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STABILITY**

Miguel A. Segoviano

Charles Goodhart

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Working Papers of the Central Bank of Chile
Agustinas 1180, Santiago, Chile
Teléfono: (56-2) 3882475; Fax: (56-2) 3882231

DISTRESS DEPENDENCE AND FINANCIAL STABILITY

Miguel A. Segoviano
International Monetary Fund

Charles Goodhart
London School of Economics

Abstract

This paper defines a set of systemic financial stability indicators which measure distress dependence among the financial institutions in a system, thereby allowing to analyze stability from three complementary perspectives: common distress in the system, distress between specific banks, and cascade effects associated with a specific bank. Our approach defines the banking system as a portfolio of banks and infers the system's multivariate density (BSMD) from which the proposed measures are estimated. The BSMD embeds the banks' default inter-dependence structure that captures linear and non-linear distress dependencies among the banks in the system, and its changes at different times of the economic cycle. The BSMD is recovered using the CIMDO-approach, a new approach that, in the presence of restricted data, improves density specification without explicitly imposing parametric forms that, under restricted data sets, are difficult to model. Thus, the proposed measures can be constructed from a very limited set of publicly available data and can be provided for a wide range of both developing and developed countries.

Resumen

Este trabajo define una serie de medidas sistémicas de estabilidad financiera que consideran la dependencia de aprietos entre las instituciones financieras en un sistema, permitiendo así analizar la estabilidad desde tres perspectivas complementarias: aprietos comunes en el sistema, aprietos entre bancos específicos, y efectos cascada asociados con un banco en particular. Nuestro enfoque define el sistema bancario como un portafolio de bancos e infiere la densidad multivariada del sistema (BSMD, por sus siglas en inglés) desde la cual se estiman las medidas propuestas. La BSMD se obtiene utilizando el enfoque CIMDO, un nuevo enfoque que, en presencia de datos restringidos, mejora la especificación de la densidad sin imponer explícitamente formas paramétricas que, con bases de datos restringidas, son difíciles de modelar. Por lo tanto, las medidas propuestas pueden construirse con un conjunto muy limitado de datos públicos disponibles y pueden aplicarse en un amplio rango de países tanto en desarrollo como desarrollados.

I. INTRODUCTION

The proper estimation of distress dependence amongst the banks in a system is of key importance for the surveillance of stability of the banking system. Financial supervisors recognize the importance of assessing not only the risk of distress i.e., large losses and possible default of a specific bank, but also the impact that such an event would have on other banks in the system. Clearly, the event of simultaneous large losses in various banks would affect a banking system's stability, and thus represents a major concern for supervisors. Bank's distress dependence is based on the fact that banks are usually linked—either directly, through the inter-bank deposit market and participations in syndicated loans, or indirectly, through lending to common sectors and proprietary trades. Banks' distress dependence varies across the economic cycle, and tends to rise in times of distress since the fortunes of banks decline concurrently through either contagion after idiosyncratic shocks, affecting inter-bank deposit markets and participations in syndicated loans—direct links—or through negative systemic shocks, affecting lending to common sectors and proprietary trades—indirect links. Therefore, in such periods, the banking system's joint probability of distress (JPoD); i.e., the probability that all the banks in the system experience large losses simultaneously, which embeds banks' distress dependence, may experience larger and nonlinear increases than those experienced by the probabilities of distress (PoDs) of individual banks. Consequently, it becomes essential for the proper estimation of the banking system's stability to incorporate banks' distress dependence and its changes across the economic cycle.

In this paper, we follow Segoviano and Goodhart (2009) to estimate a set of banking stability measures (BSMs) that embed the banks' distress inter-dependence structure, which captures not only linear (correlation) but also non-linear distress dependencies among the banks in the system. Moreover, the structure of linear and non-linear distress dependencies changes as banks' probabilities of distress (PoDs) change; hence, the proposed stability measures incorporate changes in distress dependence that are consistent with the economic cycle. This is a key advantage over traditional risk models that most of the time incorporate only linear dependence (correlation structure), and assume it constant throughout the economic cycle.² The proposed BSMs represent a set of tools to analyze (define) stability from three different, yet, complementary perspectives, by allowing the quantification of (a) “tail risk” in the banks of the system, (b) distress between specific banks, and (c) cascade effects; i.e., distress in the system associated triggered by distress of a specific bank.

² In contrast to correlation, which only captures linear dependence, copula functions characterize the whole dependence structure; i.e., linear and non-linear dependence, embedded in multivariate densities (Nelsen, 1999). Thus, in order to characterize banks' distress dependence we employ a novel non-parametric copula approach; i.e., the CIMDO-copula (Segoviano, 2009), described below. In comparison to traditional methodologies to model parametric copula functions, the CIMDO-copula avoids the difficulties of explicitly choosing the

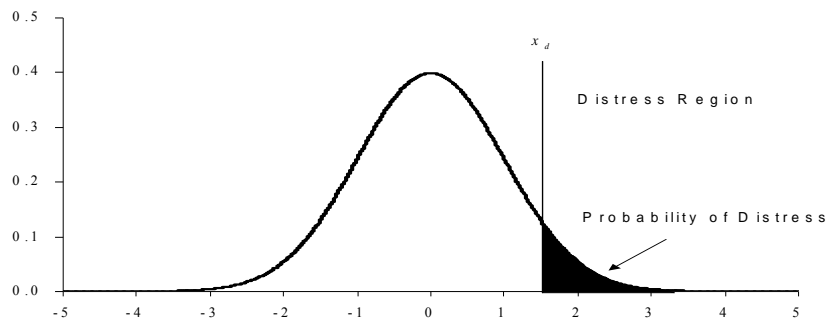
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As described below, the authors conceptualize the banking system as a portfolio of banks comprising the core, systemically important banks in any country. They proceed by inferring the banking system’s portfolio multivariate density (BSMD) from which a set of BSMs is constructed. They show how these BSMs can be constructed from a very limited set of data, e.g., empirical measurements of distress of individual banks. Such measurements can be estimated using alternative approaches, depending on data availability; thus, the data set that is necessary to estimate the BSMs is available in most countries. Consequently, such measures can be provided for a wide group of developing, as well as developed, countries. Moreover, in this paper the authors incorporate into the analysis non-bank financial institutions, other corporates, and sovereigns; hence, distress dependence between the banking sector and other sectors can be analyzed. Being able to establish such a set of measures with a minimum of basic components makes it feasible to undertake a wider range of comparative analysis, both time series and cross-section. This implementation flexibility is of relevance for banking stability surveillance, since cross-border financial linkages are growing and becoming significant; as has been highlighted by the financial market turmoil of recent months. Thus, surveillance of banking stability cannot stop at national borders. In Section II, it is described how distress-dependence is modeled by Segoviano and Goodhart (2009). Section III, provides a summary of the Banking Stability Measures proposed by the authors. Section IV shows how these measures can be employed to analyse stability from different perspectives. Finally, conclusions are presented in Section V.

II. DISTRESS DEPENDENCE IN THE FINANCIAL SYSTEM

Quantitative estimation of distress dependence among banks and/or other financial institutions is a difficult task. Information restrictions and difficulties in modeling distress dependence arise due to the fact that distress is an extreme event and can be viewed as a tail event that is defined in the “distress region” of the probability distribution that describes the implied asset price movements of a bank (Figure 1).

Figure 1. The Probability of Distress



Source: Segoviano and Goodhart (2009).

parametric form of the copula function to be used and calibrating its parameters, since CIMDO-copula functions are inferred directly (implicitly) from the joint movements of the individual banks’ PoDs.

The fact that distress is a tail event makes the often used correlation coefficient inadequate to capture bank distress dependence and the standard approach to model parametric copula functions difficult to implement. In our modeling of banking systems' stability and distress dependence, we replicate Segoviano and Goodhart (2009), and proceed as follows (Figure 2):

Step 1: We conceptualize the banking system as a *portfolio* of banks.

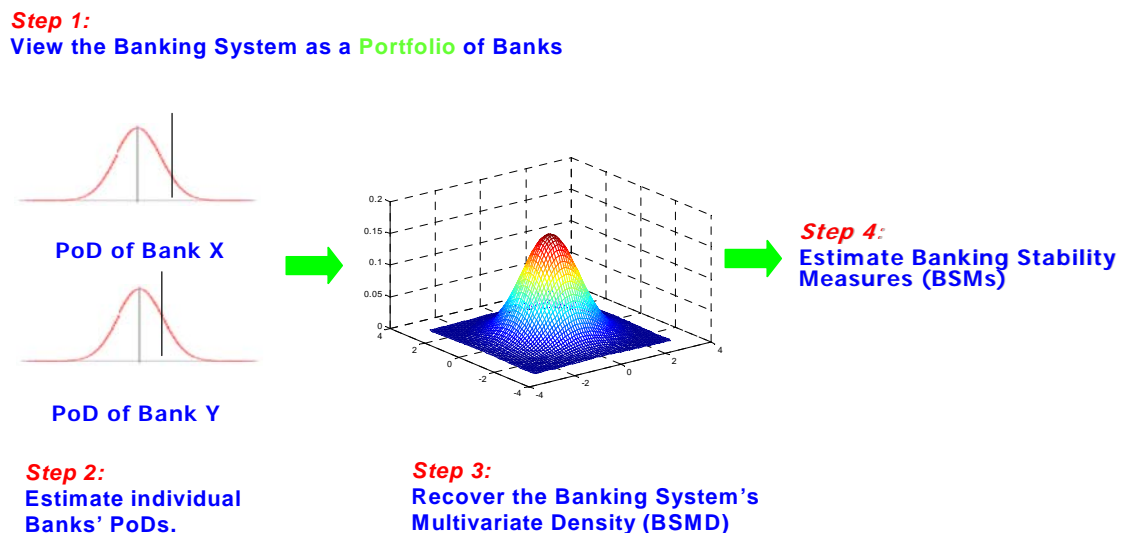
Step 2: For each of the banks included in the portfolio, we obtain empirical measurements of probabilities of distress (PoDs).

Step 3: Making use of the Consistent Information Multivariate Density Optimizing (CIMDO) methodology, presented in Segoviano (2006) and summarized below, and taking as input variables the individual banks' PoDs estimated in the previous step, we recover the *banking system's (portfolio) multivariate density* (BSMD).

Step 4: Based on the BSMD, we estimate the proposed banking stability measures (BSMs).

The Banking System Multivariate Density (BSMD) characterizes both the individual and *joint* asset value movements of the portfolio of banks representing the banking system (Figure 2).

Figure 2. The Banking System's Multivariate Density



Source: Segoviano and Goodhart (2009).

A. The Importance of Time-Varying Distress-Dependence

The BSMD is recovered using the Consistent Information Multivariate Density Optimizing (CIMDO) methodology (Segoviano, 2006b), which offers key technical improvements over traditional risk models that usually account only for linear dependence (correlations) that are assumed to remain constant over the cycle or a fixed period of time. The BSMD embeds banks' distress dependence structure—characterized by the CIMDO-copula function (Segoviano, 2009)—that captures linear and non-linear distress dependencies among the banks in the system, and allows for these to change throughout the economic cycle, reflecting the fact that distress dependence increases in periods of distress. This implies that systemic risks rise faster than individual risks.

In order to illustrate this point, for a portfolio of globally active banks we estimate the average probability of default, and the joint probability of default using alternative assumptions to describe the BSMD; i.e., a multivariate t-density (t-JPoD), and using the CIMDO density (JPoD).³ The joint probability of default represents the probability of all the banks included in the portfolio become distressed. Accordingly, this is estimated by integrating the alternative BSMD across the region of default of each of the marginal densities that compose them.

Daily percentage changes of the JPoD are larger than daily percentage changes of the average of individual PoDs and the t-JPoD. This empirical fact provides evidence that in times of distress, not only do individual PoDs increase (as captured by the three alternative measures), but so does distress dependence (as captured by the JPoD). Therefore, systemic risk may experience larger and nonlinear increases than those experienced by the probabilities of distress (PoDs) of individual banks and by those implied under a density distribution with fixed correlation parameters. Consequently, measures of financial stability that are based on averages, indexes and/or assume fixed correlation parameters through time could be misleading.

The CIMDO methodology embeds a *reduced-form* or *non-parametric* approach to model copulas that seems to capture adequately default dependence and its changes at different points of the economic cycle. This methodology is easily implementable under the data constraints affecting bank distress dependence modeling and produces robust estimates under the PIT criterion.⁴ In order to show such improvements in the modeling of distress dependence—thus, in our proposed measures of stability—in what follows, we (i) model the BSMD using the CIMDO methodology, and (ii) illustrate the advantages embedded in the CIMDO-Copula to characterize distress dependence among the banks in the banking system.

³ The degrees of freedom and correlation parameters that characterize the employed multivariate t density are estimated with empirically observed data.

⁴ The PIT criterion for multivariate density's evaluation is presented in Diebold et al (1999).

B. The CIMDO Approach: Modeling the Banking System Multivariate Density

We recover the BSMD employing the CIMDO methodology and empirical measures of probabilities of distress (PoDs) of individual banks. There are alternative approaches to estimate individual banks' probabilities of distress. For example, (i) the Structural Approach (SA), (ii) Credit Default Swaps (CDS), and (iii) Out of the Money Option Prices (OOM). It is important to emphasize the fact that individual banks' PoDs are exogenous variables in the CIMDO framework; thus, it can be implemented with any alternative approach to estimate PoDs. This fact provides great flexibility in the estimation of the BSMD.

The CIMDO-methodology is based on the minimum cross-entropy approach (Kullback, 1959). Under this approach, a *posterior* multivariate distribution p —the CIMDO-density—is recovered using an optimization procedure by which a *prior* density q is updated with empirical information via a set of constraints. Thus, the *posterior* density satisfies the constraints imposed on the *prior* density. In this case, the banks' empirically estimated PoDs represent the information used to formulate the constraint set. Accordingly the CIMDO-density—the BSMD—is the *posterior* density that is closest to the *prior* distribution and that is *consistent* with the empirically estimated PoDs of the banks making up the system.

In order to formalize these ideas, we proceed by defining a banking system—portfolio of banks—comprising two banks; i.e., bank X and bank Y, whose logarithmic returns are characterized by the random variables x and y . Hence we define the CIMDO-objective function as:⁵

$$C[p,q]=\int \int p(x,y)\ln \left[\frac{p(x,y)}{q(x,y)} \right] dx dy, \text{ where } q(x,y) \text{ and } p(x,y) \in \mathbb{R}^2.$$

It is important to point out that the *prior* distribution follows a parametric form q that is consistent with economic intuition (e.g., default is triggered by a drop in the firm's asset value below a threshold value) and with theoretical models (i.e., the structural approach to model risk). However, the parametric density q is usually inconsistent with the empirically observed measures of distress. Hence, the information provided by the empirical measures of distress of each bank in the system is of prime importance for the recovery of the *posterior* distribution. In order to incorporate this information into the *posterior* density, we formulate consistency-constraint equations that have to be fulfilled when optimizing the CIMDO-objective function. These constraints are imposed on the marginal densities of the multivariate *posterior* density, and are of the form:

⁵ A detailed definition and development of the CIMDO objective function and constraint set, as well as the optimization procedure that is followed to solve the CIMDO functional is presented in Segoviano (2006b).

$$\iint p(x, y) \chi_{(x_d^x, \infty)} dx dy = PoD_t^x, \iint p(x, y) \chi_{(x_d^y, \infty)} dy dx = PoD_t^y \quad (1)$$

where $p(x, y)$ is the *posterior* multivariate distribution that represents the unknown to be solved. PoD_t^x and PoD_t^y are the empirically estimated probabilities of distress (PoDs) of each of the banks in the system, and $\chi_{[x_d^x, \infty)}$, $\chi_{[x_d^y, \infty)}$ are indicating functions defined with the distress thresholds x_d^x, x_d^y , estimated for each bank in the portfolio. In order to ensure that the solution for $p(x, y)$ represents a valid density, the conditions that $p(x, y) \geq 0$ and the probability additivity constraint $\iint p(x, y) dx dy = 1$, also need to be satisfied. Once the set of constraints is defined, the CIMDO-density is recovered by minimizing the functional:

$$L[p, q] = \iint p(x, y) \ln p(x, y) dx dy - \iint p(x, y) \ln q(x, y) dx dy + \quad (2)$$

$$\lambda_1 \left[\iint p(x, y) \chi_{[x_d^x, \infty)} dx dy - PoD_t^x \right] + \lambda_2 \left[\iint p(x, y) \chi_{[x_d^y, \infty)} dy dx - PoD_t^y \right] + \mu \left[\iint p(x, y) dx dy - 1 \right]$$

where λ_1, λ_2 represent the Lagrange multipliers of the consistency constraints and μ represents the Lagrange multiplier of the probability additivity constraint. By using the calculus of variations, the optimization procedure can be performed. Hence, the optimal solution is represented by a *posterior* multivariate density that takes the form

$$\widehat{p}(x, y) = q(x, y) \exp \left\{ - \left[1 + \widehat{\mu} + (\widehat{\lambda}_1 \chi_{[x_d^x, \infty)}) + (\widehat{\lambda}_2 \chi_{[x_d^y, \infty)}) \right] \right\} \quad (3)$$

Intuitively, imposing the constraint set on the objective function guarantees that the *posterior* multivariate distribution—the BSMD—contains marginal densities that satisfy the PoDs observed empirically for each bank in the banking portfolio. CIMDO-recovered distributions outperform the most commonly used parametric multivariate densities in the modeling of portfolio risk under the Probability Integral Transformation (PIT) criterion.⁶ This is because when recovering multivariate distributions through the CIMDO approach, the available information embeded in the constraint set is used to adjust the “shape” of the multivariate density via the optimization procedure described above. This appears to be a more efficient manner of using the empirically observed information than under parametric approaches, which adjust the “shape” of parametric distributions via fixed sets of parameters. A detailed development of the PIT criterion and Monte Carlo studies used to evaluate specifications of the CIMDO-density are presented in Segoviano (2006b).

⁶ The standard and conditional normal distributions, the t-distribution, and the mixture of normal distributions.

C. The CIMDO-copula: Distress Dependence among Institutions in the System

The BSMD embeds the structure of linear and nonlinear default dependence among the banks included in the portfolio that is used to represent the banking system. Such dependence structure is characterized by the copula function of the BSMD; i.e., the CIMDO-copula, which changes at each period of time, consistently with changes in the empirically observed PoDs. In order to illustrate this point, we heuristically introduce the copula approach to characterize dependence structures of random variables and explain the particular advantages of the CIMDO-copula. For further details see Segoviano (2008).

The copula approach

The copula approach is based on the fact that any multivariate density, which characterizes the stochastic behavior of a group of random variables, can be broken into two subsets of information: (i) information of each random variable; i.e., the marginal distribution of each variable; and (ii) information about the dependence structure among the random variables. Thus, in order to recover the latter, the copula approach *sterilizes* the marginal information of each variable, consequently isolating the dependence structure embedded in the multivariate density. *Sterilization* of marginal information is done by transforming the marginal distributions into uniform distributions; $\mathbf{U}(0,1)$, which are *uninformative* distributions.⁷ For example, let x and y be two random variables with individual distributions $x \sim F$, $y \sim H$ and a joint distribution $(x, y) \sim G$. To transform x and y into two random variables with uniform distributions $\mathbf{U}(0,1)$ we define two new variables as $u = F(x)$, $v = H(y)$, both distributed as $\mathbf{U}(0,1)$ with joint density $c[u, v]$. Under the distribution of transformation of random variables, the copula function $c[u, v]$ is defined as:

$$c[u, v] = \frac{g[F^{(-1)}(u), H^{(-1)}(v)]}{f[F^{(-1)}(u)]h[H^{(-1)}(v)]}, \quad (4)$$

where g, f , and h are defined densities. From equation (4), we see that copula functions are multivariate distributions, whose marginal distributions are uniform on the interval $[0,1]$. Therefore, since each of the variables is individually (marginally) uniform; i.e. their information content has been sterilized, their joint distribution will *only* contain *dependence information*. Rewriting equation (4) in terms of x and y we get:

$$c[F(x), H(y)] = \frac{g[x, y]}{f[x]h[y]}, \quad (5)$$

⁷ For further details, proofs and a comprehensive and didactical exposition of copula theory, see Nelsen (1999), and Embrechts (1999) where also properties and different types of copula functions are presented.

From equation (5), we see that the joint density of u and v is the ratio of the joint density of x and y to the product of the marginal densities. Thus, if the variables are independent, equation (5) is equal to one.

The copula approach to model dependence possesses many positive features when compared to correlations. In comparison to correlation, the dependence structure as characterized by copula functions, describes linear and non-linear dependencies of any type of multivariate densities, and along their entire domain. Additionally, copula functions are invariant under increasing and continuous transformations of the marginal distributions. Under the standard procedure, first, a given parametric copula is chosen and calibrated to describe the dependence structure among the random variables characterized by a multivariate density. Then, marginal distributions that characterize the individual behavior of the random variables are modeled separately. Lastly, the marginal distributions are “coupled” with the chosen copula function to “construct” a multivariate distribution. Therefore, the modeling of dependence with *standard parametric* copulas embeds two important shortcomings:

(i) It requires modelers to deal with the choice, proper specification and calibration of *parametric* copula functions; i.e., the copula choice problem (CCP). The CCP is in general a challenging task, since results are very sensitive to the functional form and parameter values of the chosen copula functions (Frey and McNeil, 2001). In order to specify the correct functional form and parameters, it is necessary to have information on the joint distribution of the variables of interest, in this case, joint distributions of distress, which are not available.

(ii) The commonly employed parametric copula functions in portfolio risk measurement require the specification of correlation parameters, which are usually specified to remain fixed through time (see Appendix 1). Thus, the dependence structure that is characterized with *parametric* copula functions, although improving the modeling of dependence vs. correlations, still embeds the problem of characterizing dependence that remains fixed through time.⁸

The CIMDO-copula

Our approach to model multivariate densities is the inverse of the standard copula approach. We first infer the CIMDO-density as explained in Section III.A. The CIMDO-density embeds the dependence structure among the random variables that it characterizes; therefore, once we have inferred the CIMDO-density, we can extract the copula function describing

⁸ Note that even if correlation parameters are dynamically updated using rolling windows, correlations remain fixed within such rolling windows. Moreover, the choice of the length of such rolling windows remain subjective most of the time.

such dependence structure, i.e., the CIMDO-copula. This is done by estimating the marginal densities from the multivariate density and using Sklar's theorem (Sklar, 1959).

The CIMDO-copula maintains all the benefits of the copula approach:

- (i) It describes linear and non-linear dependencies among the variables described by the CIMDO-density. Such dependence structure is invariant under increasing and continuous transformations of the marginal distributions.
- (ii) 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 (see discussion below), where our main interest lies i.e., to characterize *distress* dependence.

However, the CIMDO-copula avoids the drawbacks implied by the use of *standard parametric* copulas:

- (i) It circumvents the Copula Choice Problem. The explicit choice and calibration of parametric copula functions is avoided because the CIMDO-copula is extracted from the CIMDO-density (as explained above); therefore, in contrast with most copula models, the CIMDO-copula is recovered without explicitly imposing parametric forms that, under restricted data sets, are difficult to model empirically and frequently wrongly specified. It is important to note that under such information constraints, i.e., when only information of marginal probabilities of distress exist; the CIMDO-copula is not only easily implementable, it outperforms the most common parametric copulas used in portfolio risk modeling under the PIT criterion. This is specially on the tail of the copula function, where distress dependence is characterized. See Appendix 3 for a summary of this evaluation criterion and its results.
- (ii) The CIMDO-copula avoids the imposition of constant correlation parameter assumptions. It updates “automatically” when the probabilities of distress are employed to infer the CIMDO-density change. Therefore, the CIMDO-copula incorporates banks' distress dependencies that change, according to the dissimilar effects of shocks on individual banks' probabilities of distress, and that are consistent with the economic cycle.

In order to formalize these ideas, note that if the CIMDO-density is of the form presented in equation (3), Appendix 2 shows that the CIMDO-copula, $c_c(u, v)$, is represented by

$$c_c(u, v) = \frac{q[F_c^{-1}(u), H_c^{-1}(v)] \exp\left\{-\left[1 + \hat{\mu}\right]\right\}}{\int_{-\infty}^{+\infty} q[F_c^{-1}(u), y] \exp\left\{-\hat{\lambda}_2 \chi_{x_y^y}(y)\right\} dy \int_{-\infty}^{+\infty} q[x, H_c^{-1}(v)] \exp\left\{-\hat{\lambda}_1 \chi_{x_x^x}(x)\right\} dx} \quad (6)$$

where $u = F_c(x) \Leftrightarrow x = F_c^{-1}(u)$, and $v = H_c(y) \Leftrightarrow y = H_c^{-1}(v)$.

Equation (6) shows that the CIMDO-copula is a nonlinear function of λ_1, λ_2 and μ , the Lagrange multipliers of the CIMDO functional presented in equation (2). Like all optimization problems, the Lagrange multipliers reflect the change in the objective function's value as a result of a marginal change in the constraint set. Therefore, as the empirical PoDs of individual banks change at each period of time, the Lagrange multipliers change, the values of the constraint set change, and the CIMDO-copula changes; consequently, the default dependence among the banks in the system changes.

Thus, as already mentioned, the default dependence gets updated “automatically” with changes in empirical PoDs at each period of time. This is a relevant improvement over most risk models, which usually account only for linear dependence (correlation) that is also assumed to remain constant over the cycle or a fixed period of time.

III. BANKING STABILITY MEASURES

The BSMD characterizes the probability of distress of the individual banks included in the portfolio, their distress dependence, and changes across the economic cycle. This is a rich set of information that allows us to analyze (define) banking stability from three different, yet complementary, perspectives. For this purpose, we define a set of BSMs to quantify:

- (a) “Tail risk”; i.e., common distress of the financial institutions in a system.
- (b) Distress between specific institutions.
- (c) “Cascade effects”; i.e., distress in the system associated by distress in a specific institution.

We hope that the complementary perspectives of financial stability brought by the proposed BSMs, represent a useful tool set to help financial supervisors to identify how risks are evolving and where contagion might most easily develop. For illustration purposes, and to make it easier to present definitions below, we proceed by defining a banking system—portfolio of banks—comprising three banks, whose asset values are characterized by the random variables x and y and r . Hence, following the procedure described in Section III.A, we infer the CIMDO-density function, which takes the form:

$$\widehat{p(x, y, r)} = q(x, y, r) \exp \left\{ - \left[1 + \widehat{\mu} + (\widehat{\lambda}_1 \chi_{[x_d^x, \infty)}) + (\widehat{\lambda}_2 \chi_{[x_d^y, \infty)}) + (\widehat{\lambda}_3 \chi_{[x_d^r, \infty)}) \right] \right\}. \quad (7)$$

where $q(x, y, r)$ and $p(x, y, r) \in \mathbb{R}^3$.

A. Perspective 1: Tail Risk

In order to analyze common distress in the banks comprising the system, we propose the *Joint Probability of Distress* (JPoD) and the *Banking Stability Index* (BSI).

The Joint Probability of Distress

The Joint Probability of Distress (JPoD) represents the probability of all the banks in the system (portfolio) becoming distressed, i.e., *the tail risk* of the system. The JPoD embeds not only changes in the individual banks' PoDs, it also captures changes in the distress dependence among the banks, which increases in times of financial distress; therefore, in such periods, the banking system's JPoD may experience larger and nonlinear increases than those experienced by the (average) PoDs of individual banks. For the hypothetical banking system defined in equation (7) the JPoD is defined as $P(X \cap Y \cap R)$ and it is estimated by integrating the density (BSMD) as follows:

$$\int_{x_d^x}^{\infty} \int_{x_d^y}^{\infty} \int_{x_d^r}^{\infty} \widehat{p}(x, y, r) dx dy dr = JPoD \quad (8)$$

The Banking Stability Index

The *Banking Stability Index* (BSI) is based on the conditional expectation of default probability measure developed by Huang (1992).⁹ The BSI reflects the *expected number of banks becoming distressed* given that *at least one* bank has become distressed. A higher number signifies increased instability. For example, for a system of two banks, the BSI is defined as follows:

$$BSI = \frac{P(X \geq x_d^x) + P(Y \geq x_d^y)}{1 - P(X < x_d^x, Y < x_d^y)} \quad (9)$$

The BSI represents a probability measure that conditions on *any bank* becoming distressed, without indicating the specific bank.¹⁰

B. Perspective 2: Distress Between Specific Banks

Distress Dependence Matrix

For each period under analysis, for each pair of banks in the portfolio, we estimate the set of pairwise conditional probabilities of distress, which are presented in the *Distress Dependence Matrix* (DiDe). This matrix contains the probability of distress of *the bank specified in the row*, given that *the bank specified in the column* becomes distressed. Although conditional probabilities do not imply causation, this set of pairwise conditional probabilities can provide important insights into interlinkages and the likelihood of contagion between the banks in the system. For the hypothetical banking system defined in equation (7), at a given date, the DiDe is represented in Table 1.

⁹ This function is presented in Huang (1992). For empirical applications see Hartmann et al (2001).

¹⁰ Huang (1992) shows that this measure can also be interpreted as a relative measure of *banking linkage*. When the BSI=1 in the limit, banking linkage is weak (asymptotic independence). As the value of the BSI increases, banking linkage increases (asymptotic dependence).

Table 1. Distress Dependence Matrix

	Bank X	Bank Y	Bank R
Bank X	1	P(X/Y)	P(X/R)
Bank Y	P(Y/X)	1	P(Y/R)
Bank R	P(R/X)	P(R/Y)	1

Source: Segoviano and Goodhart (2009).

Where for example, the probability of distress of bank X conditional on bank Y becoming

distressed is estimated by
$$P\left(X \geq x_d^x \mid Y \geq x_d^y\right) = \frac{P\left(X \geq x_d^x, Y \geq x_d^y\right)}{P\left(Y \geq x_d^y\right)}. \quad (10)$$

C. Perspective 3: Cascade Effects

The Probability of Cascade Effects.

This indicator characterizes the likelihood that one, two, or more institutions, up to the total number of FIs in the system become distressed given that a *specific* FI becomes distressed. Therefore, this measure quantifies the potential “cascade” effects in the system given distress in a *specific* bank. Consequently, we propose this measure as an indicator to quantify the systemic importance of a *specific* bank if it becomes distressed. Again, it is worth noting that conditional probabilities do not imply causation; however, we consider that the PAO can provide important insights into *systemic* interlinkages among the banks comprising a system. For example, in a banking system with four banks, X, Y, Z, and R, the PCE can be defined as follows:

$$PCE = P(Y/X) + P(Z/X) + P(R/X) - [P(Y \cap R/X) + P(Y \cap Z/X) + P(Z \cap R/X)] + P(Y \cap R \cap Z/X) \quad (11)$$

IV. BANKING STABILITY MEASURES: EMPIRICAL RESULTS

We have used the BSM proposed by Segoviano and Goodhart (2009) to examine relative changes in stability over time in the following cases:

- (i) Financial Stability and spillovers among country/regions.
- (ii) Spillovers between foreign banks (from developed countries) and emerging market Sovereigns.
- (iii) Spillovers between developed country’s banks and developed Sovereigns.

(iv) Spillovers between the banking system and corporate sectors.

Our estimations are performed from 2005 up to February 2009 using only publicly available data, and include major American and European banks and sovereigns in Latin America, eastern Europe, Europe, and Asia. Implementation flexibility in our approach is of relevance for banking stability surveillance, since cross-border financial linkages are growing and becoming increasingly significant, as has been highlighted by the financial market turmoil of recent months. Thus, surveillance of banking stability cannot stop at national borders.

A. Estimation of Probabilities of Distress of Individual Banks

The proposed BSMs can be constructed from a very limited set of data, e.g., empirical measurements of distress of individual banks; i.e., probabilities of distress (PoDs). Such measurements can be estimated using alternative approaches e.g., Merton-type models, credit default swaps (CDS), option prices, bond spreads, depending on data availability; thus, the data set that is necessary to estimate the BSMs is available in most countries. Consequently, such measures can be provided for a wide group of developing, and developed, countries. Being able to establish such a set of measures with a minimum of basic components, makes it feasible to undertake a wider range of comparative analysis, both time series and cross-section. In the applications explained below we employed CDS-PoDs, since they appeared the best available indicator of distress for the banks under analysis. However, note that the estimation of the proposed BSMs is not intrinsically related to CDS-PoDs. Thus, if we found a better approach, it would be straightforward to replace the chosen PoD approach in the estimation of the BSMs, since PoDs are exogenous variables in this framework.¹¹

B. Financial Stability and Spillovers among regions¹²

In order to analyze financial stability across regions, we included major American, European and Asian banks, which were grouped in alternative portfolios. We observe the following:

¹¹ Arguments against using CDS-PoDs highlight that CDS spreads may overshoot at times; however, they do not generally stay wrong for long. Rating agencies have mentioned that CDS spreads frequently anticipate rating changes. Though the magnitude of the moves may at times be unrealistic, the direction is usually a good distress signal. For these reasons, and due to the problems encountered with the other approaches (which we consider more serious), we decided to use CDS-PoDs to estimate the proposed BSMs.

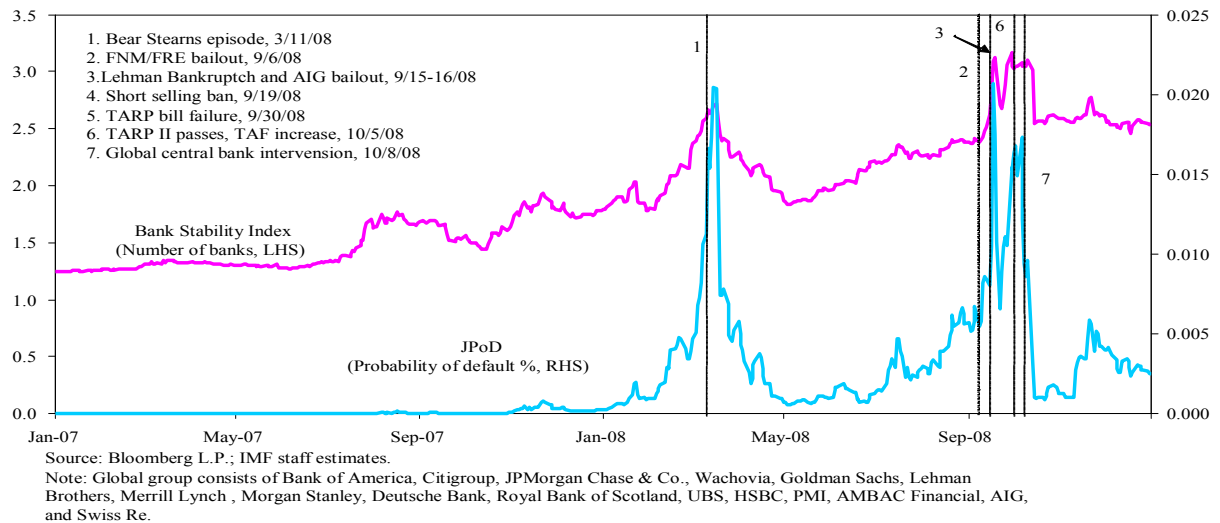
¹² The authors would like to thank Tamim Bayoumi for insightful discussions and contributions in the analysis of these empirical results.

Perspective 1: Tail Risk

- FI's are highly interconnected, with distress in one FI associated with high probability of distress elsewhere.** This is clearly indicated by the JPoD and the BSI. Moreover, movements in the JPoD and BSI coincide with events that were considered relevant by the markets on specific dates (Figure 3). Note also that risks vary by the geographical location and business line of the FI (Figure 4).

Figure 3. Tail Risk: January 2007-February 2009

BSI: Number of FI's, LHS, JPoD: Probability, RHS

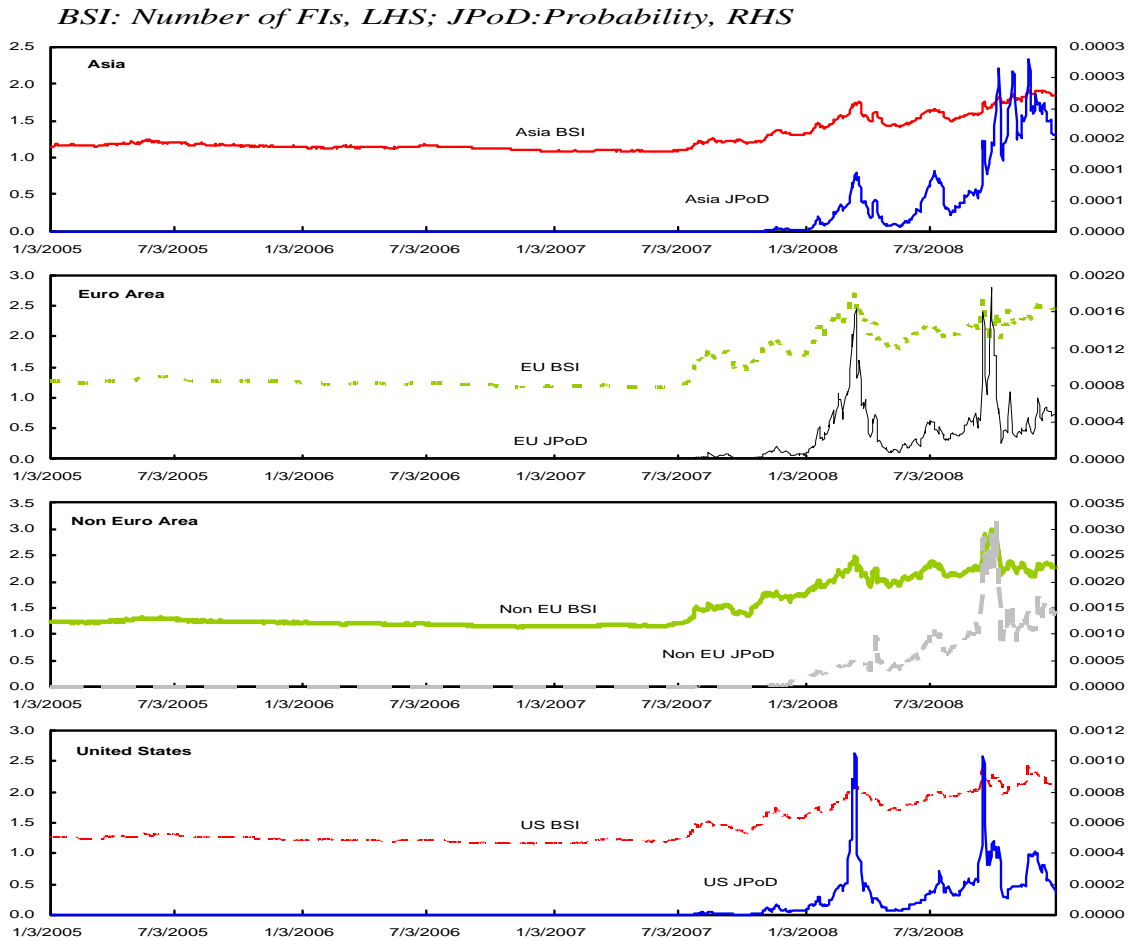


Perspective 2: Distress between Specific Institutions

From Table 2 we can observe the following:

- Distress dependence across major U.S. FIs have increased greatly.** This is clearly shown by the conditional PoDs presented in the DiDe. On average, if any of the US FIs fell into distress, the average probability of the other FIs being distressed increased from 23 percent on July 1, 2007 to 41 percent on September 12, 2008.
- By September, Lehman and AIG vulnerability had increased significantly.** This is revealed by Lehman's and AIG's large PoDs conditional on any other FI falling into distress, which increased from 30 and 15 percent (respectively) on July 1, 2007 to 52 and 44 percent (respectively) on August 15, reaching 56 and 55 percent (respectively) on average on September 12, 2008 (row-average Lehman and AIG). Moreover, a Lehman default was estimated on September 12 to raise the chances of distress elsewhere by 46 percent. In other words, the PoD of any other bank conditional on Lehman falling into distress went from 25 percent on July 1, 2007 to 37 percent on September 12, 2008 (column-average Lehman).

Figure 4. Tail Risk by Regions: January 2007-February 2009



Source: Authors' calculations.

Note that a similar effect in the system would have been caused by the distress of AIG, since the PoD of any other bank conditional on AIG falling into distress went from 20 percent on July 1, 2007 to 34 percent on September 12, 2008 (column-average AIG).

- Lehman's connections to the other major U.S. banks were similar to AIG's.** This can be seen by comparing the chances of each one of the U.S. banks being affected by distress in Lehman and AIG (column Lehman vs. column AIG) on September 12. Links were particularly close between Lehman, AIG, Washington Mutual, and Wachovia, all of which were particularly exposed to housing. On September 12, a Lehman bankruptcy implied chances of 88, 43, and 27 percent that WaMu, AIG, and Wachovia, respectively, would fall into distress.

- Distress Dependence appears to be an early warning indicator.** It is also very interesting to note that up to a month earlier than the Lehman event, distress dependence was already signaling that a default of Lehman or AIG would have caused significant disruptions to the system. This is revealed by the PoD of any other bank conditional on Lehman or AIG falling into distress, which increased significantly to 41 and 39 percent (respectively) on August 15, 2008 (column-average Lehman and AIG). Moreover, On August 15, a Lehman bankruptcy implied chances of 77, 32, and 37 percent that WaMu, AIG, and Wachovia, respectively, would fall into distress. The bankruptcy of Lehman appears to have sealed the fate of AIG and Washington Mutual, while putting greatly increased pressure on Wachovia, as indicated by the DiDe. Even though distress dependence does not imply causation, these results show that the analysis of distress dependence, even several weeks prior to a distress event, can provide useful insights of how distress in a specific institution can affect other institutions and ultimately the stability of the system.

Table 2. Distress Dependence Matrix

July 1, 2007	Citi	BAC	JPM	Wacho	WAMU	GS	LEH	MER	MS	AIG	Row average
Citibank	1.00	0.09	0.08	0.08	0.05	0.06	0.06	0.06	0.06	0.05	0.16
Bank of America	0.08	1.00	0.22	0.21	0.08	0.08	0.07	0.09	0.09	0.11	0.20
J.P. Morgan Chase	0.10	0.33	1.00	0.23	0.09	0.14	0.12	0.14	0.12	0.11	0.24
Wachovia Bank	0.08	0.27	0.20	1.00	0.08	0.08	0.07	0.08	0.08	0.10	0.20
WAMU	0.14	0.25	0.18	0.20	1.00	0.10	0.10	0.13	0.11	0.12	0.23
Goldman Sachs	0.13	0.20	0.23	0.16	0.08	1.00	0.27	0.23	0.26	0.13	0.27
Lehman Brothers	0.16	0.24	0.25	0.19	0.11	0.35	1.00	0.29	0.26	0.14	0.30
Merrill Lynch	0.15	0.26	0.27	0.19	0.13	0.28	0.26	1.00	0.26	0.15	0.30
Morgan Stanley	0.15	0.25	0.23	0.19	0.10	0.30	0.23	0.25	1.00	0.12	0.28
AIG	0.05	0.11	0.07	0.08	0.04	0.05	0.04	0.05	0.04	1.00	0.15
<i>Column average</i>	0.20	0.30	0.27	0.25	0.17	0.24	0.22	0.23	0.23	0.20	0.23

August 15, 2008	Citi	BAC	JPM	Wacho	WAMU	GS	LEH	MER	MS	AIG	Row average
Citibank	1.00	0.32	0.32	0.23	0.13	0.28	0.23	0.23	0.25	0.21	0.32
Bank of America	0.20	1.00	0.42	0.24	0.09	0.24	0.17	0.19	0.21	0.19	0.30
J.P. Morgan Chase	0.18	0.37	1.00	0.20	0.07	0.25	0.17	0.18	0.20	0.15	0.28
Wachovia Bank	0.41	0.69	0.65	1.00	0.23	0.45	0.37	0.39	0.41	0.39	0.50
WAMU	0.83	0.92	0.89	0.85	1.00	0.80	0.77	0.82	0.80	0.78	0.85
Goldman Sachs	0.21	0.28	0.34	0.19	0.09	1.00	0.28	0.26	0.32	0.18	0.31
Lehman Brothers	0.42	0.51	0.56	0.38	0.22	0.69	1.00	0.52	0.54	0.35	0.52
Merrill Lynch	0.39	0.52	0.58	0.37	0.21	0.61	0.48	1.00	0.53	0.35	0.50
Morgan Stanley	0.31	0.41	0.44	0.28	0.15	0.52	0.35	0.37	1.00	0.24	0.41
AIG	0.36	0.52	0.48	0.38	0.20	0.41	0.32	0.35	0.34	1.00	0.44
<i>Column average</i>	0.43	0.55	0.57	0.41	0.24	0.53	0.41	0.43	0.46	0.39	0.44

September 12, 2008	Citi	BAC	JPM	Wacho	WAMU	GS	LEH	MER	MS	AIG	Row average
Citigroup	1.00	0.20	0.19	0.14	0.07	0.17	0.13	0.14	0.16	0.11	0.23
Bank of America	0.14	1.00	0.31	0.18	0.05	0.16	0.10	0.13	0.15	0.11	0.23
JPMorgan	0.13	0.29	1.00	0.16	0.05	0.19	0.11	0.14	0.16	0.09	0.23
Wachovia	0.34	0.60	0.55	1.00	0.17	0.36	0.27	0.31	0.34	0.29	0.42
Washington Mutual	0.93	0.97	0.95	0.94	1.00	0.91	0.88	0.92	0.91	0.89	0.93
Goldman Sachs	0.15	0.19	0.24	0.13	0.06	1.00	0.18	0.20	0.27	0.11	0.25
Lehman	0.47	0.53	0.58	0.43	0.25	0.75	1.00	0.59	0.62	0.37	0.56
Merrill Lynch	0.32	0.41	0.47	0.30	0.16	0.53	0.37	1.00	0.48	0.26	0.43
Morgan Stanley	0.21	0.28	0.29	0.19	0.09	0.40	0.22	0.27	1.00	0.14	0.31
AIG	0.50	0.66	0.59	0.53	0.29	0.54	0.43	0.49	0.47	1.00	0.55
<i>Column average</i>	0.42	0.51	0.52	0.40	0.22	0.50	0.37	0.42	0.46	0.34	0.41

Source: Authors' calculations.

Perspective 3: Cascade Effects

- **The probability of cascade effects (PCE) signaled large effects in the markets if Lehman or AIG became distressed.** The PCE for these institutions reached 97 percent and 95 respectively on September 12, 2008. Thus, the PCE was also signaling the possible “domino” effect observed in the days after Lehman’s collapse (Figure 5). Note that the PCE for both institutions had already increased by August, 2008. This analysis (perspective 3) is in line with the insights brought by the DiDe (perspective 2), which indicated Lehman’s distress would be associated with distress in several institutions.

Figure 5. Probability of Cascade Effects if Lehman/AIG fall in Distress



Source: Authors' calculations.

C. Spillovers Between Foreign Banks' and Emerging Market Sovereigns

We extend our methodology to analyze how rising problems in advanced country banking systems are linked with increasing risks to emerging markets. For this purpose, we use CDS spreads written on sovereign and banks' bonds to derive probabilities of distress of banks and sovereigns. Therefore, such PoDs represent markets' views of risks of distress for these banks and countries. While absolute risks are discussed, the focus is largely on cross distress dependence of risks and what they can say about emerging vulnerabilities (perspective 2). More precisely, using publicly available data we estimate cross vulnerabilities between Latin American, eastern European, and Asian emerging markets and the advanced country banks with larger regional presences in these regions. The countries and banks analyzed are:

- **Latin America.** Countries: Mexico, Colombia, Brazil and Chile. Banks: BBVA, Santander, Citigroup, Scotia Bank and HSBC.
- **Eastern Europe.** Countries: Bulgaria, Croatia, Hungary and Slovakia. Banks: Intesa, Unicredito, Erste, Societe Generale, and Citigroup.
- **Asia.** Countries: China, Korea, Thailand, Malaysia, the Philippines, and Indonesia. Banks: Citigroup, JP Morgan Chase, HSBC, Standard and Chartered, BNP, Deutsche, and DBS.

The key observation from the analysis is that concerns about bank solvency and emerging market instability appear to be highly interlinked. To illustrate these interlinkages, we present Distress Dependence Matrices estimated for each of these regions.¹³ In order to analyze how distress dependence has evolved over time, we also estimate the time series of the conditional probabilities of distress of banks/countries if other banks/countries default.¹⁴

Distress between Foreign Banks and Emerging Market Sovereigns

- **The analysis shows that risks in sovereigns and banks increased markedly after October 2008.** In the run-up to the crisis, there was little concern about risks to sovereigns and parent banks in Eastern Europe, and risk perceptions in Latin America and Asia were falling. From July 2007 to September 2008, both sovereign risk and bank risk increased and moved in tandem, but from October 2008, risk in sovereigns has been significantly higher than in banks (Figure 6). This may reflect the deepening downturn in emerging economies in late 2008 and the support received by banks in developed countries from their sovereigns.

¹³ These matrices can be estimated for each day. They report links across countries (bottom right, quadrant 4), and across banks (top left, quadrant 1). The bottom left (quadrant 3) reports how sovereign distress is conditional on bank problems, while the top right (quadrant 2) indicates the opposite link.

¹⁴ Note that there is a daily time series for each of the quadrants described in the previous footnote. Each observation in the time series corresponds to the average of the conditional probabilities in each quadrant, at each day.

- **Bank problems appear to have a significant impact on sovereign distress.** This is seen by comparing the probability of distress of the emerging market sovereigns conditional on distress in the mature market banks in July 2007 and in September 2008. In the last quarter of 2008, sovereign risk conditional on bank risk has increased further (Figure 7).
- **Banks' geographical role matter in sovereign distress.** Quadrant 3 of the distress dependence matrices (Table 3) show distress of Spanish banks to be associated with the highest distress in Latin America and Italian banks in eastern Europe. Distress of Standard Chartered is associated with significant stress in Asia (quadrant 3, column-average). These results suggest that geographic roles matter, since these banks have a substantial presence in the respective regions under analysis.
- **Direct links between banks and countries matter.** Distress in countries with a particularly large foreign bank presence—such as Mexico and Czech Republic—is more strongly associated with potential banking distress (quadrant 2). Direct links from individual banks to countries also matter—for example, distress at Citigroup, Intesa, and DBS are relatively more important for Mexico, Hungary, and Indonesia, than for other countries (quadrant 3).
- **The results also illustrate the influence of systemic risk, which constitutes an indirect link on Asia, over and above direct regional and bilateral links.** Direct ownership and lending by foreign banks is generally lower in Asia than in eastern Europe or Latin America, insulating banking systems somewhat from these direct links, and increasing the relative importance of indirect links involving bank and/or sovereign distress. In addition, links between banks may be somewhat less important for emerging Asia, as borrowing through debt markets tends to play a larger role in local financial systems. Indirect effects are particularly evident in Korea and Indonesia. An important strength of our approach is that market prices reflect perceptions of *direct links and indirect links*. For the former, market presence might be an important element, as in Latin America and eastern Europe; however, for the latter, liquidity pressures and systemic banking distress/macroeconomic spillovers might play an important role. This feature of our approach appears to be particularly relevant in Asia.
- **Overall, the results indicate that systemic bank risks and emerging market vulnerabilities appear to be highly dependent.** This likely reflects the fact that distress in individual banks is a bellwether for the state of the overall financial system, via direct or indirect links.

Table 3. Distress Dependence Matrices. Sovereigns and Banks

(as of February 11, 2009)

Latin America

	BBVA	SANTANDER	CITI	HSBC	row average		MEXICO	COLOMBIA	BRAZIL	CHILE	row average
BBVA	1.000000	0.725706	0.326296	0.637743	0.672436	BBVA	0.275122	0.256586	0.275776	0.361877	0.292340
SANTANDER	0.728609	1.000000	0.315021	0.627339	0.667742	SANTANDER	0.275571	0.255282	0.275471	0.359497	0.291455
CITI	0.751264	0.722414	1.000000	0.776343	0.812505	CITI	0.592785	0.463909	0.541666	0.637557	0.558979
HSBC	0.586723	0.574852	0.310214	1.000000	0.617947	HSBC	0.255741	0.234477	0.253395	0.334707	0.269580
column average	0.766649	0.755743	0.487883	0.760356	0.692658	column average	0.349805	0.302564	0.336577	0.423410	0.353089
	BBVA	SANTANDER	CITI	HSBC	row average		MEXICO	COLOMBIA	BRAZIL	CHILE	row average
MEXICO	0.865202	0.863165	0.809673	0.874189	0.853057	MEXICO	1.000000	0.651145	0.803716	0.872234	0.831774
COLOMBIA	0.823127	0.815681	0.646378	0.817612	0.775700	COLOMBIA	0.664230	1.000000	0.660733	0.754643	0.769902
BRAZIL	0.821372	0.817196	0.700703	0.820338	0.789902	BRAZIL	0.761189	0.613444	1.000000	0.800777	0.793853
CHILE	0.738229	0.730452	0.564896	0.742177	0.693939	CHILE	0.565809	0.479885	0.548478	1.000000	0.648543
column average	0.811983	0.806623	0.680412	0.813579	0.778149	column average	0.747807	0.686118	0.753232	0.856914	0.761018

Eastern Europe

	INTESA	UNICREDITO	ERSTE	SOCIETE	CITI	row average		BULGARIA	CROATIA	HUNGARY	SLOVAKIA	ESTONIA	CZECH REP	row average
INTESA	1.000000	0.475783	0.301497	0.450473	0.210372	0.487625	INTESA	0.139906	0.177797	0.192062	0.176178	0.166857	0.242417	0.182536
UNICREDITO	0.599617	1.000000	0.365881	0.550721	0.266108	0.556465	UNICREDITO	0.178771	0.220875	0.236603	0.225381	0.205656	0.313147	0.230072
ERSTE	0.557821	0.537140	1.000000	0.574143	0.338382	0.601497	ERSTE	0.261211	0.309007	0.346445	0.278363	0.286297	0.469552	0.325146
SOCIETE	0.384907	0.373383	0.265153	1.000000	0.183779	0.441444	SOCIETE	0.124492	0.146027	0.154783	0.150164	0.131893	0.201566	0.151487
CITI	0.518365	0.520285	0.450654	0.529977	1.000000	0.603856	CITI	0.307667	0.361306	0.378085	0.403829	0.334969	0.439626	0.370914
column average	0.612142	0.581318	0.476637	0.621063	0.399728	0.538178	column average	0.202409	0.243003	0.261595	0.246783	0.225134	0.333261	0.252031
	INTESA	UNICREDITO	ERSTE	SOCIETE	CITI	row average		BULGARIA	CROATIA	HUNGARY	SLOVAKIA	ESTONIA	CZECH REP	row average
BULGARIA	0.708755	0.718608	0.715218	0.738093	0.632545	0.702644	BULGARIA	1.000000	0.707068	0.668112	0.758508	0.710653	0.777554	0.770316
CROATIA	0.804806	0.793321	0.756003	0.773592	0.663734	0.758291	CROATIA	0.631785	1.000000	0.678201	0.703084	0.680053	0.820782	0.752318
HUNGARY	0.831557	0.812840	0.810723	0.784304	0.664342	0.780753	HUNGARY	0.571006	0.648697	1.000000	0.650592	0.640253	0.852863	0.727235
SLOVAKIA	0.352204	0.357517	0.300776	0.351336	0.327638	0.337894	SLOVAKIA	0.299327	0.310517	0.300402	1.000000	0.314773	0.396426	0.436908
ESTONIA	0.687141	0.672014	0.637246	0.635676	0.559833	0.638382	ESTONIA	0.577698	0.618698	0.608981	0.648420	1.000000	0.731451	0.697541
CZECH REP	0.610193	0.625443	0.638816	0.593791	0.449097	0.583468	CZECH REP	0.386346	0.456421	0.495831	0.499141	0.447083	1.000000	0.547470
column average	0.665776	0.663290	0.643130	0.646132	0.549531	0.633572	column average	0.577694	0.623567	0.625254	0.709957	0.632136	0.763180	0.655298

Asia

	HSBC	STDCHA	CITI	DEUT	BNP	DBS	JPMOR	row average		Korea	Malaysia	Thailand	China	Philippines	Indonesia	row average
HSBC	1.000000	0.400728	0.240106	0.467571	0.594485	0.243707	0.277133	0.460533	HSBC	0.200850	0.199495	0.193485	0.218316	0.135680	0.129475	0.179550
STDCHA	0.731765	1.000000	0.373773	0.653803	0.785633	0.399322	0.422132	0.623775	STDCHA	0.362310	0.379956	0.351305	0.355753	0.267159	0.240644	0.326188
CITI	0.600891	0.512247	1.000000	0.680894	0.650505	0.358004	0.847451	0.664285	CITI	0.336656	0.362956	0.325657	0.361394	0.257380	0.248554	0.315433
DEUT	0.390320	0.298881	0.227122	1.000000	0.570166	0.182848	0.299087	0.424061	DEUT	0.154272	0.177260	0.147623	0.160394	0.118085	0.100092	0.142954
BNP	0.349454	0.252899	0.152794	0.401492	1.000000	0.154917	0.194071	0.357947	BNP	0.122491	0.140713	0.122536	0.128010	0.088965	0.077133	0.113308
DBS	0.476818	0.427845	0.279885	0.428549	0.515625	1.000000	0.296335	0.489294	DBS	0.469029	0.509939	0.441641	0.389318	0.307138	0.306915	0.403997
JPMOR	0.274964	0.229358	0.335977	0.355477	0.327567	0.150275	1.000000	0.381946	JPMOR	0.134889	0.147226	0.131452	0.154671	0.095170	0.096777	0.126697
column average	0.546316	0.445994	0.372808	0.569684	0.634855	0.355582	0.476601	0.485977	column average	0.254357	0.273935	0.244814	0.252551	0.181368	0.171370	0.229732
	HSBC	STDCHA	CITI	DEUT	BNP	DBS	JPMOR	row average		Korea	Malaysia	Thailand	China	Philippines	Indonesia	row average
Korea	0.594517	0.587287	0.398186	0.547021	0.616806	0.709589	0.402420	0.550832	Korea	1.000000	0.686822	0.605330	0.614034	0.484226	0.438772	0.638198
Malaysia	0.419980	0.438035	0.305322	0.447027	0.503945	0.548694	0.312387	0.425056	Malaysia	0.488483	1.000000	0.460463	0.463792	0.380784	0.334829	0.521392
Thailand	0.410019	0.407681	0.275756	0.374748	0.441744	0.478346	0.280762	0.381294	Thailand	0.433370	0.463506	1.000000	0.377362	0.299046	0.299040	0.477221
China	0.413471	0.368967	0.273494	0.363895	0.412435	0.376860	0.295244	0.377666	China	0.392881	0.417240	0.337257	1.000000	0.275819	0.253024	0.446037
Philippines	0.472991	0.510020	0.358525	0.493129	0.527604	0.547252	0.334387	0.463415	Philippines	0.570289	0.630551	0.477141	0.507694	1.000000	0.415918	0.600265
Indonesia	0.681152	0.693283	0.522499	0.630787	0.690313	0.825260	0.513146	0.650920	Indonesia	0.779839	0.836727	0.742386	0.702845	0.627663	1.000000	0.781577
column average	0.498688	0.500879	0.355630	0.476101	0.532141	0.581000	0.356391	0.471547	column average	0.610810	0.672474	0.603763	0.610955	0.509756	0.456931	0.577448

Source: IMF staff estimates.

Figure 6. Probabilities of Distress

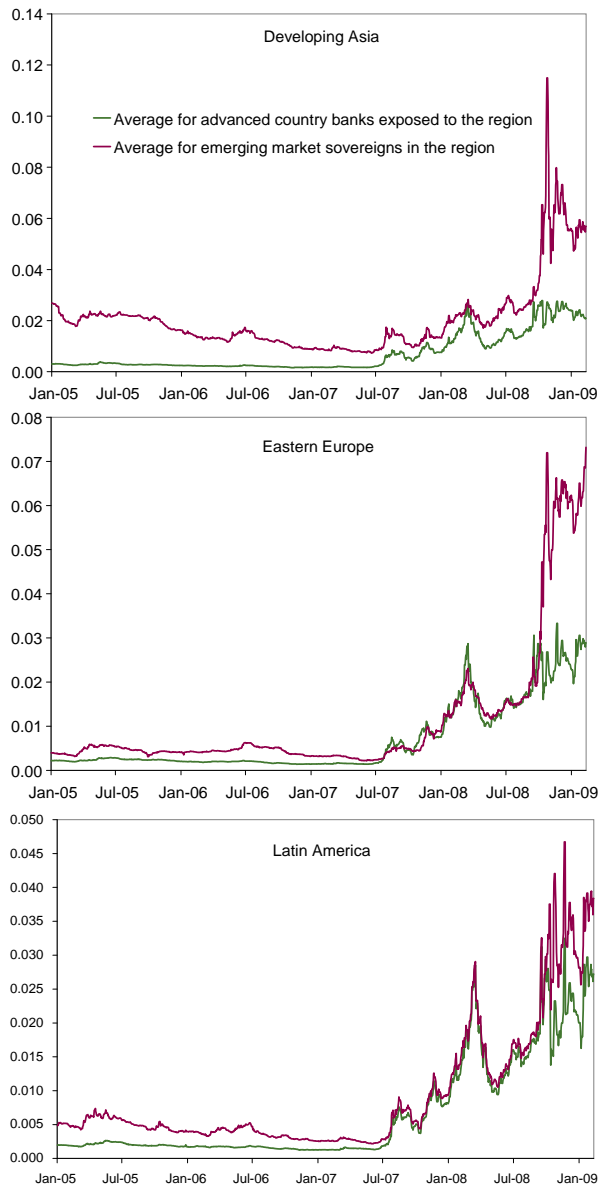
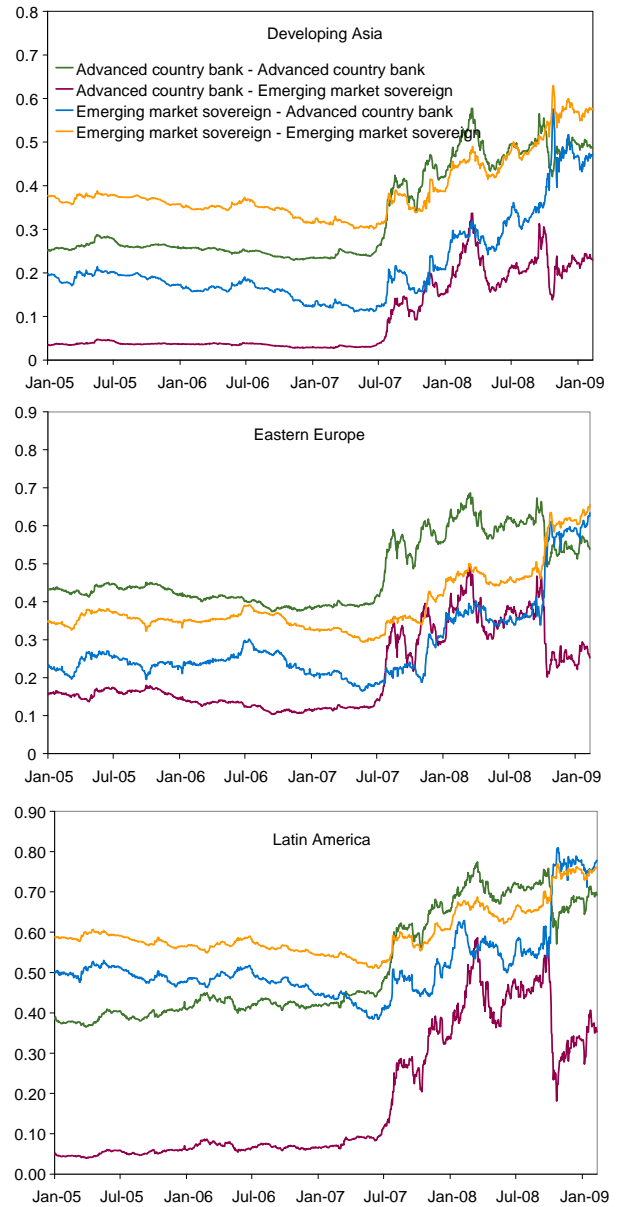


Figure 7. Distress Dependence through Time

(Average conditional probabilities for the region)



Source: Authors' calculations

D. Spillovers Between developed countries' banks and their Sovereigns.

This section applies the proposed model to study the transmission of shocks from banks in developed countries (with large exposures to emerging markets; i.e., Austria, U.K., France and Germany) to their own Sovereigns.

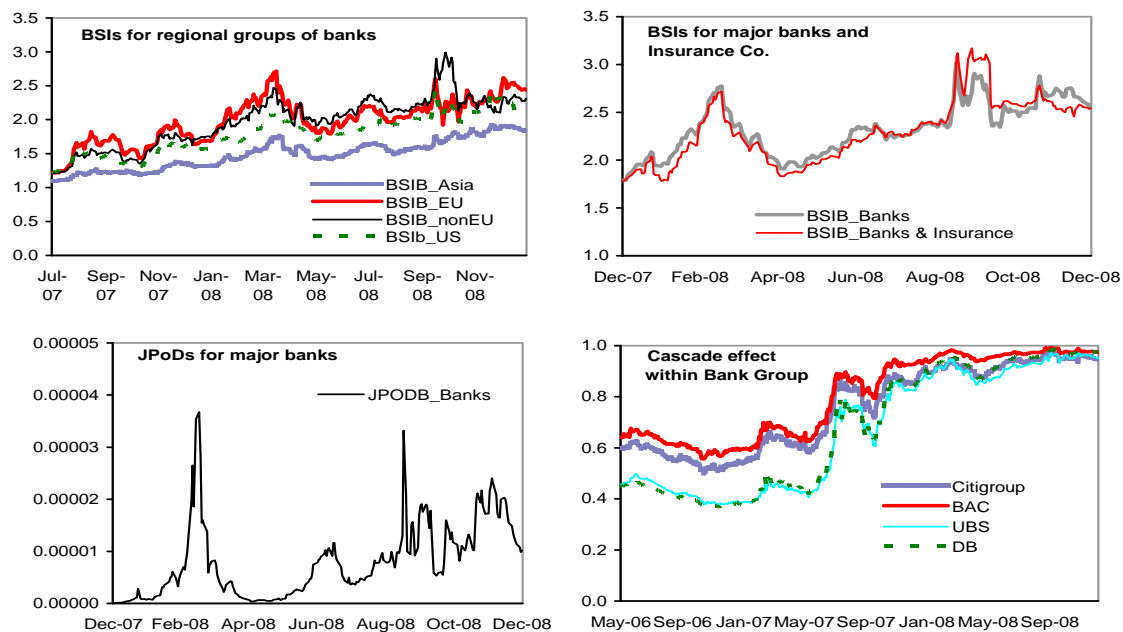
Tail Risk and Cascade Effects

- **Measures of bank interconnectedness started to rise at the onset of the crisis.** The joint probability of distress (JPOD) and Bank Stability Index indicate that systemic “tail risk” has risen substantially (Figure 8).
- **The probability of cascade effects has also increased substantially,** suggesting that future shocks would be transmitted quickly through the financial system (Figure 8).

Distress between banks and Sovereigns in developed economies

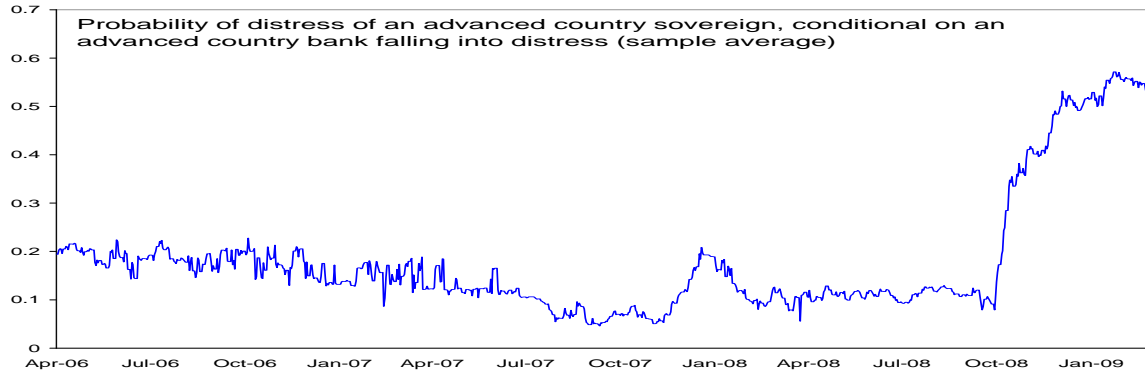
- **Links between advanced country banks and Sovereigns increased markedly after October.** As the fiscal costs of potential bank bailouts have become apparent, banking sector concerns and sovereign risk have become increasingly intertwined. This is significant in Austria and the U.K. (Figure 9).

Figure 8. Tail Risk and Cascade Effects

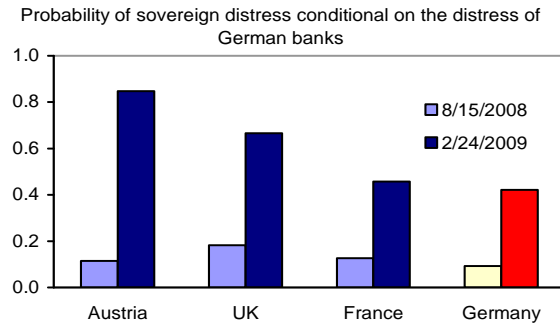
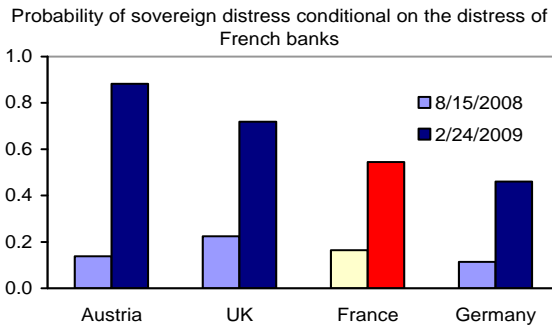
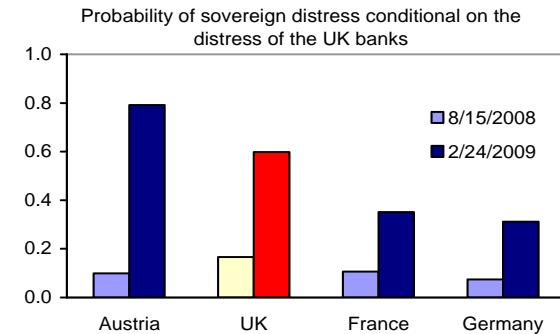
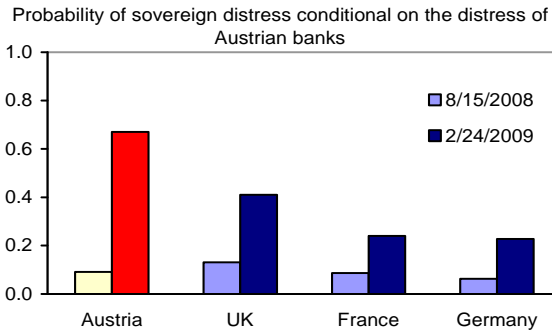
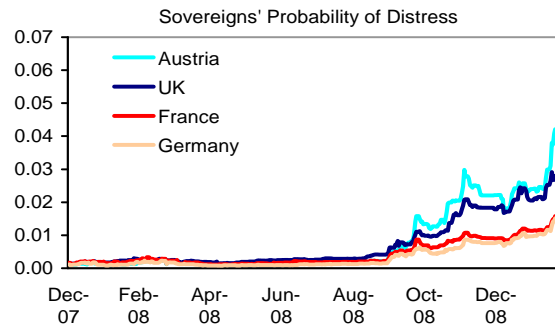
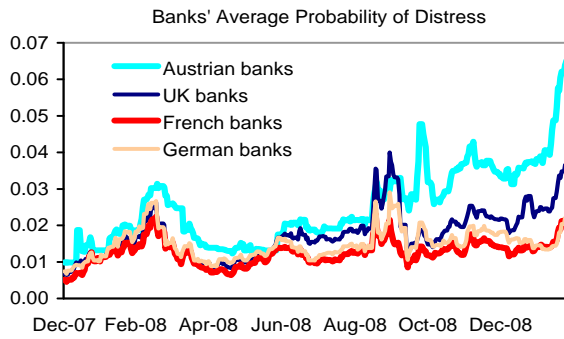


Source: IMF staff estimates.

Figure 9. Distress between Banks and Sovereigns in Developed Economies



Source: IMF staff estimates.



Source: Bloomberg and IMF staff estimates.

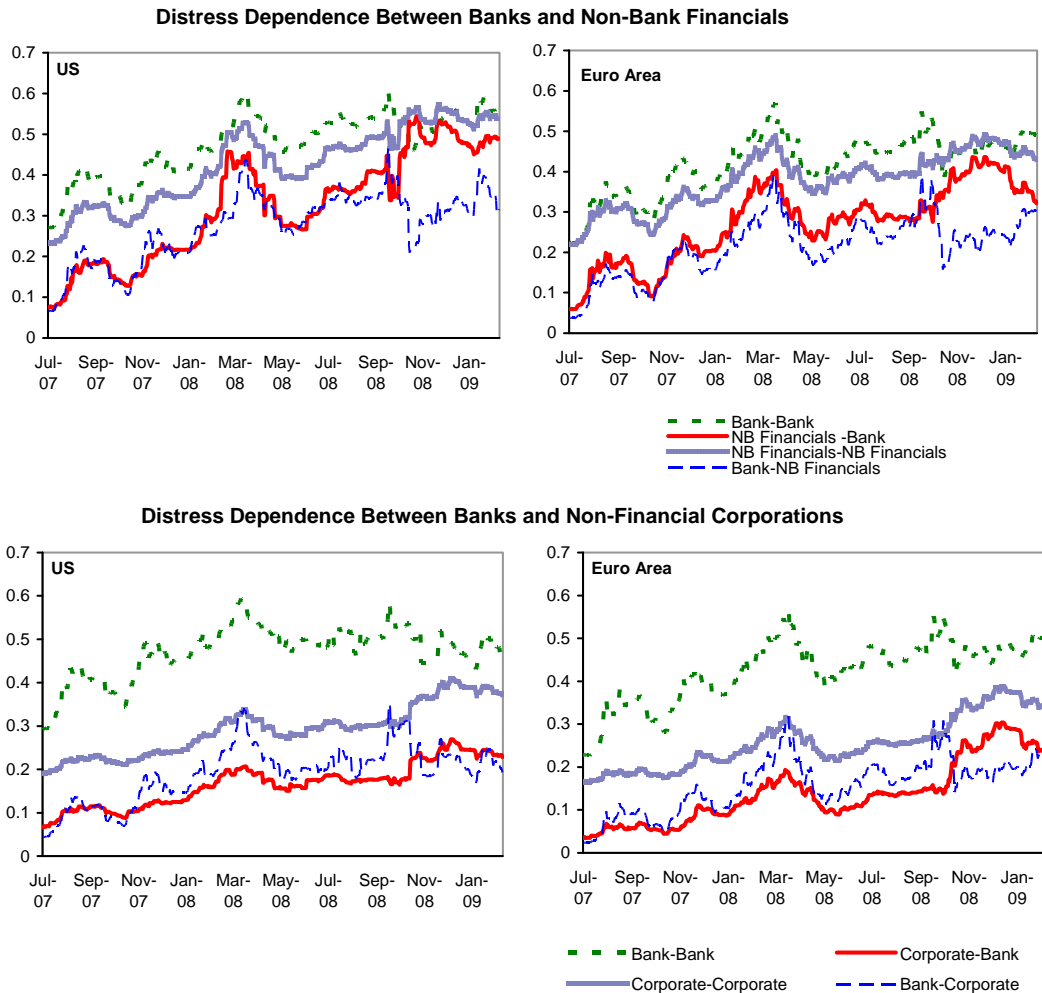
E. Spillovers Between the banking system and corporate sectors.

In order to analyze spillovers between the banking system and the corporate sector, we estimated linkages between non-bank financials, other corporates and banks in the U.S. and Europe

Distress Between Banks and Corporates

- **Banks in developed countries have become gradually more interlinked with non-banks and non-financial corporates.** Banks became less dependent on other corporates in late 2008 (likely due to public support), but spillovers to other corporates continued to rise (Figure 10). This is evidence of spillovers of the banking crisis into the real economy.

Figure 10. Distress between Banks and Corporations in Developed Economies



Source: IMF staff estimates.

V. CONCLUSIONS

The purpose of this paper is to estimate the BSM proposed by Segoviano and Goodhart (2009) to analyze financial stability of the main banks in any country, or region, so that this portfolio of banks' relative stability as a group can be tracked over time and compared in a cross-section of comparative groupings. This framework that has several advantages.

- It provides measures that allow to analyze (define) stability from three different, yet, complementary perspectives.
- It can be constructed from a very limited set of data, i.e., the empirical measurements of default probabilities of individual banks. Such measurements can be estimated using alternative approaches, depending on data availability; thus, the data set that is necessary for the estimation is available in many countries, both developed and developing, as long as there is reasonable data to reflect individual banks' PoDs.
- It embeds the banks' default interdependence structure (copula function), which captures linear and non-linear default dependencies among the main banks in a system.
- It allows the quantification of changes in the banks' default interdependence structure at specific points in time; hence, it can be useful to quantify the empirically observed increases in dependencies in periods of distress, and relax the commonly used assumption in risk measurement models of fixed correlations across time.

The empirical part of the paper applied this methodology to a number of country and regional examples using publicly available information up to February 2009. This implementation flexibility is of relevance for banking stability surveillance, since cross-border financial linkages are growing and becoming significant, as has been highlighted by the financial market turmoil of recent months. Thus, surveillance of banking stability cannot stop at national borders.

APPENDIX I. COPULA FUNCTIONS

Let x and y be two random variables with individual distributions $x \sim F, y \sim H$ and a joint distribution $(x, y) \sim G$. The joint distribution contains three *types* of information. Individual (marginal) information on the variable x , individual (marginal) information on the variable y and information on the dependence between x and y . In order to model the dependence structure between the two random variables, the copula approach *sterilizes* the marginal information on x and y from their joint distribution; consequently, isolating the dependence structure. *Sterilization* of marginal information is done by transforming the distribution of x and y into a uniform distribution; $\mathbf{U}(0,1)$, which is *uninformative*. Under this distribution the random variables have an equal probability of taking a value between 0 and 1 and a zero probability of taking a value outside $[0,1]$. Therefore, this distribution is typically thought of as being *uninformative*. In order to transform x and y into $\mathbf{U}(0,1)$ we use the Probability Integral Transformation (PIT), presented in Appendix 3.

Under the PIT, two new variables are defined as $u = F(x), v = H(y)$, both distributed as $\mathbf{U}(0,1)$ with joint density $c[u, v]$. Under the distribution of transformation of random variables (Cassella and Berger, 1990), the copula function $c[u, v]$ is defined as:

$$c[u, v] = \frac{g[F^{(-1)}(u), H^{(-1)}(v)]}{f[F^{(-1)}(u)]h[H^{(-1)}(v)]}, \quad (12)$$

where $g, f,$ and h are defined densities.

From equation (12), we see that copula functions are multivariate distributions, whose marginal distributions are uniform on the interval $[0,1]$. Therefore, since each of the variables is individually (marginally) uniform (i.e. their information content has been sterilized via the PIT), their joint distribution will *only* contain *dependence information*. Rewriting equation (1) in terms of x and y we get

$$c[F(x), H(y)] = \frac{g[x, y]}{f[x]h[y]}, \quad (13)$$

From equation (13), we see that the joint density of u and v is the ratio of the joint density of x and y to the product of the marginal densities. Therefore, if the variables are independent, equation (13) is equal to one.

Sklar's Theorem

The following theorem is due to Sklar (1959) and is known as Sklar's Theorem. It is a relevant result regarding copula functions, and is used in all applications of copulas. Let G be a joint distribution function with marginals F and H . Then there exists a copula C such that for all x, y in \mathbb{R} ,

$$G[x, y] = C[F(x), H(y)]. \quad (14)$$

If F and H are continuous, then C is unique; otherwise, C is uniquely determined on $\text{Ran}F \times \text{Ran}H$. Conversely, if C is a copula and F and H are distribution functions, then the multivariate function G defined by equation (14) is a joint distribution function with univariate margins F and H . Then, the dependence structure is completely characterized by the copula C (Nelsen, 1999). Nelsen also provides the following corollary to Sklar's theorem.

Corollary: Let G be any joint distribution with continuous marginals F and H . Let $F^{(-1)}(u), H^{(-1)}(v)$ denote the (quasi) inverses of the marginal distributions. Then there exists a unique copula $C: [0,1] \times [0,1] \rightarrow [0,1]$ such that, $g[F^{(-1)}(u), H^{(-1)}(v)] \forall \in [0,1] \times [0,1]$. If the cross partial derivatives of equation (3) are taken, we obtain:

$$g[x, y] = f[x]h[y]c[F(x), H(y)]. \quad (15)$$

The converse of Sklar's theorem implies that we can *couple* together any marginal distributions, of any family, with any copula function and a valid joint density will be defined. The corollary implies that from any joint distribution we can extract the implied copula and marginal distributions (Nelsen, 1999).

Parametric Copula Functions

In the finance literature, it is common to see the Gaussian-copula and the t -copula for modeling dependence among financial assets. These are defined as follows (Embrechts, Lindskog, McNeil, 2001):

Gaussian-copula: The copula of the bivariate normal distribution can be written as:

$$C_R^{Ga}(u, v) = \int_{-\infty}^{\Phi^{-1}(u)} \int_{-\infty}^{\Phi^{-1}(v)} \frac{1}{2\pi(1-\rho^2)^{1/2}} \exp\left\{-\frac{s^2 - 2\rho st + t^2}{2(1-\rho^2)}\right\} ds dt. \quad (16)$$

Where ρ is the linear correlation coefficient of the corresponding bivariate normal distribution, and Φ^{-1} denotes the inverse of the distribution function of the univariate standard normal distribution.

t -copula: The copula of the bivariate t -distribution with ν degrees of freedom and correlation ρ is:

$$C_{\nu\rho}^t(u, v) = \int_{-\infty}^{t_v^{-1}(u)} \int_{-\infty}^{t_v^{-1}(v)} \frac{1}{2\pi(1-\rho^2)^{1/2}} \left\{1 + \frac{s^2 - 2\rho st + t^2}{\nu(1-\rho^2)}\right\}^{-(\nu+2)/2} ds dt. \quad (17)$$

Where $t_v^{-1}(v)$ denotes the inverse of the distribution function of the standard univariate t -distribution with ν degrees of freedom. As it can be seen, this copula depends only on ρ and ν .

APPENDIX II. CIMDO-COPULA

In order to provide a heuristic explanation of the CIMDO-copula, we compare the copula of a bivariate CIMDO-distribution and a bivariate distribution of the form that the *prior* density in the entropy functional would be set; e.g., a *t*-distribution. First, we recall from equation (1) that copula functions were defined as

$$c[u, v] = \frac{g[F^{(-1)}(u), H^{(-1)}(v)]}{f[F^{(-1)}(u)]h[H^{(-1)}(v)]}.$$

Assume that the prior has a density function $q(x, y)$. Hence, its marginal cumulative distribution functions are of the form, $u = F(x) = \int_{-\infty}^{\bar{x}} \int_{-\infty}^{+\infty} q(x, y) dy dx$, and

$$v = H(y) = \int_{-\infty}^{\bar{y}} \int_{-\infty}^{+\infty} q(x, y) dx dy; \text{ where } u = F(x) \Leftrightarrow x = F^{-1}(u), \text{ and } v = H(y) \Leftrightarrow y = H^{-1}(v).$$

Therefore, its marginal densities are of the form, $f(x) = \int_{-\infty}^{+\infty} q(x, y) dy$, and

$$h(y) = \int_{-\infty}^{+\infty} q(x, y) dx.$$

Substituting these into the copula definition we get, the copula of the prior, $c_q(u, v)$,

$$c_q(u, v) = \frac{q[F^{-1}(u), H^{-1}(v)]}{\int_{-\infty}^{+\infty} q[F^{-1}(u), y] dy \int_{-\infty}^{+\infty} q[x, H^{-1}(v)] dx}. \quad (18)$$

Similarly, assume that the CIMDO distribution with $q(x, y)$ as the prior is of the form,

$$\widehat{p}(x, y) = q(x, y) \exp \left\{ - \left[1 + \widehat{\mu} + (\widehat{\lambda}_1 \chi_{[x_d^x, \infty)}^x) + (\widehat{\lambda}_2 \chi_{[x_d^y, \infty)}^y) \right] \right\}. \text{ We also define}$$

$$u = F_c(x) \Leftrightarrow x = F_c^{-1}(u), \text{ and } v = H_c(y) \Leftrightarrow y = H_c^{-1}(v).$$

Its marginal densities take the form,

$$f_c(x) = \int_{-\infty}^{+\infty} q(x, y) \exp \left\{ - \left[1 + \widehat{\mu} + (\widehat{\lambda}_1 \chi_{x_d^x}^x(x)) + (\widehat{\lambda}_2 \chi_{x_d^y}^y(y)) \right] \right\} dy, \text{ and}$$

$$h_c(y) = \int_{-\infty}^{+\infty} q(x, y) \exp \left\{ - \left[1 + \widehat{\mu} + (\widehat{\lambda}_1 \chi_{x_d^x}^x(x)) + (\widehat{\lambda}_2 \chi_{x_d^y}^y(y)) \right] \right\} dx.$$

Substituting these into the copula definition we get, the CIMDO-copula, $c_c(u, v)$,

$$c_c(u, v) = \frac{q[F_c^{-1}(u), H_c^{-1}(v)] \exp \left\{ - \left[1 + \widehat{\mu} \right] \right\}}{\int_{-\infty}^{+\infty} q[F_c^{-1}(u), y] \exp \left\{ - \widehat{\lambda}_2 \chi_{x_d^y}^y(y) \right\} dy \int_{-\infty}^{+\infty} q[x, H_c^{-1}(v)] \exp \left\{ - \widehat{\lambda}_1 \chi_{x_d^x}^x(x) \right\} dx}. \quad (19)$$

Equation (14) shows that the CIMDO-copula is a nonlinear function of $\widehat{\mu}$, $\widehat{\lambda}_1$, and $\widehat{\lambda}_2$, which change as the PoDs of the banks under analysis change. Therefore, the CIMDO-copula captures changes in PoDs, as these change at different periods of the economic cycle.

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