated leverage ratio from the model shows that it diverged from the balance sheet measure of leverage well before each institution's "default event." This suggests that an estimate of the implied leverage may be one measure that better reflects the risks being undertaken by the firm on a real-time basis than other accounting-based ratios.

The models described above still suffer from the limitation that they focus on individual FIs without addressing how groups of FIs might be related to one another—the key component for systemic risks. The sections below relax those constraints by jointly examining groups of FIs.

[28]Default events are listed in Annex 3.3.

Box 3.2. *Option*-iPoD Measures of Risk Across Financial Institutions

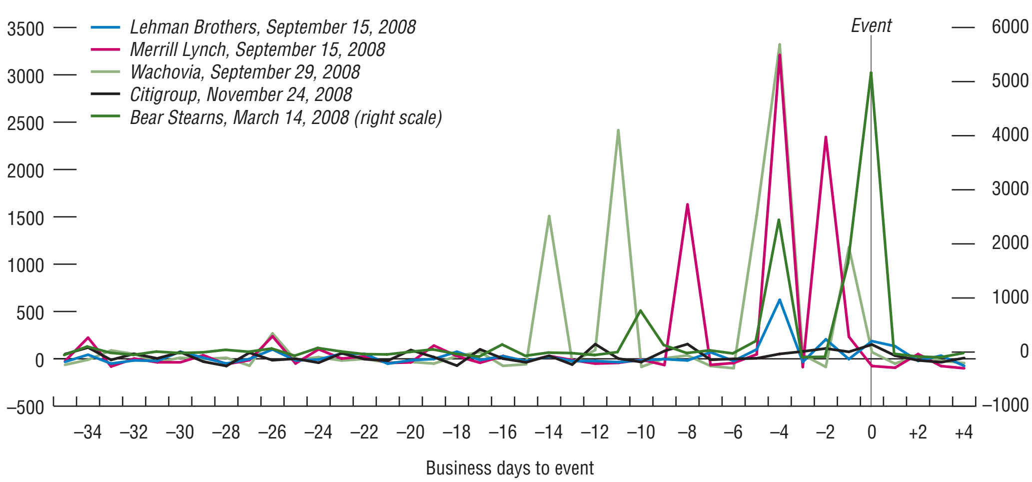
This box introduces two new risk indicators based on the prices of equity-options.[1] *The option-iPoD measures the probability of default, while the option-leverage measures the likelihood that the leverage ratio will cross a prespecified threshold. In the current crisis, these measures have performed well.*

The methodology estimates the risk-neutral probability density function of the value of the assets of an individual institution, which is used to obtain the probability of default, the *option*-iPoD, and the expected development of balance sheet variables, such as assets, equity, and leverage.[2]

The probability density function allows one to compute the risk-neutral likelihood that the ratio of the estimated market value of assets to equity, the *option*-leverage, will cross a prespecified threshold. This likelihood can be interpreted as a forward-looking measure of capital-at-risk, and thus, together with *option*-iPoD, might become a useful tool in the supervision of financial institutions.

The added value of this methodology resides in the relaxation of two key assumptions, typically imposed in related structural credit-risk frameworks: a prespecified probability density function of the value of the assets and a prespecified default barrier, an assumed value below which the firm is expected to default. Following Kullback (1959) and Kullback and Leibler (1951), an optimization problem in which the current market prices of equity-options represent the problem's constraints is solved. As a consequence, a nonparametric density function is obtained that captures the well-documented deviations of asset prices from log-normality.[3]

Option-iPoD: An Indication of Impending Failure
(Percentage change with respect to the previous day)



Sources: Bloomberg, L.P.; and IMF staff estimates.
Note: *Option*-iPoD is the probability of default implied by option prices.

Note: Christian Capuano prepared this box.

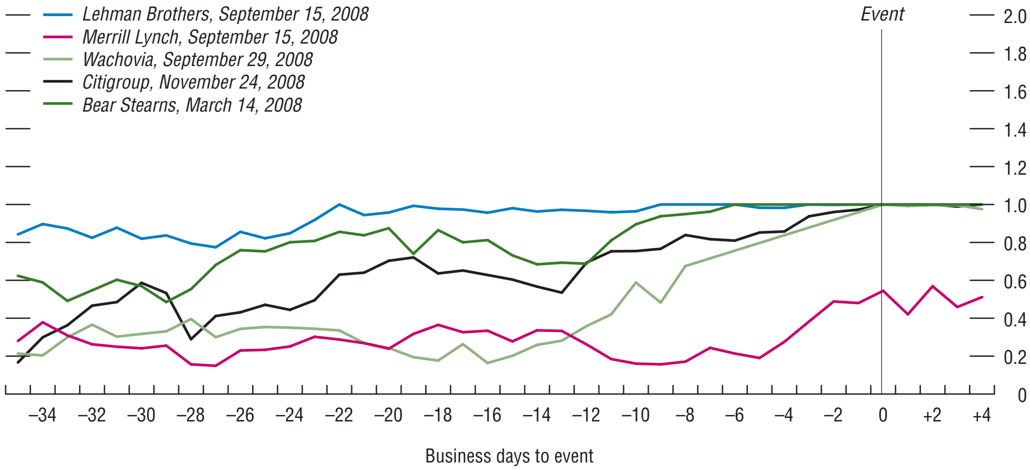
[1]The methodology is developed in Capuano (2008).

[2]Capuano (2008) describes how to extend the methodology to obtain useful output for risk management, such as an estimated credit-spread and the so-called Greek letters.

[3]This type of optimization problem is known as a minimum cross-entropy problem. Cover and Thomas (2006) discuss the statistical properties of cross-entropy, which, in intuitive terms, can be interpreted as a measure of relative distance between two probability density functions. Buchen and Kelly (1996) discuss a similar framework to extract a probability density function from equity options. Because of put-call parity, a well-known no-arbitrage relationship, researchers need to specify whether they want to use call or put prices (or a combination) as constraints.

Box 3.2 *(continued)*

Option-Leverage: A Forward-Looking Measure of Distress
(LIkelihood option-Leverage > 30)



Sources: Bloomberg, L.P.; and IMF staff estimates.
Note: Option-leverage is the ratio of the estimated market value of assets to equity. Likelihood option-leverage > 40 for Bear Stearns and Lehman Brothers.

The economic structure of the model follows Merton (1974).[4] Most notably, instead of prespecifying a value for the default barrier—which is calibrated, in general, to the current value of on-balance-sheet liabilities—a key improvement over existing methodologies is to use the linear independence of the option-price constraints to treat the default barrier as a free parameter, and obtain a default barrier that is optimally estimated within the model.

Since financial institutions carry out extensive off-balance-sheet activities, an optimally estimated default barrier is particularly attractive for financial stability purposes because it allows one to estimate a market-implied capital structure, which in times of distress might be expected to significantly differ from the last reported balance sheet.

In order to investigate how this methodology has performed during the current financial crisis, a countdown to the event has been constructed—starting 35 business days prior to their collapse—for Bear Stearns, Lehman Brothers, Merrill Lynch, Wachovia, and Citigroup.[5]

For this purpose, the PoD implied by the price of equity options is estimated by focusing on the contract whose expiration was the closest to the day of the event. In addition, after optimally estimating the capital structure of the selected institutions, the likelihood that option-leverage would hit a prespecified threshold by the expiration of the option contract is computed.[6]

[4]In its simplest version, Merton (1974) postulates that the value of equity corresponds to the value of a call option contract written on the assets of the institution, with exercise (strike) price corresponding to the institution's on-balance-sheet liabilities.

[5]A robustness check would need to be conducted with an extended sample, including institutions that have not collapsed. In this sample, data availability on specific option contracts prevents the countdown to be further extended.

[6]While the selected thresholds cannot be directly compared with the Federal Deposit Insurance Corporation Tier 1 leverage ratio, which is based on Tier 1 capital, they nonetheless provide a useful insight on the current capital structure as perceived by the equity options market.

Box 3.2 *(concluded)*

In the selected episodes, *option*-iPoD has performed well (see figure). On several occasions prior to the event, and for all institutions, *option*-iPoD jumped up by a multiplicative factor. Ex post, the pattern of warning signals seems to have been particularly informative for Bear Stearns, Merrill Lynch, and Wachovia, while less so for Lehman Brothers and Citigroup.

The analysis of the likelihood that *option*-leverage will cross a specific threshold provides an economic interpretation of these events (see figure). During the countdown, the divergence between the reported balance sheet and the estimated capital structure of the selected institutions became more pronounced.

This appears particularly true for Bear Stearns and Lehman Brothers, suggesting that markets might have been aware of the significantly weaker liability structure of these investment banks and of the associated potential risks. Early during the countdown, this divergence also became evident for Citigroup and Wachovia.

In consideration of the forward-looking nature of this methodology, the proposed risk indicators appear to have been performing well during the current crisis, providing early warning signals of distress. When complemented with other market and nonmarket information, *option*-iPoD and *option*-leverage might become a useful tool for the daily surveillance of financial and nonfinancial institutions.

Measures of Risk Based on Groupings of Financial Institutions

The analysis based on market perceptions presented thus far, based on CDS and equity prices, has been for individual FIs. The sections that follow address these issues from an aggregate perspective by looking at measures based on CDS and equity prices for several groupings of global FIs. While a formal test of this dynamic relationship is not performed in this chapter, and is reserved for future work, the subsections present snapshots of how various potential measures of systemic risk appear to have coincided during the current crisis. Finally, the analysis is extended to include risks in emerging markets, as these countries were viewed by some as being “decoupled” during the earlier part of the crisis.

Tail Risks of Financial Institutions Based on Equity Options

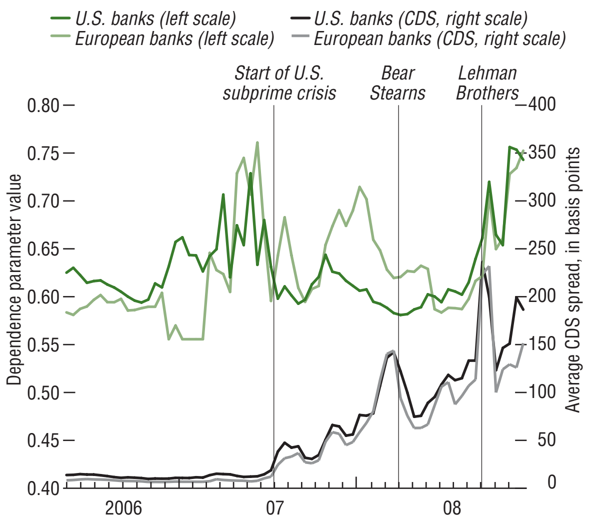
As noted above, the notion of systemic risk requires moving away from traditional measures of correlation between different financial entities toward nonlinear, time-varying measures of dependence, particularly as financial markets become more integrated. In addition, standard correlations do not account for the variation over time in the degree of dependence, especially during episodes characterized by rising uncertainty about asset prices and illiquidity of overall financial markets. In times of stress, illiquid markets sap diversification opportunities contributing to increased correlation, making accurate estimates of the impact of higher volatility on asset prices difficult to interpret. For these reasons, the examination of tail dependencies is likely a better choice when attempting to discern systemic risks.

Since equity is the most junior contingent claim on the future asset performance of firms (equity holders are paid last from the firm’s profits), equity derivatives contain forward-looking information of market participants’ perceptions of downside risk. Moreover, the information content of prices has shifted from price levels to higher moments such as the variance, skewness, and kurtosis over the course of the crisis as investors reposition themselves in response to uncertainty and information asymmetries (Kim and Verrecchia, 1997). Thus, this section uses implied volatilities from at-the-money equity options to examine simultaneous co-movements in the left-hand tails of the equity distribution as a measure of "tail dependence" and the magnitude of systemic risk.[29] Implied volatilities can, in principle, be more revealing of information pertinent to systemic risks than equity prices alone. More specifically, the combined probability of the average co-movement as well as very large negative shocks to several financial institutions can be estimated (Box 3.3).

The examination of multivariate dependence highlights two periods of high systemic risk induced by large tail events—the buildup prior to the subprime fallout (June 2007) and the largely coincident period associated with the collapse of Lehman Brothers (September 2008). Extreme co-movements of equity prices (Figure 3.5) did not follow but preceded the bailout of Bear Stearns. From a visual inspection, the results also seem to indicate that higher moments from equity price data may lead price data on credit-sensitive assets and implied default probabilities of CDS spreads, though more thorough analysis will need to be done to verify this claim.

These indicators also show that systemic risk has been increasing since February 2007. Average dependence among the global sample of banks and insurance companies (Core 1 and Core 2) increased by almost 30 percent, while joint tail risk declined by about the same order of magnitude (Figure 3.6), indicating that co-movements of *large* changes in equity volatility occur *more frequently*. This means that extremes (and aberrant swings in equity risk) have become the norm rather than the exception over the last year. As average dependence continues to increase above the historical trend, the

Figure 3.5. U.S. and European Banks: Joint Tail Risk of Implied Volatilities



Sources: Bloomberg, L.P.; and IMF staff estimates.
Note: Sample period: 5/18/2005–12/31/2008 (946 obs.) of implied volatility derived from at-the-money equity put options of three banks in each the United States and Europe. Rolling window (one year) estimation with bi-monthly updating. The line shows the estimated joint tail dependence ("asymptotic tail behavior") based on a nonparametric specification of a trivariate extreme value distribution (logistic model) with a convex dependence function whose upper/lower limits are derived under complete dependence/independence. U.S. banks = Bank of America, Citibank, and JPMorgan Chase & Co. European banks = Deutsche Bank, Royal Bank of Scotland, and UBS. CDS = credit default swap.

[29]Note that the use of implied volatilities from out-of-the-money equity put options would be a superior input variable for our approach. Due to the lack of continuous prices on non-U.S. banks, we have chosen at-the-money options instead.

recent surge of tail risk (from historic lows)—together with the sharp increase in skewness and kurtosis—represents elevated systemic risks. In sum, these indicators of systemic risk appear to have detected rising, and now elevated, risk, potentially providing some advance notice for policymakers.

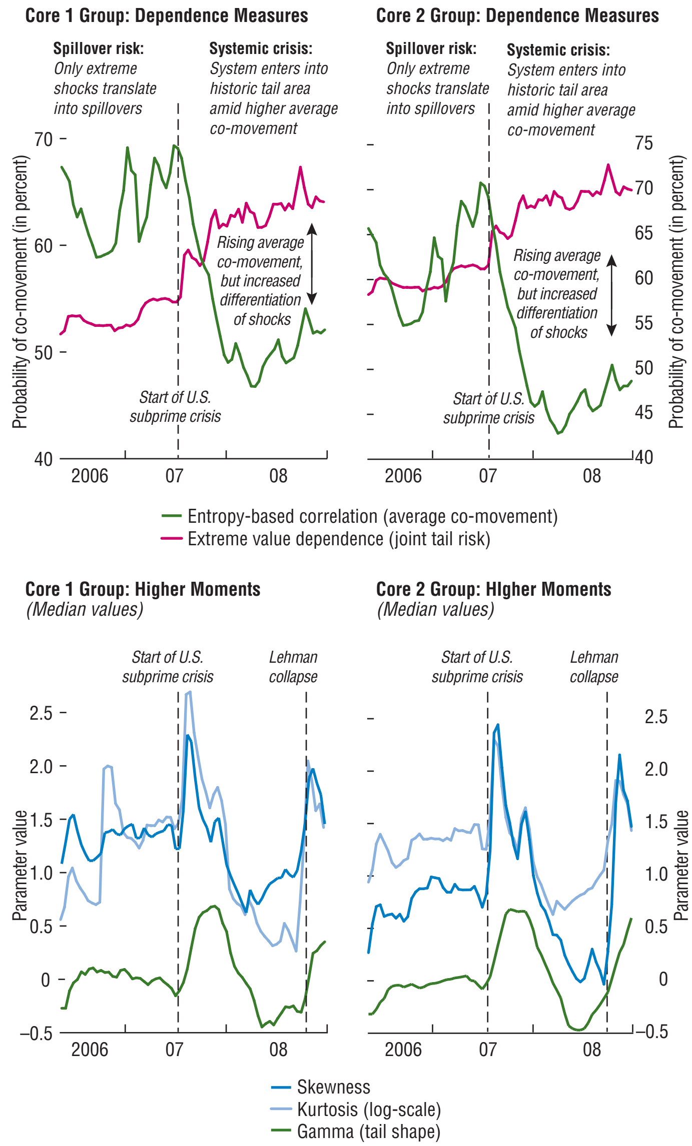
Common Distress in the System and Cascade Effects

This section models the joint distress among several specific groups of FIs using a slightly different technical approach than the one above (Segoviano and Goodhart, 2009). The joint statistical distribution of the implied asset values of a group of FIs—the financial system multivariate density (FSMD)—implicitly characterizes both the individual and joint asset value movements of a chosen portfolio of FIs (see Box 3.4).[30] The FSMD thus captures interdependence among the FIs' distress proxy variable (the probability of default), which captures the FIs' linear (correlations) and nonlinear distress dependence and their changes throughout the economic cycle, reflecting the fact that dependence increases in periods of distress—a key technical improvement over traditional risk models. Using the joint (multivariate) distribution, other measures of financial stability can be derived: (1) common distress of the financial institutions in a system; (2) distress between specific institutions; and (3) distress in the system resulting from distress in a specific institution.[31] The three measures represent an advantage over the analysis of any single one of them, since one can identify how risks

[30]The FSMD is recovered using a particular technique, the consistent information multivariate density optimizing (CIMDO) methodology (Segoviano, 2006), which is a nonparametric framework based on the cross-entropy approach (Kullback, 1959).

[31]The second measure—distress between specific institutions—is analyzed in Chapter 2. These conditional probabilities, summarized in a distress dependence matrix, should not only be seen as an indication of bilateral stress among FIs, since the overall dependencies across the institutions in the sample are included in the multivariate distribution from which the matrix is constructed.

Figure 3.6. Higher Moments and Multivariate Dependence of Implied Equity Volatility



Sources: Bloomberg L.P.; Datastream; and IMF staff estimates.

Note: Estimates are based on implied volatility derived from at-the-money equity put options. Rolling window (one year) estimation with bi-monthly updating. The gamma parameter represents the shape parameter of the generalized extreme value distribution, estimated via the linear ratio of spacings method. The higher the tail shape parameter ("gamma"), the greater the univariate tail risk. The entropy-based correlation coefficient is based on the expected mutual information and the joint distribution of individual entropies of each constituent time-series vector. It represents the nonparametric estimate of general multivariate dependence. In contrast, the nonparametric estimate of multivariate extreme value dependence represents the joint tail risk of ordered maxima. For Core 1 and Core 2 Groups, see Annex 3.2.

Box 3.3. Higher Moments and Multivariate Dependence of Implied Volatilities from Equity Options as Measures of Systemic Risk

This box describes the use of equity options to evaluate the magnitude of systemic risk jointly posed by financial institutions based on a measure for the joint tail dependence across institutions and their average co-movement.

If firms are leveraged, the seniority of creditors implied by the capital structure suggests that equity is the most sensitive contingent claim on asset performance. Thus, we would expect equity prices in cash and derivatives markets to reflect even small changes in expectations of default risk.[1] This becomes even more important during times of stress, when the ability to use options as forward looking measures to hedge the downside risk of equity is more valuable (Gray and Jobst, forthcoming).

Recent research finds that if the volatility of equity prices is negatively skewed (left-tailed), so are the implied underlying asset distributions, which in turn are related to default risk (see Box 3.1). Thus, higher moments of equity price dynamics better account for nonlinearities of changes in default risk if large risk exposures become more frequent than suggested by the assumption of normal distributions. This means that accounting for higher moments of equity options can deliver important insights about significant changes in asset values of firms, which, in the presence of fat tails, results in a higher probability of default, and thus, higher spreads (Zou, 2003). Fat tails would indicate that market perception of severe downside equity risk has increased, and estimating economic capital based on volatility alone becomes unreliable, upsetting the basic tenets of the risk-based regulatory framework.

Since the concept of conventional correlation can give misleading information about systemic risks if distributions are skewed, it is important to use higher moments (derived from individual firms' equity options) to obtain nonlinear measures of dependence (Jobst, 2007a). Two models accounting for time-varying dependence are presented: (1) multivariate extreme value dependence (based on a limit law for joint asymptotic tail behavior); and (2) a dependence measure based on "entropy," which is a measure dispersion. While the former measures changes of joint tail risk, the latter delivers a nonparametric estimate of general multivariate dependence.

First, a nonparametric measure of joint tail dependence based on multivariate extreme value theory is defined in order to quantify the possibility of common extreme shocks (Coles, Heffernan, and Tawn, 1999; Poon, Rockinger, and Tawn, 2004; Stephenson, 2003; and Jobst, 2007b). As an integral part of this approach, this dependence structure links the univariate marginal distributions in a way that formally captures joint asymptotic tail behavior. Using the empirical distribution avoids problems associated with modeling specific parameters that may or may not fit these distributions well—a problem potentially exacerbated during stressful periods.[2] This method of measuring "tail dependence" is better suited to analyzing extreme linkages of multiple entities than the traditional (pairwise) correlation-based approach.

Second, average dependence in the multivariate case based on the concept of entropy is

Note: Dale Gray and Andy Jobst prepared this box.

[1]Since the capital structure of firms establishes a natural linkage between the cost of insuring against default risk (via credit default swap spreads), on one hand, and claims on future earnings (via equity), on the other, changes in expectations of future firm performance influence the market values of both.

[2]This approach is distinct from previous studies of joint patterns of extreme behavior. For instance, Longin (2000) derives point estimates of the extreme marginal distribution of a portfolio of assets based on the simple correlation between the series of individual maxima and minima. However, in the absence of a principled standard definition of order in a high-dimensional vectorial space, the simple aggregation of marginal extremes (without considering a dependence structure) does not necessarily concur with the joint distribution of the extreme marginal distributions. See also Embrechts, Lindskog, and McNeil (2003) regarding this issue.

investigated. Since the entropy of a set of variables is maximized if observed data are uniformly distributed, minimizing joint entropy indicates the maximum degree of dependence. In order to derive an overall measure of dependence between several variables (called "expected mutual information"), the effects of lower dependences are eliminated from the sum of both the overall entropy and the individual entropy of each financial institution's univariate marginal distribution by subtracting all joint entropies that do not include all variables (Preuss, 1980; and Theil, 1969). A scaled entropy-based measure of dependence (called "entropy correlation") can then be computed based on the reciprocal of the marginal contribution of each univariate entropy to the expected mutual information and analyzed. This method is suitable to extend the concept of "average dependence" to the multivariate case.

In the chapter, both models are applied to the implied volatilities of at-the-money equity put options of all financial institutions in our samples (Core 1 and 2). Our main findings confirm that both models yield complementary findings that provide comprehensive and timely information about the magnitude of systemic risk and possible developments going forward.

are evolving and which groups of institutions or a single institution may suffer from the distress of another. This methodology can be flexibly implemented, since the PoDs of individual FIs represent the input variables, which can be estimated using alternative approaches. Although in this exercise we used PoDs derived from CDS spreads, it would be straightforward to replace these input variables. This approach is also used to analyze the joint risks across banks in advanced economies and emerging market sovereigns for countries where such banks have large exposures (see Annex 1.3 in Chapter 1).

Common distress in the system: JPoD and BSI.

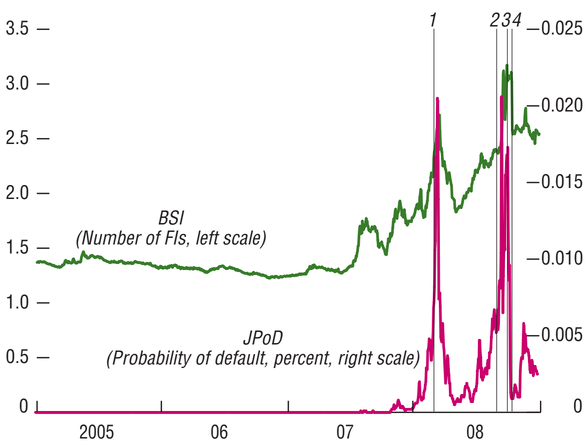
Two variables are employed to analyze common distress: the JPoD, and the BSI. These show larger and nonlinear increases in distress for groups of FIs than for the individual component FIs.[32] Estimations of the JPoD and the BSI are performed from January 1, 2005 to December 31, 2008 and include major U.S., European, and Asian banks, which were grouped in alternative ways in Annex 3.2. The JPoD variable measures the joint probability of default of all the institutions in the sample, and the BSI measures the expected number of other institutions that would fall into distress if a specific institution were to default.

The results indicate that distress in one FI is associated with a high probability of distress elsewhere. Moreover, movements in the JPoD and BSI coincide with events that were considered by the markets to be particularly disruptive on specific dates (Figure 3.7). Risks also vary by the geographical location and business line of the FI in the various groups (Figure 3.8). Distress dependence across FIs rises during times of crisis, indicating that systemic risks, as implied by the JPoD and the BSI, can rise faster than idiosyncratic (individual) risks. Figure 3.9 shows that this is the case—daily percentage changes of the JPoD are larger than daily percentage changes of the average of individual PoDs. This empirical fact provides evidence that in times of distress, not only do individual PoDs increase, but so does distress dependence. Therefore, measures of financial stability that are based on averages or indices could be misleading.

Cascade effects. Another use of the joint probability distribution is the probability of cascade effects, which examines the likelihood that one or more FIs in the system become distressed given that a specific FI becomes distressed. It is a useful indicator to quantify the systemic importance of a specific FI, since it provides a direct

[32]See Segoviano and Goodhart (2009) for definitions.

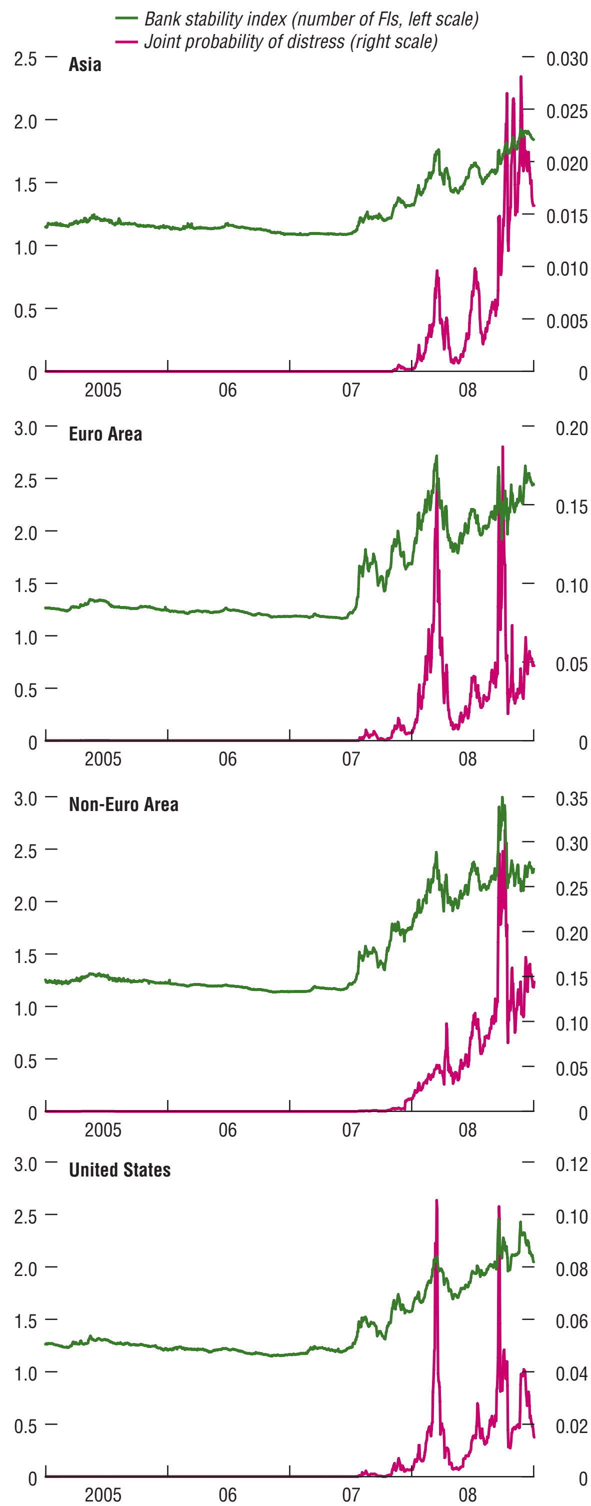
Figure 3.7. Joint Probability of Distress (JPoD) and Banking Stability Index (BSI): Core 2 Group



Sources: Bloomberg L.P.; and IMF staff estimates.
Note: FIs = financial institutions. TARP = Troubled Assets Relief Program. For Core 2 Group, see Annex 3.2.

1. Bear Stearns episode (3/11/08)
2. Lehman bankruptcy and AIG bailout (9/15-16/08)
3. TARP bill failure (9/30/08)
4. Global central bank intervention (10/8/08)

Figure 3.8. Joint Probability of Distress and Banking Stability Index: By Geographic Region



Sources: Bloomberg L.P.; and IMF staff estimates.
Note: For financial institutions in each region, see Annex 3.2.

measure of its effect on the system as a whole. As an example, the probability of cascade effects is estimated given that Lehman or AIG became distressed. These probabilities reached 97 percent and 95, respectively, on September 12, 2008, signaling a possible "domino" effect in the days after Lehman's collapse (Figure 3.10). Note that the probability of cascade effects for both institutions had already increased by August 2007, well before Lehman collapsed.

Identifying Systemic Risks Through Regime Shifts

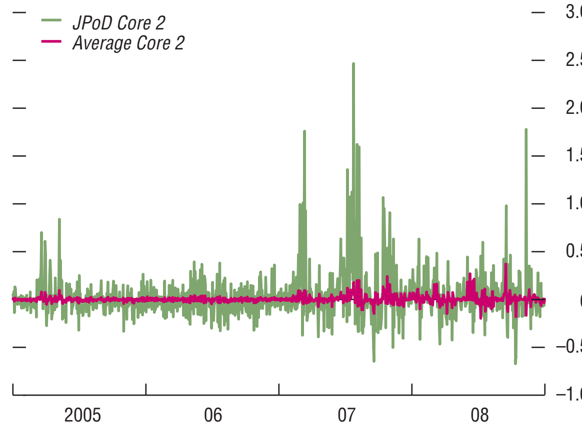
The next objective is to examine when the JPoD and the BSI, as aggregate measures of FIs' stability, switch from low- and medium-volatility regimes into a high one, and vice-versa (Hesse and Segoviano, forthcoming). Remaining in the high-volatility regime could indicate that the crisis has become systemic. From this perspective, the BSI is of particular interest, in that it measures the expected number of distressed institutions given that at least one institution becomes distressed.

The univariate Markov-Switching autoregressive conditional heteroskedacticity (SWARCH) model developed by Hamilton and Susmel (1994) is used.[33] The models are based on daily data in first differences from January 1, 2006, to December 31, 2008. Figure 3.11 (first panel) shows the SWARCH model using the BSI measure for the Core 1 group of banks (United States, Europe, and Asia) and the probability of being in the high-volatility state. The results show the following:

- After the beginning of the subprime crisis, the model only oscillates between the high and medium states, while the precrisis period was characterized by a low-volatility regime.

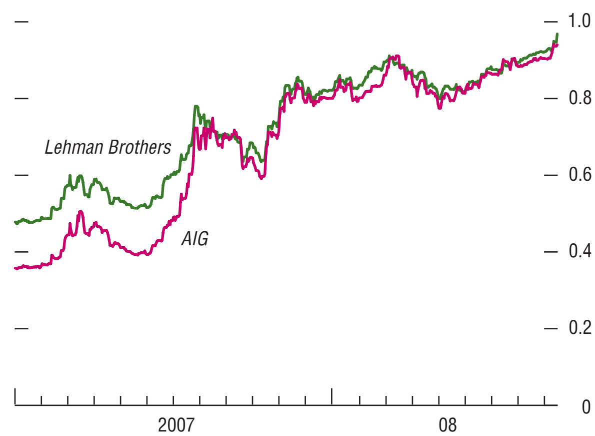
[33]This model allows for a time-varying variance and state-dependent ARCH parameters—features that are present in the types of financial data underpinning the BSI and JPoD. Moreover, the technique allows the data to determine the transition across the regimes rather than the researcher making an ad hoc determination.

Figure 3.9. Daily Percentage Change: Joint and Average Probability of Distress, Core 2 Group



Sources: Bloomberg L.P.; and IMF staff estimates.
Note: JPoD = Joint probability of distress. For Core 2 institutions, see Annex 3.2.

Figure 3.10. Probability of Cascade Effects



Sources: Bloomberg L.P.; and IMF staff estimates.

Box 3.4. The Consistent Information Multivariate Density Optimizing Approach

This box provides details about how the financial system multivariate density (FSMD) is obtained from the data, demonstrating the advantages of the consistent information multivariate density optimizing (CIMDO) technique relative to other more traditional ones.

The FSMD embeds the banks' distress dependence structure, characterized by the CIMDO-copula function (Segoviano, forthcoming), which captures linear (correlations) and nonlinear distress dependence among the financial institutions in the system, and their changes throughout the economic cycle, reflecting the fact that dependence increases in periods of distress. These are key technical improvements over traditional risk models, which usually account only for linear dependence that is assumed to remain constant over the cycle or a fixed period of time.[1]

Empirically, the CIMDO methodology is a tool to recover the FSMD and hence to acquire the joint relationships across the individual financial institutions at the portfolio level. As such, it requires as inputs (exogenous variables), measures of the probabilities of default (PoDs) of individual financial institutions that represent the financial system, which can be estimated using alternative approaches; for example, the structural approach, option prices and credit default swap (CDS) spreads. The underlying data for use in the CIMDO approach is important, as the results are a reflection of the input data. Athanasopoulou, Segoviano, and Tieman (forthcoming) present an extensive empirical analysis of different versions of the structural approach and the CDS approaches to assess their estimates of the PoD. Our analysis shows that while no approach is free of issues, the CDS-PoDs appear to be a good distress signal. For this reason, the FSMD in this paper uses CDS-PoDs. However, further statistical analysis to improve the estimation of individual PoDs is ongoing. Thus, if a better approach is found, it is straightforward to replace the chosen PoDs with another set.

The CIMDO starts with a formal, parameterized distribution of the financial institutions' input data (a prior) and then arrives at a final distribution (the posterior) by imposing constraints that assure that the overall multivariate distribution contains marginal probability densities that satisfy the constraints associated with the PoDs of each of the constituent financial institutions. CIMDO-recovered distributions outperform the most commonly used parametric multivariate densities in the modeling of portfolio risk under the probability integral transformation criterion (a measure of how well densities approximate the underlying data). This is because when recovering multivariate distributions through the CIMDO approach, the available information embedded in the constraints is used to adjust the "shape" of the multivariate density. This appears to allow the distribution to more closely adapt to the changes in entire distribution over time, but particularly in the tail of the distribution, relative to other approaches, which adjust the "shape" of parametric distributions via fixed sets of parameters.

Once the CIMDO density is estimated, its copula function is recovered. Note that this is an inverse approach to the standard copula modeling, which first chooses and parameterizes the copula function and then "couples" marginals to define multivariate densities. Indeed, the standard approach to model parametric copula functions is difficult to implement, since modelers have to deal with the choice, proper specification, and calibration of the copula functions. In contrast, the CIMDO methodology does not require the modeler to choose ex ante a copula function to define distress dependence; that is,

Note: Miguel Segoviano prepared this box.

[1]This paper shows that the structural approach produces, at times, estimates that appear inconsistent with actual default probabilities due to problems related to lack of liquidity in certain markets and generalized risk aversion in times of distress. Credit default swaps-probabilities of default also appeared to be affected by these problems, and at times they overshoot. However, although the magnitude of the moves may occasionally be unrealistic, the direction is usually a good distress signal.

the form of the copula function is defined by the data. Thus, the CIMDO-copula provides key improvements and avoids drawbacks implied by the use of standard parametric copulas as it incorporates, endogenously, changes in distress dependence and avoids the imposition of constant correlation parameters.

However, the CIMDO-copula maintains the benefits of the copula approach to model dependence: first, it describes linear and nonlinear dependencies among the variables described by the CIMDO-density; and second, it characterizes the dependence structure along the entire domain of the CIMDO-density. Nevertheless, the dependence structure characterized by the CIMDO-copula appears to be more robust in the tail of the density, where our main interest lies, that is, to characterize tail risk dependence.

By recovering the FSMD, which embeds financial institutions' distress dependence, Segoviano and Goodhart (2009) can produce three measures that allow policymakers to examine different aspects of systemic risk. This permits policymakers to identify not only how common risks are evolving, but also where distress might most easily develop and how distress in a specific institution can affect other institutions, thus enabling them to make an assessment of the stability of the financial system.

- The model enters the high-volatility state in late July 2007—the beginning of the subprime crisis—and the variations into and out of this state are mostly coincident with the periods in which there are large central bank interventions and new policy initiatives, and unsurprisingly, the Lehman closure.
- In two cases of the five variations examined (Figure 3.11, panels 2 and 3) there is a movement into the high-volatility state in late February 2007. As discussed before, this corresponds to the sharp Shanghai stock market correction as well as the first abrupt ABX (BBB) price decline of subprime mortgages.[34]
- There are some differences in 2008 between U.S. investment banks and European banks (Figure 3.11, panels 4 and 5). The latter appear to be in the high-volatility state most of the time, which could be explained by the higher variance of their BSI.

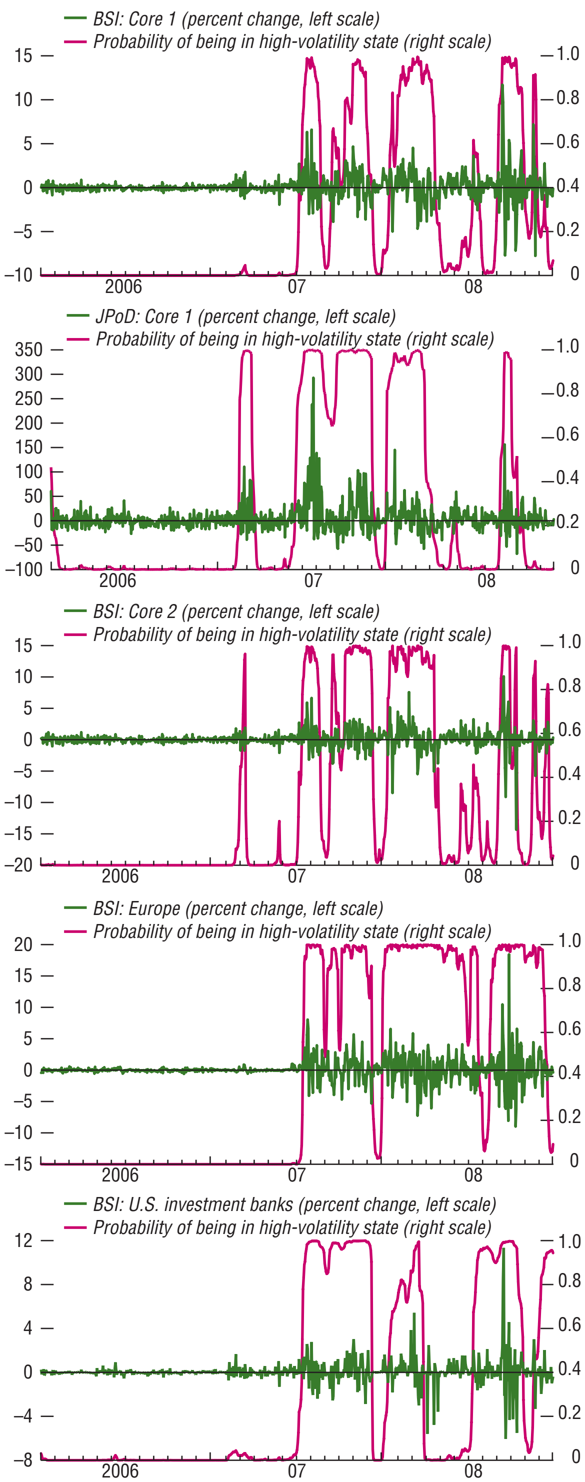
Overall, the SWARCH models are useful analytical tool to discern when aggregate measure of FIs' stability (in this case, the BSI and JPoD) switch volatility regimes. Persistent high-volatility states such as the first months of the subprime crisis, the months surrounding the Bear Stearns rescue, and the Lehman episode suggest that the financial system had entered a systemic crisis, while until Lehman's collapse, many commentators thought the crisis was contained. Of course, this method should not be used in isolation but be complemented by other systemic risk indicators. While the JPoD and BSI indicators measure different attributes of systemic risk, i.e., the joint probability of distress versus the conditional expectation of distress probability, it is reassuring that the main crisis events are picked up by both data series. For some of the events studied, notably the February 2007 episode, the threshold of volatility only stays in the high mode for a short period of time, making it difficult, ex ante, to tell whether the financial system was going to remain in this elevated volatility state and whether it had thus entered a systemic crisis.

[34]These two events were roughly coincident. While it is difficult to prove whether they were related events, they appear be consistent with the rebalancing portfolios by investors with high-yield positions.

Role of Global Market Conditions During Episodes of Stress

This section examines how various proxies for global market conditions can influence the

Figure 3.11. Markov-Regime Switching ARCH Model: Joint Probability of Distress and Banking Stability Index



Sources: Bloomberg L.P.; and IMF staff estimates.
Note: JPoD = joint probability of distress; BSI = banking stability index. For Core 1 and Core 2 groups, see Annex 3.2.

incidence of systemic risk.[35] As noted above, the value of assets on the books of FIs are highly dependent on the underlying financial environment—such factors as the interest rate environment (low or high) or the level of risk appetite—and, as such, global market conditions are thus important in determining their market value and ultimately the strength or weakness of financial institutions and the probability of a systemic episode.

Markov-Regime Switching Analysis

Markov-regime switching techniques take an integrated approach to analyzing financial stress. The SWARCH model of Hamilton and Susmel (1994) is particularly well-suited for the purpose since it differentiates between different volatility states (e.g., low, medium, and high), derived from the time-varying nature of volatility that occurs in many high-frequency financial variables, particularly during times of stress.[36]

A SWARCH model of the euro-U.S. dollar forex swap reveals that the variable moves from a low- to a medium-volatility regime in the beginning of August 2007 before entering the high-volatility state right after the Lehman collapse in September 2008, remaining there until the end of November 2008 (Figure 3.12). Many non-U.S. banks, especially European ones, faced a shortage of U.S. dollar funding for their conduits and structured investment vehicles from the summer of 2007 onward. As the interbank market for dollar funding dried up due to heightened counterparty and liquidity risks, these banks increasingly engaged in foreign exchange swap arrangements, (Baba, Packer, and Nagano, 2008), leading to higher volatility.[37] The move of the forex swap into the

[35]See González-Hermosillo and Hesse (forthcoming).

[36]Univariate SWARCH models are adopted here with variables in first differences to account for the nonstationarity of the variables. The mean equation is an AR(1) process and the variance is time-varying with the ARCH parameters being state dependent.

[37]In particular, both euro and sterling were used as the funding currencies for the dollar foreign exchange swaps. The spillovers from the interbank market to the foreign exchange swap market led to a situation whereby

high-volatility state on September 15, 2008 reflects the sharp increase in counterparty risk after the Lehman failure, a sizable dollar shortage with margins and haircuts increasing across the board, and the breakdown of the LIBOR market.

Turning to the VIX, Figure 3.13 shows the results of a daily SWARCH model from 1998 to end-2008.[38] The probability of being in the high-volatility state varies considerably, spiking during previously identified episodes of instability. Indeed, the findings show the switch to the high-volatility regime in late February 2007 when the Chinese stock market corrected sharply and the first round of ABX (BBB) price declines occurred, suggesting a potential warning sign of systemic fragilities. The Lehman event then triggered a rapid movement of the VIX into the high-volatility regime, where it remained until the end of the sample period. Since the beginning of the subprime crisis, the VIX has only oscillated between the medium- and high-volatility regimes, in contrast to the predominantly low-volatility regime predominant during 2003–07.

The SWARCH model is also estimated for the three-month TED spread (Figure 3.14).[39] This indicator of short-term bank credit risk moved decidedly into a high-volatility regime during the summer of 2007 and persisted there for much of 2008.

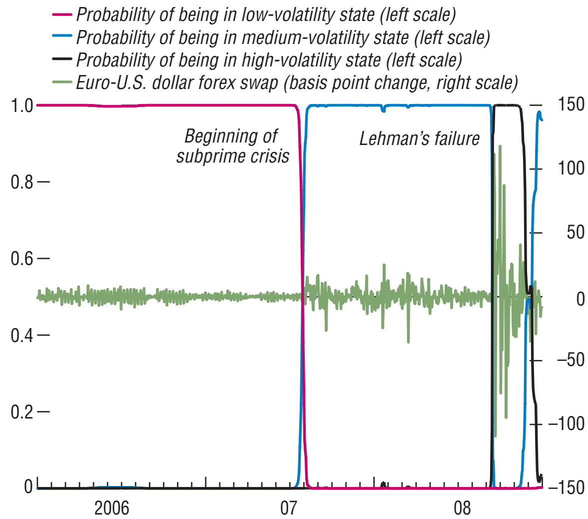
Several of the measures examined (the VIX index and the TED spread) also pick up other periods of stress in global financial markets, such

foreign exchange swap prices deviated from that implied by covered interest parity conditions. With the turbulence becoming more persistent, many non-U.S. financial institutions also increasingly engaged in the longer-term foreign exchange swaps. This episode especially highlighted the international interconnectedness of banks' funding requirements through foreign exchange swap markets and their impaired liquidity.

[38]The VIX, the Chicago Board Options Exchange volatility index, is a measure of the implied volatility of S&P 500 index options over the next 30 days and calculated from a weighted average of option prices. The model based on VIX is estimated in first differences due to nonstationarity. This suggests that it may be useful to examine higher than second moments in the probability density function.

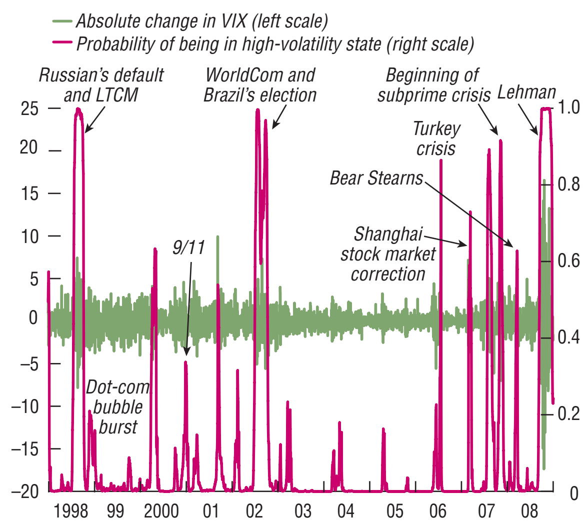
[39]The TED spread is the difference between the three-month LIBOR and the three-month treasury bill rate.

Figure 3.12. Euro-Dollar Forex Swap



Sources: Bloomberg, L.P.; JPMorgan Chase & Co.; and IMF staff estimates.

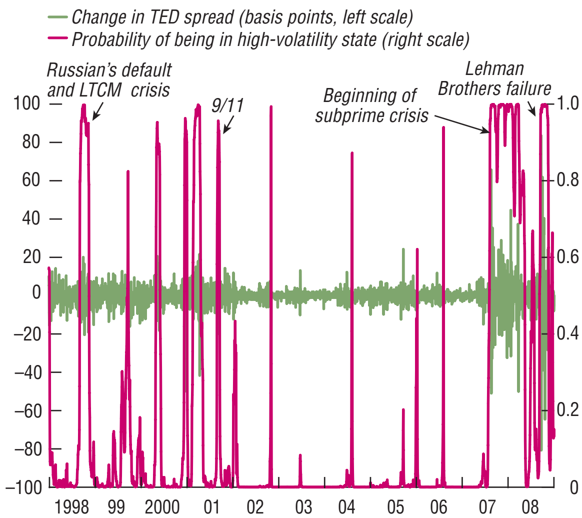
Figure 3.13. Markov-Switching ARCH Model of VIX



Sources: Bloomberg, L.P.; and IMF staff estimates.

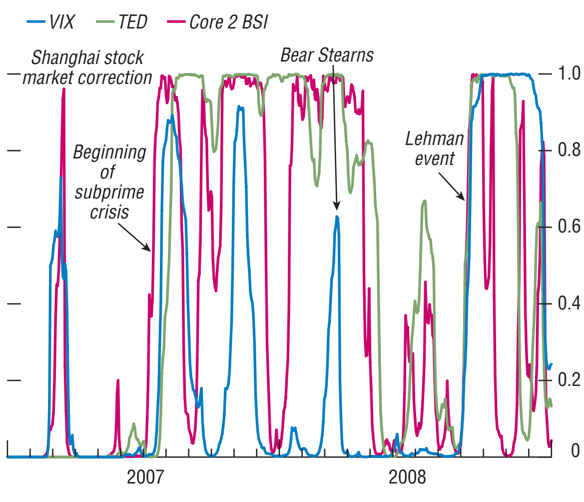
Note: ARCH = autoregressive conditional heteroskedasticity; LTCM = Long-Term Capital Management; VIX = Chicago Board Options Exchange volatility index.

Figure 3.14. Markov-Switching ARCH Model of TED Spread



Sources: Bloomberg, L.P.; and IMF staff estimates.
Note: ARCH = autoregressive conditioned heteroskedasticity; LTCM = Long-Term Capital Management; TED = the spread between the three-month LIBOR and treasury bill rates.

Figure 3.15. Markov-Switching ARCH Model of VIX, TED Spread, and Core 2 BSI
(Probability of being in a high-volatility state)



Sources: Bloomberg L.P.; and IMF staff estimates.
Note: BSI = banking stability index. For Core 2 group, see Annex 3.2.

as Russia's default and Long-Term Capital Management crisis in August/September 1998, the liquidity shock of 9/11, and other episodes of crisis in emerging markets as well as the dotcom bubble and the WorldCom scandal.[40] While the recent persistence of the high-volatility period for the TED spread is unprecedented over the past decade, that for the VIX is not, suggesting a greater relative stress in credit markets during this crisis episode.

The analysis is extended to include the interaction of risks with emerging markets that, as discussed in Chapter 1, have been a key link during the latter stages of the crisis. In particular, the interconnection between financial markets in advanced economies and emerging markets is examined in Box 3.5. The results show that problems in advanced economies readily spilled over into emerging markets as investors sought the safest and most liquid global assets. Similarly, an extension of the approach in Box 3.4 is used to examine cross-country vulnerabilities between emerging market sovereigns and specific banks in advanced economies with a large regional presence in those countries (see Annex 1.3 in Chapter 1), finding such spillovers increased dramatically throughout the crisis.

While not integrated with the measures in the sections above, the regime-shifting model can add to the assessment of systemic risks by overlaying the results to see if multiple measures demonstrate high levels of volatility simultaneously (Figure 3.15). The results show that the global market indicators examined here sometimes do not remain in the high-volatility state for long, with some exceptions such as the TED spread. This suggests they should be used in combination with other tools to help policymakers detect systemic crises.

[40]Robustness tests were performed by estimating the model prior to the Lehman collapse. It also signaled a high probability of being in a high-volatility state over this period. It is worth noting that several relevant data series (such as CDS) did not exist prior to the early 2000s.

Box 3.5. Spillovers to Emerging Markets: A Multivariate GARCH Analysis

This box examines the financial interlinkages between advanced and emerging market countries during the financial crisis.

Although standard correlations are typically flawed methods of examining spillovers and the potential for systemic risks to spread, a dynamic conditional correlation (DCC) generalized autoregressive conditional heteroskedasticity (GARCH) model by Engle (2002) can be used to avoid many of the pitfalls.[1] To examine the interlinkages between advanced and emerging market countries, the model is applied for the sample period 2003–08 (Frank and Hesse, forthcoming). A few pertinent variables are used in order to analyze the co-movements: the three-month U.S. LIBOR-OIS (overnight index swap) spread, proxying for funding liquidity and general stress in the interbank market segment; the S&P 500 as well as bond spreads; and stock market and credit default swap (CDS) measures for some selected emerging market countries or indices.

The findings suggest that implied correlations between the LIBOR spread and Emerging Markets Bond Index Plus (EMBI+) bond spreads of Asian, European, and Latin American countries sharply increase after the subprime crisis (see first panel of figure). In addition, the Chinese stock market correction in February 2007 led to a temporary spike of the correlation measures from 0.20 to almost 0.50. The Lehman collapse caused the largest increase of co-movements between these variables. Similarly, according to the second panel of the figure, the relationship between the S&P 500 and the EMBI+ regional bond spreads encounters a potential break during the Chinese episode, then correlations increase from the beginning of the subprime crisis and reach their peak after the Lehman failure. In terms of regional differences, it appears that the magnitude of co-movements between the S&P 500 and the EMBI spread for Latin American countries dominates the other regional spreads.

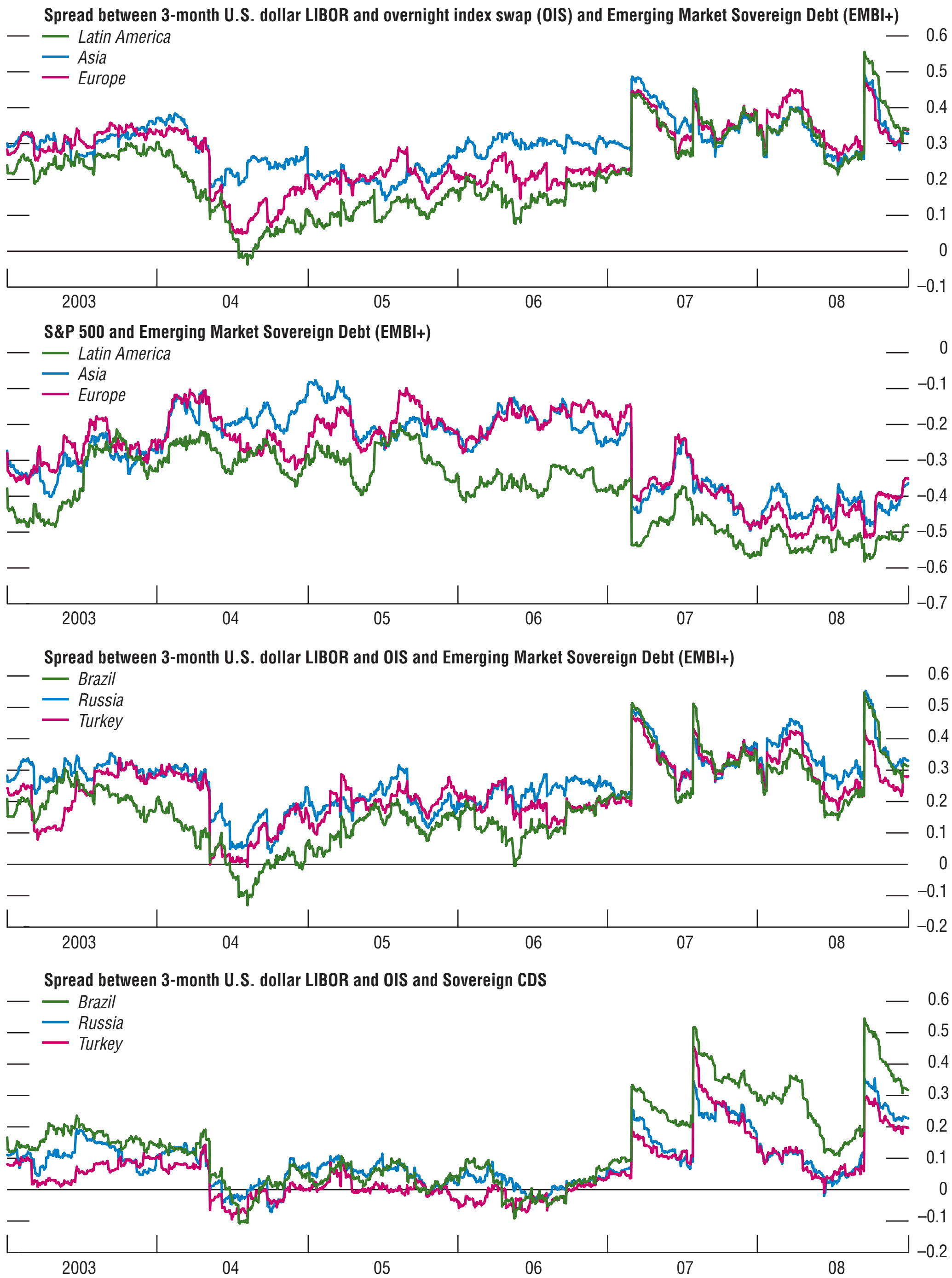
The third and fourth panels of the figure examine possible individual country interlinkages. The LIBOR spread is related to sovereign bond and sovereign CDS spreads of the emerging market countries of Brazil, Russia, and Turkey. As before, the Chinese episode in February 2007 is evident and so are the subprime and the Lehman collapse in increasing correlation magnitude order. The Bear Stearns rescue in March 2008 also becomes visible, with co-movements sharply reversing their downward trend prior to that.

Overall, the findings from the DCC GARCH models indicate that the notion of possible decoupling (in the financial markets) had been misplaced. It is true that emerging market stock markets reached their peak in November 2007 and later, but interlinkages between funding stress and equity markets in advanced economies and emerging market financial indicators were highly correlated and have seen sharp increases during specific crisis moments. Given the interconnectedness of global financial markets, investors' increase in global risk aversion from problems in advanced economies rapidly spilled over into emerging market countries, as investors sought to pull out from those countries and only invest into the safest and most liquid assets in their home countries such as government bonds.

Note: Heiko Hesse prepared this box.

[1]The variables in the daily DCC multivariate GARCH framework are in first differences to account for nonstationarity during the crisis period. In addition, the S&P 500 is included in order to account for common shocks. The models are extended to account for explicit structural breaks using Capiello, Engle, and Sheppard (2006). Using the same methodology, Frank, González-Hermosillo, and Hesse (2008) examine the transmission of liquidity spillovers across asset markets in the United States during the subprime crisis.

Implied Correlations from Dynamic Conditional Correlation Model



Sources: Bloomberg, L.P.; and IMF staff estimates.

Policy Implications

For those responsible for safeguarding financial stability, monitoring measures of systemic stress is now critical. This crisis has highlighted the dangers of focusing supervisory practices and risk management simply on ensuring that individual institutions are adequately capitalized and capable of surviving reasonable stress events. The current crisis has demonstrated that a systemic approach is now urgently needed, since complex financial systems can potentially amplify the actions of single firms to a degree that can have damaging collective effects. Indeed, a seemingly well-capitalized and liquid institution can nevertheless become distressed through the actions of its peers, a "run" by wholesale creditors, or even contagious declines of equity values.

The issue now facing authorities is not *whether* to attempt to identify systemic risks, but how best to do so in an interconnected global financial system with incomplete information. This chapter has reviewed and developed both balance sheet and market-based indicators to assess the degree to which they gave some degree of forewarning of either a particular institution's impending failure, or of severe knock-on effects. Some of the advanced techniques presented here are new and therefore more analysis is needed before a definitive judgment as to the optimal set of measures can be made. Indeed, given the complexity of the nature of systemic risks, it would be prudent to use various techniques and measures in order to arrive at robust results. A number of recommendations flow from the results.

Financial Soundness Indicators

Mixed results were found regarding the standard FSIs' ability to highlight those firms that proved to be vulnerable. Basic leverage ratios were most reliable, while capital-to-asset ratios (including risk-adjusted ratios) and nonperforming loan data proved of little predictive power. In the current crisis, key vulnerabilities have been unanticipated due to off-balance-sheet exposures and lenders' dependence on wholesale funding. Indeed, many "failed" institutions still met regulatory minimum capital requirements. However, FSIs are still helpful in assessing individual and systemic vulnerabilities when reliable market data may not be available—particularly in less-developed financial markets—as they can provide both an indication of rising vulnerabilities and a check when other information reveals weaknesses. For countries with more sophisticated sources of information, FSIs could be usefully reevaluated, perhaps refocusing them on basic leverage ratios and ROA as a proxy for risk-taking. Of course, FSIs should be complemented by other measures and systemic stress tests, and be broadened to better capture off-balance-sheet exposures and liquidity mismatches.

Market-Based Indicators

Low equity volatility and tight credit and CDS spreads were symptoms of, and contributors to, strong risk appetite prior to February 2007. As such, indicators derived from market data generally provided coincident, rather than forward-looking, indications of the break in sentiment and transition to a systemic crisis. However, some measures illustrated above (Table 3.5) are successful in providing an indication of how vulnerable a group of FIs is to the default of any one FI, and hence provide some signal of how "systemic" an individual default can be. Such indicators complement those showing the degree of interconnectedness among FIs (Chapter 2).

Moreover, some indicators, especially those derived from implied volatility from equity options, seem to have given more reliable forward signals of impending banking system and individual institution stress (see Figure 3.10). Nevertheless, these signs of increasing implied volatility provided only a few months' notice that systemic risks were rising, and further work is needed to confirm that such forewarnings were timelier than CDS spreads.

Table 3.5. Summary of Various Methodologies: Limitations and Policy Implications

	Weaknesses/Conditions When Measure May Be Misleading	Policy Implications
Accounting balance sheet	When nonlinearity likely; feedback effects present; forward-looking requirements; high-frequency; multiple-institutions.	Should include indicators on leverage and stock market performance for individual financial institutions.
Conditional correlation matrices and cluster analysis	When nonlinearity likely.	Help policymakers gauge the co-movements and interconnections among financial institutions on a frequent basis.
Option-iPoD	When equity-options are not available; subject to distortions from government injections of capital.	Help policymakers monitor default-risk and the distance to specific leverage thresholds of individual financial institutions at a daily frequency. Can be used to perform stress tests.
Higher moments and multivariate dependence	Variations in data frequency and estimation window might require adjustments to the calibration algorithm of tail dependence when extremes are rare.	Provide policymakers with an indication of both nonlinear and time-varying linkages between financial institutions at different magnitudes of common shocks.
Multivariate time-varying distress dependence	Depends on the inputs used in the methodology. If credit default swap used, subject to distortions from government guarantees.	Provide policymakers with information to identify not only how common risks are evolving, but where spillovers might most easily develop and how distress in a specific institution can affect other institutions.
Markov-regime switching	Does not accommodate multivariate settings.	Provides useful information about status of systemic risk when certain variables (e.g., bank stability indicators or global market variables), change their volatility (or mean) states. The techniques are readily available and could be updated on a frequent basis.
DCC GARCH models	Cannot make causal statements and does not elucidate feedback effects.	Can help policymakers to gauge the extent of co-movements between domestic and global (foreign) market conditions in normal as well as stressful periods.

Source: IMF staff.

Volatility Regime Indicators

There is also evidence that observing shifts in volatility regimes can be helpful in detecting the degree to which the financial system is suffering a systemic event. However, in some cases this signal proves to be relatively short-lived. Nonetheless, regime-switching indicators can show moves to medium- and high-volatility states and hence can be used to assess the degree of current fragility and uncertainty. Such indicators may also be useful in establishing whether and when a systemic crisis is subsiding, particularly if the low-volatility state persists, and thus when the withdrawal supportive crisis measures can be safely considered.

Policy Messages

The findings in this chapter point to a number of broad policy messages:

- *Collect and publish more, relevant data.* While publicly available market indicators for FIs (equity and options prices, CDS spreads) can yield useful indicators of systemic stress, alternative signals are probably being missed because other relevant data are not being collected or published by supervisors in a systematic fashion. Most notably, bank FSIs would become more useful with the inclusion of off-balance-sheet exposures in a standardized manner; the state of market liquidity could be assessed more easily with the publication of volumes and bid-ask spreads in credit markets; and systemic interconnections could be properly assessed through the collection and aggregation of individual cross-border counterparty exposures. Overall levels of leverage—potentially including for hedge funds—would provide information on the potential vulnerability of a financial system to shocks.

- *Diversify information sources and have a comprehensive plan in place for systemic events.* Some market-based indicators—using higher moments of FIs' equity prices—did give a few months' notice of rising systemic risks prior to July 2007. However, it would have been difficult to know at the time whether these signals were prescient. In general, policymakers should not depend on receiving unambiguous signals of impending systemic crisis from market prices, and they should be complemented with other indicators of potential stress (including FSIs and macroeconomic vulnerabilities). Comprehensive policies that are clearly communicated can serve to reduce uncertainty and improve overall market preparedness. The relatively short notice of systemic crisis, and high degree of noise in some signals, mean that policymakers should rely on a number of tools and measures to arrive at a robust assessment of when systemic risks are bound to materialize. In particular, stress tests that take into account systemic effects and interconnections should be implemented. Moreover, a comprehensive and coordinated crisis preparedness plan needs to be in place *before* systemic events are detected.
- *Take care when interpreting market signals during the crisis.* If supervisors and central bankers are planning to use market-based data to assess systemic risk, it is important that they recognize that policy interventions themselves may affect their informational content. For instance, prohibitions on short selling or other impediments to the free flow of information into prices are likely to distort signals given by market prices. Similarly, the introduction of government guarantees for bank debt can alter the informational content of FIs' CDS spreads and equity prices (Box 3.6). As such, market-based indicators may only contain relatively unbiased information about systemic risk in the early phases of a crisis, prior to policy actions. Further work on the indicators, to control for policy responses is needed.
- *Charge for contributions to systemic risk through higher capital requirements.* Some of the analysis presented here allows for the calibration of the contribution of individual institutions to systemic risk, providing a starting point for additional regulatory capital to be required to penalize practices that add to systemic risk giving due attention to potential procyclicality. In addition, indicators of distress could also be used to adduce the appropriate perimeter of regulation, or intensity of supervision, thereby allowing institutions whose failure is unlikely to cause distress to others to be less intensively supervised.

Conclusions

Although every measure of systemic risk has limitations to some degree, and indeed all models are by nature simplifications of the complexity of the real world, this chapter discusses various tools that can be used to shed light on potential systemic events. Thus far, financial sector regulation and supervision have focused on the risk of failure of each financial institution in isolation. The analysis presented here suggests that regulators should take into account the risk of *both* individual and systemic failures. Indeed, some proposals have begun to surface on how to account for systemic risks in prudential regulation (e.g., Acharya, 2009; and Pedersen and Roubini, 2009). Some rely on the assumption that correlation among FIs is a good proxy for detecting systemic risks. As discussed above, measures based solely on asset return correlations are constrained in their ability to detect (and address) systemic risks, since they fail to capture the "fat-tailed" nature and changes in the probability distribution of asset returns of key FIs, which are characteristic of systemic crises. This suggests that prudential norms based on simple return correlations will be insufficient to capture systemic risk, and will need to be broadened. The results suggest that authorities need to diversify their sources of information and the tools used to detect systemic risk.

Box 3.6. The Transformation of Bank Risk into Sovereign Risk—The Tale of Credit Default Swaps

In the fall of 2008, the introduction of government guarantees on bank liabilities prompted a decline in bank credit default swap (CDS) spreads, making the spreads less informative and increasing costs to the government. In several countries with large banking systems this has also led to a convergence of sovereign and bank CDS spreads, which can result in feedback effects between sovereign and bank spreads.

In 2008–09, a number of developed-country governments provided financial guarantees on bank liabilities, which prompted a sharp decline in bank CDS spreads, as default risk was transferred to the sovereign. This has had several consequences.

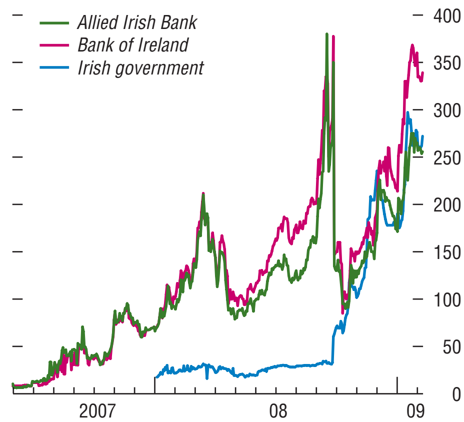
First, information from bank CDS on default risk becomes less informative as government intervention distorts the interpretation of credit market signals. Using information from equity markets in a contingent claims approach (CCA) model may provide a more accurate view on whether bank risk is increasing or subsiding. From a systemic point of view it may be desirable to shift focus to the joint probability of banks falling below certain “minimum” capital or “prompt corrective action” thresholds rather than a joint probability of default (since the government is insuring liability holders against the costs of default).

Second, potential costs to the government of the guarantees have led to a rise in sovereign CDS spreads. This is particularly true where the financial system is large compared with the government’s balance sheet or GDP. The banks’ credit spreads depend on (1) retained risk, which is low given the application of government guarantees and assurances of continuing support; and (2) the government sovereign credit spread, since investors view the banks’ creditworthiness as dependent on that of the sovereign guarantor. (The CCA model assumes that the government’s contingent liability—the value of the explicit or implicit sovereign guarantee—is a fraction α of the total P_F implied put option to the financial sector. The remainder, $(1–\alpha)P_F$, is credit risk remaining in the debt and deposits of the financial sector, as described in Gray, Merton, and Bodie, 2008.) Thus, bank credit spreads should be equal to or greater than sovereign spreads.

In Ireland, after financial guarantees were granted to banks, their CDS spreads declined and converged toward that of the sovereign.

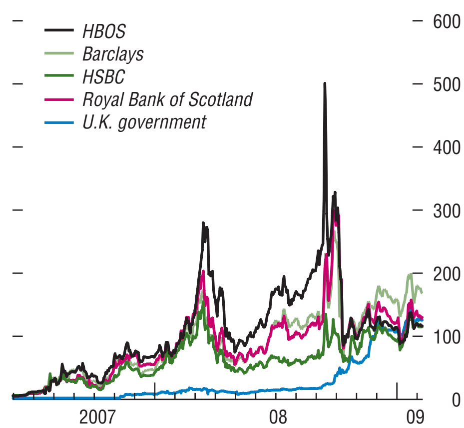
Note: Dale Gray prepared this box.

Irish Banks and Sovereign Five-Year Credit Default Swap Spreads
(In basis points)



Source: Bloomberg L.P.

U.K. Banks and Sovereign Five-Year Credit Default Swap Spreads
(In basis points)



Source: Bloomberg L.P.

Box 3.6 *(concluded)*

A similar pattern was evident in the United Kingdom, after financial guarantees were introduced for new bank-issued debt (see figure).

This inter-relationship of spreads could lead to a destabilizing feedback process where both bank and sovereign CDS spreads increase in response to shocks to bank assets and/or to the sovereign's revenue potential. In some situations (as in Iceland), this vicious cycle can escalate to a point where the inability of the government to provide sufficient credible guarantees to banks leads to a simultaneous systemic financial and sovereign debt crisis. On the other hand, improvement in bank and sovereign balance sheets can lead to a virtuous cycle as bank and sovereign spreads decline. Countries in a currency union do not have the option to use the exchange rate as an independent policy tool to restore macroeconomic stability. In such circumstances, the potential for sovereign default needs to be contained through measures to limit the downside risk of exposure to the banking system and fiscal measures to restore credibility.

Annex 3.1. Financial Soundness Indicators

	Core Set
Deposit-taking institutions' capital adequacy	Regulatory capital to risk-weighted assets
	Regulatory Tier 1 capital to risk-weighted assets
Asset quality	Nonperforming loans to total gross loans
	Nonperforming loans net of provisions to capital
	Sectoral distribution of loans to total loans
	Large exposures to capital
Earnings and profitability	Return on assets
	Return on equity
	Interest margin to gross income
	Noninterest expenses to gross income
Liquidity	Liquid assets to total assets (liquid asset ratio)
	Liquid assets to short-term liabilities
Sensitivity to market risk	Duration of assets
	Duration of liabilities
	Net open position in foreign exchange to capital
	Encouraged Set
Deposit-taking institutions	Capital to assets
	Geographical distribution of loans to total loans
	Gross liability position in financial derivatives to capital
	Trading income to total income
	Personnel expenses to noninterest expenses
	Spread between highest and lowest interbank rate
	Customer deposits to total (noninterbank) loans
	Foreign currency-denominated loans to total loans
	Foreign currency-denominated liabilities to total liabilities
	Net open position in equities to capital
Market liquidity	Average bid-ask spread in the securities market
	Average daily turnover ratio in the securities market
Nonbank financial institutions	Assets to total financial system assets
	Assets to GDP
Corporate sector	Total debt to equity
	Return on equity
	Earnings to interest and principal expenses
	Corporate net foreign exhange exposure to equity
	Number of applications for protection from creditors
Households	Household debt to GDP
	Household debt service and principal payments to income
Real estate markets	Real estate prices
	Residential real estate loans to total loans
	Commercial real estate loans to total loans

Source: Sundararajan and others (2002).

Annex 3.2. Groups of Selected Financial Institutions

Core Groups		Regions		Insurance Companies
Core 1	Core 2	Europe	Asia/United States	
Australia & New Zealand Banking Group	AIG	**Euro area**	**Asia**	AIG (AIG)
Bank of America	Ambac Financial	Intesa Sanpaolo (ISP)	Australia & New Zealand Banking Group (ANZ)	Allianz (ALV)
Bank of China	Bank of America	BNP Paribas (BNP)	Bank of China (BOC)	Ambac Financial (ABK)
Citigroup	Citigroup	Commerzbank (CBK)	DBS Group (DBS)	AXA (AXA)
Deutsche Bank	Deutsche Bank	Deutsche Bank (DBK)	ICICI Bank (IBN)	MBIA (MBI)
Goldman Sachs	Goldman Sachs	Fortis (FORB)	Industrial Bank of Korea (IBK)	Munich Re (MUV)
HSBC	HSBC	ING Group (INGA)	Mitsubishi UFJ Financial (MUF)	PMI (PMI)
Industrial Bank of Korea	JPMorgan Chase & Co.	Santander Hispano Group (SAN)	Nomura (NOM)	Prudential Plc (PRU)
JPMorgan Chase & Co.	Lehman Brothers	Société Generale (GLE)	State Bank of India (SBIN)	Swiss Re (RUKN)
Lehman Brothers	Merrill Lynch	UniCredito (UCG)	Sumitomo Mitsui Financial (SMF)	
Merrill Lynch	Morgan Stanley			
Mitsubishi UFJ	Royal Bank of Scotland	**Non-euro area**	**United States**	
Morgan Stanley	Swiss Re	Barclays (BARC)	Bank of America (BAC)	
Royal Bank of Scotland	UBS	Credit Suisse (CSGN)	Bear Stearns (BSC)	
UBS	Wachovia	Danske (DANSK)	Citigroup (C)	
Wachovia		HBOS (HBOS)	Goldman Sachs (GS)	
		HSBC (HSBA)	JPMorgan Chase & Co. (JPM)	
		LloydsTSB (LLOY)	Lehman Brothers (LEH)	
		Nordea (NDA)	Merrill Lynch (MER)	
		Royal Bank of Scotland (RBS)	Morgan Stanley (MS)	
		UBS (UBS)	Wachovia (WB)	

Annex 3.3. List of Intervened Financial Institutions

Date(s) of Intervention	Country	Institution
Intervened institutions - banks		
9/29/2008	United States	Wachovia
9/29/2008	Belgium/Netherlands/ Luxembourg	Fortis
10/3/2008	Belgium/Netherlands	Fortis
10/13/2008	United Kingdom	Royal Bank of Scotland, HBOS, LloydsTSB
10/16/2008	Switzerland	UBS
10/19/2008	Netherlands	ING Group
10/28/2008	United States	JPMorgan Chase & Co.
10/28/2008	United States	Bank of America
11/24/2008	United States	Citigroup
1/8/2009	Germany	Commerzbank
1/19/2009	United Kingdom	Royal Bank of Scotland

Date(s) of Intervention	Country	Institution
Intervened institutions - investment banks		
3/14/2008	United States	Bear Stearns
9/15/2008	United States	Lehman Brothers
9/15/2008	United States	Merrill Lynch
10/28/2008	United States	Goldman Sachs
10/28/2008	United States	Morgan Stanley
Intervened institutions - insurance companies		
9/16/2008	United States	AIG

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