WP/04/33

IMF Working Paper

An Option-Based Approach to Bank Vulnerabilities in Emerging Markets

Jorge A. Chan-Lau, Arnaud Jobert, and Janet Kong

INTERNATIONAL MONETARY FUND

 WP/04/33

IMF Working Paper

International Capital Markets

An Option-Based Approach to Bank Vulnerabilities in Emerging Markets[1]

Prepared by Jorge A. Chan-Lau, Arnaud Jobert, and Janet Kong

Authorized for distribution by Donald J. Mathieson

February 2004

Abstract

We measure bank vulnerability in emerging markets using the distance-to-default, a risk-neutral indicator based on Merton's (1974) structural model of credit risk. The indicator is estimated using equity prices and balance-sheet data for 38 banks in 14 emerging market countries. Results show it can predict a bank's credit deterioration up to nine months in advance. The distance-to-default, hence, may prove useful for bank monitoring purposes.

JEL Classification Numbers: G12, G15, G21

Keywords: Distance-to-default, banks, emerging markets

Author's E-Mail Address: jchanlau@imf.org; A.Jobert@statslab.cam.ac.uk; qkong@imf.org

[1] We would like to thank Jorge Canales-Kriljenko, Toni Gravelle, Alain Inze, Armando Morales, Li Lian Ong, Francisco Vasquez, and seminar participants at the IMF. Errors and omissions remain our responsibility.

Contents Page

I. INTRODUCTION

The banking system plays an important role in the economy. It facilitates economic transactions through its participation in a country's payment system, provides intermediation services that channel household savings to the corporate sector, and contributes to the process of financial development. The banking system also provides risk-sharing opportunities not available through market-based transactions.

When the banking system stops functioning, the welfare costs can be substantial since banking crises are associated with a slowdown of economic activity, higher inflation and fiscal burdens, and exchange rate crises. A quantitative measure of these costs that do not fully reflect the total costs incurred by society is the fiscal cost associated with restructuring the banking system following a banking crisis. A recent IMF study found that fiscal costs can range from 3 percent of GDP, as experienced in the United States, to as high as 50 percent of GDP, as experienced in Chile and Indonesia (IMF, 2003). Safeguarding the banking system, thus, is one of the top priorities of a country's authorities. Accomplishing this goal requires providing banks with a sound macroeconomic environment, and supervising and regulating banks effectively to ensure good governance and prudent risk management (Enoch and Green, 1997).

The repeated occurrence of banking crises during the past two decades, however, suggests that safeguarding the banking system is not an easy task. As a result, new methods have been developed to forewarn bank regulators about possible vulnerabilities at both the systemic and bank-specific levels. These methods, which could be broadly classified as "Early Warning Systems of Bank Distress," provide quantitative risk measures for the aggregate banking system and individual banks. The monitoring of systemic risk in the banking system is usually performed using econometric models that rely on macroeconomic data built upon earlier empirical work associated with balance of payment crises, for example, Demirguc-Kunt and Detragiache (1998) among others.

Monitoring risks at the bank level has led to a search for leading indicators of bank distress that complement on-site examination of banks by the supervisory authorities. In particular, the market prices of the bank's securities, equity and subordinated debt, could potentially reveal information about the bank's conditions on the assumption that markets price risk correctly. One clear advantage of using market prices rather than bank examinations is that market information is available at high frequency.

Recent empirical studies show that market prices can be helpful in forecasting bank distress. For example, in the United States subordinated yields explain bank rating changes as well as regulatory capital ratios (Evanoff and Wall, 2001), equity prices provide useful information on bank failure (Elmer and Fissel, 2001; and Gunther and others, 2001), and that both equity prices and bond yields explain ratings well (Krainer and Lopez, 2003). For European banks, risk measures constructed combining information from equity prices and balance-sheet data and using the model of corporate debt proposed by Merton (1974) predict bank failure up to 18 months in advance (Groppe and others, 2002). Also, for Asian banks during the East Asian crisis in 1997, stock-market-based indicators reacted faster than credit ratings (Bongini and others, 2002).

In this paper, we follow on the steps of Gropp and others (2002) and construct banking vulnerability indicators based on equity prices and balance-sheets for a large set of banks in emerging market countries. We find that the behavior of the indicators is distinctively different, prior to the fact, for banks affected by negative credit events than for those unaffected. The indicators can also forecast the credit event up to nine months in advance. In particular, out-of-sample results show that the indicators could have forewarned in advance about bank failures in Argentina by end-2001. Therefore, implementing this methodology on real time could be a useful addition to the policy maker's toolkit for forecasting banking crises.

The next section explains the theoretical foundations of the proposed vulnerability indicator. Data and results are discussed afterward, and the paper concludes by discussing the limitations of the approach and their possible solutions. These solutions are explained in detail in a companion paper (Chan-Lau, Jobert, and Kong, 2004). It is important to note that the methodology used in this paper and the companion piece are not restricted to analyzing banking firms. Indeed, they could also be used to analyze vulnerabilities in the corporate sector which, as suggested by Kim and Stone (1999), may play a major role in the onset of financial crises.

II. METHODOLOGY

In deriving the vulnerability indicator for emerging market banks, we closely follow Merton's approach by using an option-based structural model of credit risk (Merton, 1974). Specifically, we assume that the asset value of the firm, V, follows a Geometric Brownian Motion with drift equal to the risk-free rate, r, and volatility σ:

$$dV_t = V_t(rdt + \sigma dW_t), \tag{1}$$

where W is a standard Brownian motion.

In this setup, the firm defaults when its asset value at maturity, V_T, is equal or less than the value of its debt at maturity, D. Hence, the creditworthiness of a firm can be measured by the difference between the firm's asset value and the firm's liabilities at maturity, that is the *distance- to- default*. The smaller the distance-to-default the higher the default risk is. The expected distance-to-default, d, for a firm given its current asset value, V, and the face value of its debt, D, maturing T periods ahead, is then given by:

$$d = \log(V_T) - \log(D) = \log(V) + (r - \frac{\sigma^2}{2})T + \sigma W_T - \log(D). \tag{2}$$

Following Crosbie (1999), it is useful to normalize the distance-to-default by the firm's volatility, σ. Rearranging terms, we can define the normalized distance-to-default, DD, as:

$$DD = \frac{d}{\sigma\sqrt{T}} - \frac{W_T}{\sqrt{T}} = \frac{\log(\frac{V}{D}) + (r - \frac{\sigma^2}{2})T}{\sigma\sqrt{T}} \tag{3}$$

The normalized distance-to-default, *DD*, can be interpreted as the number of standard deviations a firm is from default, measured in terms of its asset volatility. The distance-to-default, *DD*, is derived under a risk-neutral measure that allows setting the drift of the asset value equal to the risk-free rate. Working with the risk neutral measure simplifies calculations since it eliminates the need to estimate the drift of the asset value.

Gropp and others (2002) noted that the distance-to-default, *DD*, is both a complete and unbiased indicator of firm vulnerability since it captures well the impact of three major determinants of default risk: earnings expectations, leverage, and asset risk. A rise in earnings expectations increases the firm's asset value and lowers default risk. The decline in default risk is reflected in a higher distance-to-default. Similarly, a decline in leverage makes the firm less risky resulting in a higher distance-to-default. Finally, an increase in asset volatility increases the probability of default and causes a decrease of the distance-to-default.

Calculating the distance-to-default, *DD*, requires knowing the asset value and the asset volatility of the firm. These two variables are difficult to measure accurately. However, if the face value of debt, *D*, and its maturity, *T*, are known, the two unobserved variables can be calculated from the firm's equity value, E_t, and its volatility, σ_E. The latter two variables are observable and can be expressed as functions of the asset value and the asset volatility of the firm. Therefore, the asset value and asset volatility can be recovered from the equity value and equity volatility functions.

In particular, Black and Scholes (1973) and Merton (1974) show that a firm's equity value is equivalent to an European call option on the asset value of the firm with strike price equal to the face value of debt under the assumptions of risk-neutrality, that the asset value follows a geometric brownian motion, and that default only occurs at maturity.[2] The equity value of the firm is then given by the European call pricing formula first derived by Black and Scholes (1973) and Merton (1973):

$$E_t = V_t\Phi(d_1) - D_t\exp(-rT)\Phi(d_2), \tag{4}$$

where r is the risk-free interest rate, Φ is the cumulative standard normal distribution function, and the parameters d_1 and d_2 are defined as follows:

[2] The companion paper referred earlier relaxes the risk-neutrality and constant debt level assumptions.

$$d_1 = \frac{\log(\frac{V_t}{D_t}) + (r + \frac{\sigma^2}{2})T}{\sigma\sqrt{T}}, \tag{5}$$

$$d_2 = d_1 - \sigma\sqrt{T}\ . \tag{6}$$

Equity volatility and asset volatility are linked by the following equation:

$$\Phi(d_1)\sigma V = \sigma_E E\ . \tag{7}$$

Reverse-engineering equations (4) and (7) yields the asset value, V, and the asset volatility, σ, as explained in detail in the next section.

To conclude this section, we want to note that researchers have used this methodology and several variations for various purposes since its introduction by Merton (1974). Moody's KMV is one notable commercial application of the model for predicting corporate defaults (Crosbie, 1999). Other authors, among them Jones and others (1984), Lyden and Saraniti (2000), and Eom and others (2003), have used the methodology to predict spreads on corporate bonds with certain success.

The work of Gropp and others (2002) is closer to ours. These authors applied Merton's structural model of credit risk to derive equity-based indicators for banking soundness for European banks. They found that the Merton style equity based indicator is efficient and unbiased as monitoring device. Furthermore, the equity-based indicator is forward looking and can pre-warn a crisis 12 to 18 months ahead of time. In contrast, other indicators such as uninsured bonds spreads only react relatively late to a deterioration in the fundamentals. Similarly, our objective in this paper is to apply this indicator to test the ability of the distance-to-default indicator to forecast bank vulnerability in emerging markets.

III. Data and Empirical Implementation

The objective of this paper is to calculate distance-to-default measures for banks in emerging market countries and to test their ability to forecast banking crises. To achieve this objective, it is necessary to solve for the asset value and the asset volatility of banks using equations (4)-(7). Solving these equations requires data on equity prices, market valuation, and bank's liabilities as well as a proxy for the risk-free rate. Daily equity data and market valuations are obtained from Primark Datastream LLC. Annual banks' liabilities are obtained from Bankscope, which reports banks' annual balance sheet data. The proxy for the risk-free rate used here is the one-year U.S. Treasury yield. The choice of the one-year yield is based on the assumption that bank's debt matures one year ahead, which is a standard assumption in the literature. This assumption is justified by the lack of detailed information on the maturity structure of bank's debt.
Data availability constrains the sample period to July 1997 to July 2003.[3] This sample period, however, covers a number of interesting events, including the July 1997 devaluation of the Thai bath, the spread of the 1997 East Asian crisis to the Republic of Korea in November 1997, the default on domestic debt by Russia in September 1998, and the default on sovereign debt by Argentina in 2001.

Data availability also constrain the study to 38 banks from fourteen different emerging market countries: 8 banks from Thailand, 7 banks from Hong Kong SAR, 4 banks from Brazil, 3 banks from Argentina, 3 banks from Singapore, 3 banks from Turkey, 2 banks from the Republic of Korea, 2 banks from Venezuela, 1 bank from Chile, 1 bank from Colombia, 1 bank from Czech Republic, 1 bank from Mexico, and 1 bank from Russia. The banks analyzed are listed in Table 1 below.

[3] For some banks, the starting date is after July 1997.

Table 1. Banks Used in this Study

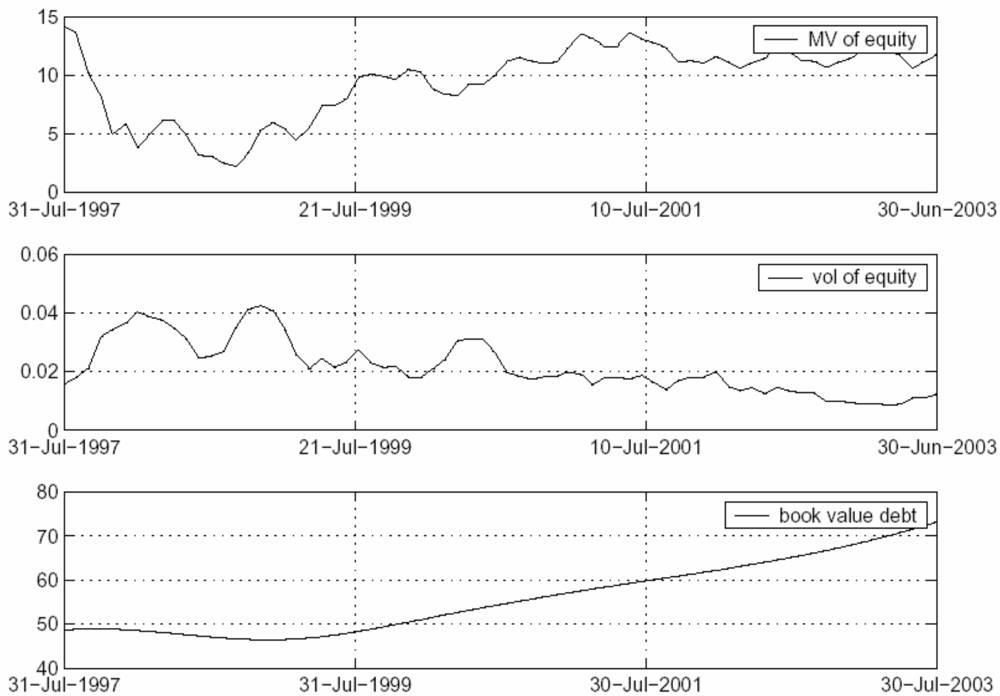
Latin America	Asia	Europe and Africa
Argentina	Republic of Korea	Czech Republic
Banco de Galicia	Koram Bank	Komercni Banka
Banco Hipotecario	Korea Exchange Bank	
Banco Rio de la Plata		Russia
	Hong Kong SAR	Gazprom Bank
Brazil	Bank of East Asia	
Banco Banespa	CITIC International Financial Holdings	South Africa
Banco Itau	Dah Sing Finance Holdings	Firstrad
Banco Mercantil de Sao Paulo	Hang Seng Bank	Nedcor
Unibanco	Liu Chong Hing Bank	
	Wing Hang Bank	Turkey
Chile	Wing Lung Bank	Akbank
Banco Credito		Finansbank
	Singapore	
Colombia	DBS Group	
Banco de Bogota	Overseas Chinese BKG	
	United Overseas Bank	
Mexico		
Grupo Financiero Banorte	Thailand	
	Bangkok Bank	
Venezuela	Bankthai	
Banco Universal	DBS Thai	
Banco de Venezuela	Kasikornbank	
	Krung Thai	
	National Finance Bank	
	Siam Commercial Bank	
	Thai Military Bank	

To implement the distance-to-default indicator empirically, we have to calculate first the monthly average market value of equity, E, and its volatility, σ_E. The equity volatility is estimated as the three-month moving average of daily equity returns in order to remove noise in high frequency market data. The value of debt is approximated as the total book value of debt, *D*. The annual debt stock data is interpolated using cubic splines to obtain monthly estimates of the book value of debt D. Once the equity value, equity volatility, and the bank's debt value are estimated, it is possible to solve for the asset value and asset volatility using the system of nonlinear equations (4) and (7). Afterwards, equation (3) is used to construct the distance-to-default, *DD*, for each bank.

The behavior of the distance-to-default, as well as the behavior of the underlying factors, is illustrated using the example of Dah Sing Finance Holdings, a bank based in Hong Kong SAR.

Figure 1 shows the market value of equity, the equity volatility, the book value of debt, the asset value, the asset volatility, and the distance-to-default indicator for this bank. It is apparent that the distance-to-default increases with default risk.[4] The distance-to-default reached its highest level around the time of the Asian crisis. Coincidently, the asset value of the bank reached its lowest level during the sample period. Equity volatility and asset volatility also reached very high levels during the crisis period. These observations are consistent with the implicit assumption in the structural approach of credit risk modeling, that equity prices reflect valuable information about the firm's fundamentals since capital markets are efficient.[5]

Figure 1. The Behavior of the Distance-to-Default and Underlying Components for Dah Sing Bank, Hong Kong SAR.

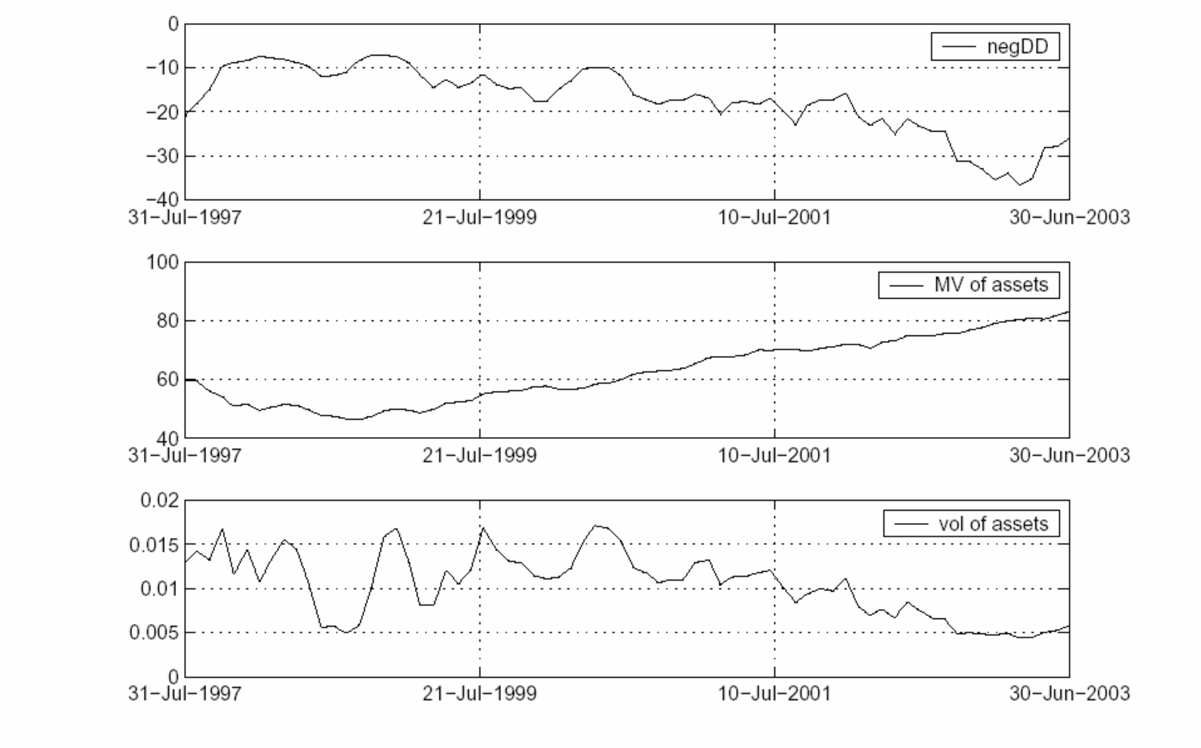


---

[4] We use the negative distance-to-default as our indicator for ease of exhibition.

[5] Complete results for the 38 banks in the sample, not reported for space limitations, are available from the authors.

Figure 1. The Behavior of the Distance-to-Default and Underlying Components for Dah Sing Bank, Hong Kong SAR (concluded).



Moreover, it is interesting to observe that the dynamics of the value of the assets tend to follow closely the dynamics of the debt, suggesting positive correlation between asset value and the book value of debt. Such a positive correlation is implicitly assumed in the Merton-type framework. Indeed, equations (4) and (7) imply that:

$$(\sigma_E - \sigma) V \Phi(d_1) = \sigma_E D \exp(-rT) \Phi(d_2) . \qquad (8)$$

The equation above has two implications. First, equity volatility is greater than asset volatility because of the leverage effect. Second, the asset value, V, and the debt value, D, are positively correlated. [6]. In the next section, we evaluate our (negative) distance-to-default indicator for its ability to forecast vulnerability in the banking system.

[6]This will prove useful for our modeling of an extended Merton-style indicator in a separate paper.

IV. Performance of the Distance-to-Default Indicator

The evaluation of the forecasting ability of the distance-to-default requires defining credit events and/or financial distress for banks. Given the limited information on these banks and the fact that none of them went into bankruptcy recently, we define bank distress as a downgrade by one of the top three rating agencies to CCC or equivalent or below. Such a definition ensures that we have enough credit events in our sample for meaningful econometric analysis. However, due to lack of credit rating data for many of the banks included in this study, the forecasting analysis is restricted to 20 banks.

A. Statistical Tests of the Indicators

First, we separate the banks into two groups for each period based on the absence or presence of a credit event in that period. Then, we calculate the distance-to-default for the two groups of banks with 3, 6, and 9 months leads respectively. Finally, we perform Welch two sample t-tests to evaluate whether the difference in the distance-to-default between both groups of banks is statistically significant for each leading period analyzed.

The results in Table 2 show that, for all three forecasting horizons, the mean distance-to-default for banks that were downgraded is significantly lower, in absolute value, than the mean distance-to-default for banks that did not experience a downgrade. Therefore, the results suggest that the distance-to-default is capable of issuing a statistically significant warning about deteriorating fundamentals of a bank as early as 9 months ahead of a credit event.

Table 2. Difference in Mean Values of the Distance-to-Default Between Downgraded and Non-Downgraded Banks Samples.

The null hypothesis is that the mean value of the distance-to-default is equal for downgraded and non-downgraded banks; the p-value is the probability that the null hypothesis is rejected in favor of the alternative hypothesis that the distance-to-default is the same for both samples.

	Lead, in months		
	3	6	9
Mean Value			
Non-downgraded banks	-22.300	-22.325	-22.470
Downgraded banks	-12.654	-13.480	-12.241
t-statistic	-7.101	-5.866	-6.620
p-value	0.000	0.000	0.000
95 percent confidence level	-7.408	-6.358	-7.682

Source: Authors' calculations.

B. In-Sample Forecasting

We also test the in-sample predictive power of the distance-to-default using logit and probit regressions. Logit and probit regressions are appropriate tools for analyzing bank downgrades since the downgrade is a zero-one variable, that is, the credit event variable takes the value of one if the bank has been downgraded to CCC or below, and zero otherwise.

The regressions are conducted as follows. Let $DEFAULT_t$ denote the dependent variable, which takes the value 1 if the corresponding bank suffered a downgrade to CCC or below in period t. Otherwise, the dependent variable takes the value *0*. Let ψ be the cumulative logit or probit distribution function, and DD_{t-x} the distance-to-default at time *t-x*. Then, the standard logit (probit) model is defined as:

$$\mathbf{P}(DEFAULT_t = 1) = \psi(\alpha_0 + \alpha_1 DD_{t-x}), \qquad (9)$$

where **P(***DEFAULT*=1) is the probability that the dependent variable is 1.

The coefficient α_1 measures the ability of the distance-to-default to predict a future credit event. These models, however, can not be directly estimated using standard algorithms because observations over time for each given bank are not independent.[7] Therefore, there may be serial correlation for within-bank observations. This problem is corrected using the generalized estimating equation approach of Liang and Zeger (1986), that is based on the use of the robust variance-covariance matrix introduced by Huber (1967).[8]

The logit and probit models are estimated for forecasting horizon of 3, 9, and 12 month to assess how far ahead the distance-to-default is able to issue a warning signal. Table 3 reports the results.

[7] Observations for different banks, though, are assumed independent from each other.

[8] A brief but detailed explanation of the technique is described in the Appendix.

Table 3. In-Sample Predictive Performance of the Distance-to-Default:
Logit and Probit Estimations.

	Logit Regression			Probit Regression		
Variable	Coefficient	Wald statistic	p-value	Coefficient	Wald statistic	p-value
			3-month lag			
Intercept	-0.188	0.040	0.842	-0.176	0.087	0.768
Distance-to-Default	0.125	15.257	0.000	0.069	10.245	0.001
			9-month lag			
Intercept	-0.520	0.205	0.651	-0.383	0.333	0.564
Distance-to-Default	0.123	4.599	0.032	0.064	3.725	0.054
			12-month lag			
Intercept	-0.944	0.424	0.515	-0.632	0.673	0.412
Distance-to-Default	0.118	1.850	0.174	0.059	1.710	0.191

Source: Authors' calculations.

The coefficient of the distance-to-default variable is positive and highly significant at the 5 percent level up to 9 months before the credit event in both the logit and the probit regressions. This result indicates that decreases in the absolute value of the distance-to-default signal a higher unconditional likelihood of bank distress or downgrade. The distance-to-default, however, is not a significant predictor of bank distress 12 months ahead. The combined in-sample results together with the statistical test results presented in the previous section suggest that the distance-to-default is an useful early warning indicator for bank distress up to a 9-month lead time. This lead time should prove sufficient for most monitoring and surveillance work in emerging market countries. In particular, the 9-month lead time of the distance-to-default may prove useful for policy makers when macroeconomic data is collected with long delays.

C. Out-of-Sample Forecasting

For an indicator to function well as an early warning signal, not only good in-sample forecasting ability is necessary but good out-of-sample forecasting performance is essential as well. Many existing models of early warning indicators usually perform well with in-sample tests but fail to predict upcoming crises with reliability. In this section, we evaluate whether the distance-to-default can predict out-of-sample credit events.

Given the rather limited sample size and lack of changes in credit ratings of many of the banks in sample, the out-of-sample forecasting exercise is restricted to two Argentine banks. These banks were downgraded in the period surrounding the sovereign default of Argentina in January

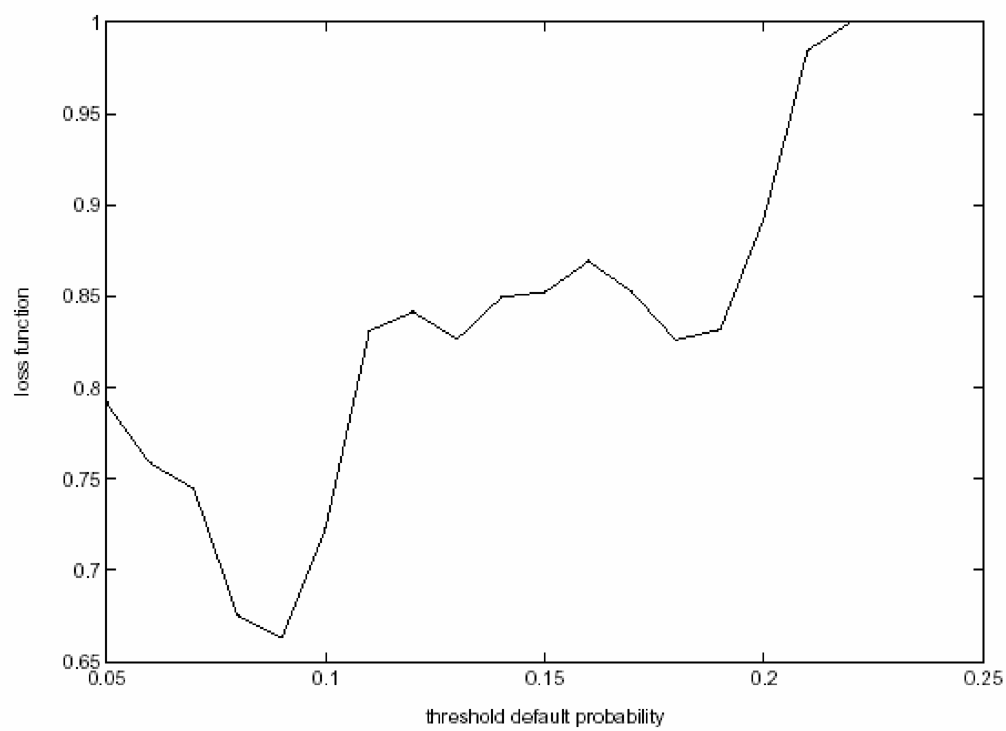
2002. It is worth noting that bank distress events in our sample tend to coincide with major financial crises in the countries and region where the banks are located. For example, a cluster of credit events happened to Asian banks around the Asian crises, then to Russian banks with the Russian default; Brazilian devaluation caused some credit events in Brazilian banks; and towards the end of our sample Argentine banks ran into problems because of the Argentina crisis.

For the out-of-sample analysis, the sample is split into two parts: one for in-sample regression to establish a forecasting model, the other for out-of-sample testing of the forecasting accuracy of the regression. The in-sample regression is used to estimate an in-sample forecasting equation. The equation is then applied to the out-of-sample period to generate out-of-sample probability estimates of bank distress. The analysis also requires establishing a signal threshold for the out-of-sample forecast. Following Kaminsky and others (1998), the optimal threshold is chosen to minimize the in-sample noise-to-signal ratio. Figure 2 shows that the optimal threshold for a three-month forecasting horizon is 9 percent.

The banks analyzed are Banco de Galicia and Banco Hipotecario, which were downgraded in January 2002 and October 2001 respectively. We choose a three-month forecasting horizon to examine whether the distance-to-default correctly predicts these two credit events. Therefore, the in-sample logit regressions are estimated up to three months before the banks were downgraded. In the case of Banco de Galicia, the in-sample period ends in November 2001, and in the case of Banco Hipotecario, in July 2001.

The logit regressions show that the probability of a downgrade 3 months ahead is 14 percent for Banco de Galicia, and 13 percent for Banco Hipotecario. Given the optimal threshold for a three-month forecasting horizon of 9 percent, as shown in Figure 2, we can conclude that the distance-to-default successfully predicted the bank downgrades three months ahead. Furthermore, we also find that the distance-to-default could have predicted well the downgrades of Banco de Galicia and Banco Hipotecario up to 9 and 5 months ahead respectively. In both cases, the probability of bank distress is equal to 11 percent, and still above the optimal threshold for the 5 and 9 month forecasting horizon.

Figure 2. Determination of the Optimal Threshold.



The strong performance of the distance-to-default in in-sample forecasting together with the out-of-sample forecasting results discussed in this section suggest that the distance-to-default could be very useful for bank monitoring and in developing early warning models of bank distress.

V. Conclusions

This paper derives a risk-neutral indicator of bank vulnerability, the distance-to-default, that can be used to assess distress in the banking system. The distance-to-default, that is based on Merton's structural model of credit risk (Merton, 1974), measures the distance between the asset value of the bank and its liabilities at any given point in time. Therefore, the lower the absolute value of the distance-to-default, the higher the default risk of the bank.

We construct the distance-to-default for 38 banks in 14 emerging market countries, and find that it is able to forecast bank distress, defined in our paper as a rating downgrade to CCC or below, up to 9 months ahead in-sample. We also map the risk-neutral indicator to an objective probability of financial distress by using logit and probit regression models. Thus, the distance-to-default can be used to construct an understandable measure of financial difficulty: default probability.

The distance-to-default not only performs well in-sample, by correctly predicting all the credit events; its out-of-sample forecasting capability is also very strong. The two credit events at the end of the sample that could be used for out-of-sample are both correctly signaled with sufficient lead time. The results obtained suggest that the risk-neutral distance-to-default indicator could be a very useful addition to the early warning system models and can be used for monitoring and surveillance purposes.

The distance-to-default, however, suffers from two inherent "weaknesses". One weakness stems from the fact that it is only a "risk-neutral" measure, so it is hard to map it into a "real world" objective measure of financial distress. We attempted to do so in this paper by mapping the indicator through a regression analysis to an objective default measure. Others who have used this type of indicator, such as Moody's KMV, have mapped the distance-to-default to historically observed default and credit event frequencies. The second weakness is due to the assumption implicit in Merton's model that the default barrier is assumed to remain constant during the period. That is, the debt of the firm remains constant until it matures. This does not appear to be a good approximation of real life operations, given that firms constantly manage and adjust their liabilities to meet corporate objectives. Future work will aim to change the assumptions about a constant default barrier by constructing a distance-to-default indicator that allows for a dynamic default barrier.

Correcting for Serial Correlation in the Logit and Probit Estimations

The forecasting ability of the distance-to-default is assessed using logit and probit regressions. However, the observations for each bank are not independent. Therefore, a simple logit or probit regression cannot be estimated because the observations for each bank are serially correlated. This is a standard problem for generalized linear models and in particular, for binary logistic regression. The problem can be addressed by adjusting the standard errors using the generalized method proposed by Huber (1967). Below, we provide a brief technical overview of the rationale underlying the Huber approach that we apply to our econometric estimation.

Generalized linear models are the standard tools for fitting regression models to univariate response data. The following holds true if these models come from an exponential family distribution, and for our purposes, for logistic regressions with binary data. Let us recall the generalized linear modeling framework. Let $Y_1, \ldots, Y_n$ be n independent random variables and assume that Y_i has a probability density function

$$f(y_i \mid \theta_i,\ \phi) = \exp\left(\frac{y_i\theta_i - b(\theta_i)}{\phi} + c(y_i,\ \phi)\right),$$

where ϕ is a scale parameter, θ_i is the canonical parameter and $b(.)$ and $c(.)$ are known functions. Standard calculations yield $\mathbf{E}(Y_i) = \mu_i = b'(\theta_i)$ and $\mathrm{var}(Y_i) = \phi b''(\theta_i) = \phi V(\mu_i)$, where $V(\mu_i)$ is the variance function describing how the variance of Y_i depends upon its mean. Furthermore, while performing the regression the mean μ_i can be linked to the covariates x_i through the link function $g(.)$, i.e.

$$g(\mu_i) = \beta^T x_i,$$

where x_i is known and β is an unknown vector of regression parameters that need to be estimated inn the canonical form, $\theta_i = \beta^T x_i$. In our case of interest, that is a binary logistic regression, $b(\theta_i) = \log(1 + \exp(\theta_i))$, $g(\mu_i) = \log(\frac{\mu_i}{1-\mu_i})$, $\mathrm{var}(Y_i) = \mu_i(1-\mu_i)$, and $\phi = 1$.

When estimating β, the score function is set to zero. That is:

$$U(\beta) = \Sigma_{i=1}^{i=n}\left(\frac{\partial\mu_i}{\partial\beta}\right)^T V(\mu_i)^{-1}(y_i - \mu_i(\beta)) = 0.$$

In general, these score equations cannot be solved analytically for β and thus an iterative method is needed to obtain the maximum likelihood estimate, $\hat{\beta}$, of β. Under certain regularity conditions, $\hat{\beta}$ is asymptotically normally distributed as $N(\beta_0,\ \Sigma(\beta_0))$, where β_0 is the true value of β and $\Sigma(\beta_0)$ is the variance-covariance matrix of $\hat{\beta}$. In practice, $\Sigma(\beta_0)$ is estimated by:

$$\hat{\Sigma}(\hat{\beta}) = \phi\left(\Sigma_{i=1}^{i=n}\left(\frac{\partial\mu_i}{\partial\beta}\right)^T V_i\left(\frac{\partial\mu_i}{\partial\beta}\right)\right)^{-1} ?_{\beta=\hat{\beta}} = \phi(\Sigma i = 1^{i=n} D_i^T V_i^{-1} D_i)^{-1} ?_{\beta=\hat{\beta}}$$

The above variance-covariance matrix $\hat{\Sigma}(\hat{\beta})$ for $\hat{\beta}$ is based upon the assumption that the variance structure for Y_i is correct. However, if this variance structure is misspecified then an alternative asymptotically valid estimator for the variance-covariance matrix of $\hat{\beta}$ can be obtained by using the information "sandwich" estimator (or robust variance-covariance matrix), $\hat{\Sigma}(\hat{\beta})\hat{\Sigma}_U(\hat{\beta})\hat{\Sigma}(\hat{\beta})$, where

$$\hat{\Sigma}_U(\hat{\beta}) = \Sigma_{i=1}^{i=n} D_i^T V_i^{-1}(y_i - \mu_i(\beta))(y_i - \mu_i(\beta))^T V_i^{-1} D_i .$$

The latter formula is due to Huber (1967). The term $(y_i - \mu_i(\beta))(y_i - \mu_i(\beta))^T$ in an estimate of $\text{var}(Y_i)$.

As for our econometric modeling, the observations are not independent within banks, while they are independent across banks. A misspecification could therefore arise when assuming independence over all our observations. In order to tackle this problem, we use a generalized estimating equation (GEE) method in a marginal approach. Such a method is implemented using the statistical package R and its setup is briefly sketched below.

Let Y_{ij} , $i = 1,...,$ n , $j = 1,...,$ m be the *j* the outcome (e.g. outcome at *j*-th time point) for the *i*-th unit (or bank), where we assume that observations on different units (in our case a sequence of 0 or 1, according to whether or not the bank has been downgraded to CCC) are independent but there is correlation between outcomes obtained on the same unit. Let $\mathbf{E}(Y_{ij} \mid x_{ij}) = \mu_{ij}$ be the marginal expectation of Y_{ij}, conditional on the covariate vector x_{ij} (the distance-to-default in our case). With the same notations as above, let the marginal or conditional expectation of the response depend on the covariates x_{ij} through the link function $g(\cdot)$. In the marginal approach we are considering here, we are interested in modeling separately the marginal expectation, $\mathbf{E}(Y_{ij}|x_{ij})$, as a function of the explanatory variables, and the within-unit correlation. In our current marginal model, our interest lies at the population-averaged response level. That is, we are interested in the average response (marginal expectation) over units that share the same covariate value. The assumptions of this approach are very similar to those for generalized linear models, except that a within-unit correlation structure for observations on the same unit is additionally specified.

We assume that that the marginal expectation is related to the covariates through the link function $g(\mu_{ij}) = \beta^T x_{ij}$, where β is the vector or regression parameters and $g(.)$ is the logistic link defined above in our case. We moreover assume that the marginal variance depends on the marginal mean according to

$$\text{var}(Y_{ij}) = \phi V(\mu_{ij}),$$

where $V(.)$ is the variance function and ϕ is the scale parameter. Finally, the correlation between Y_{ij} and Y_{ik} is assumed to be a function of the marginal means and a vector of parameters α , that is

$$corr(Y_{ij},\ Y_{ik}) = \rho(\mu_{ij},\ \mu_{ik},\ \alpha).$$

Liang and Zeger (1986) introduced the generalized estimating equation (GEE) approach for estimating the parameters from a marginal model for correlated data. This approach may be thought of as multivariate generalization of the generalized linear model. The rationale behind their approach was that increased efficiency in estimating β could be realized if we were to take account of the correlation structure (rather than assuming independence). Liang and Zeger realized, however, that specifying a plausible correlation structure (i.e. $\rho(\mu_{ij},\ \mu_{ik};\ \alpha)$) may be difficult in practice. Therefore, they suggested replacing the true correlation structure with a "working correlation matrix", $R(\alpha)$, which depends only on α and not on β and may begin to approximate the true correlation for the purpose of improving efficiency over assuming independence. If this working correlation structure was correctly specified then, in addition to the estimates of the regression parameters, β , being consistent, the standard errors of these estimates also would be consistent. However, it is quite unlikely, in general, to correctly specify the working correlation structure and a robust version for the variance-covariance matrix of the estimates of β is therefore required. The information sandwich or Huber matrix previously described enables us to deal with this problem.

References

Bongini, P., L. Laeven, and G. Majnoni, 2002, "How good is the Market at Assessing Bank Fragility? A Horse Race between Different Indicators," *Journal of Banking and Finance*, Vol. 26, pp. 1011–28.

Black, F., and M. Scholes, 1973, "The Pricing of Options and Corporate Liabilities," *Journal of Political Economy*, Vol. 81, pp. 637–54.

Crosbie, P., 1999, "Modelling Default-Risk" (unpublished; San Francisco: KMV Corporation).

Demirguc-Kunt, A., and E. Detragiache, 1998, "The Determinants of Banking Crises in Developing and Developed Countries," *IMF Staff Papers*, Vol. 45, pp. 81–109.

Elmer, P.J., and G. Fissel, 2001, "Forecasting Bank Failure from Momentum Patterns in Stock Returns" (unpublished; Washington: Federal Deposit Insurance Corporation).

Enoch, C., and J. Green, 1997, editors, *Banking Soundness and Monetary Policy* (Washington: International Monetary Fund).

Eom, Y., J. Helwege, and J. Huang, 2003, "Structural Models of Corporate Bond Pricing: An Empirical Analysis," forthcoming in *Review of Financial Studies.*

Evanoff, D., and L. Wall, 2001, "Sub-Debt Yield Spreads as Bank Risk Measures," *Journal of Financial Services Research*, Vol. 20, pp. 121–45.

Gropp, R., J. Vesala, and G. Vulpes, 2002, "Equity and Bond Market Signals as Leading Indicators of Bank Fragility," Working Paper 150 (Frankfurt: European Central Bank).

Gunther, J.W., M.E. Levonian, and R.R. Moore, 2001, "Can the Stock Market Tell Bank Supervisors Anything They Don't Already Know?," *Economic and Financial Review*, Second Quarter, pp. 2–9 (Dallas: Federal Reserve Bank of Dallas).

Huber, G., 1967, "The Behavior of Maximum Likelihood Estimators Under Non-Standard Conditions," *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability* Vol. 1, pp. 221–33.

Hoelscher, D., and M. Quintyn, 2003, *Managing Systemic Banking Crises*, Occasional Paper 224 (Washington: International Monetary Fund)

Jones, S., S. Mason, and E. Rosenfeld, 1984, "Contingent Claim Analysis of Corporate Capital Structures: An Empirical Investigation," *Journal of Finance*, Vol. 39, pp. 611–25.

Kaminsky, G., S. Lizondo, and C. Reinhart, 1998, "Leading Indicators of Currency Crises," *IMF Staff Papers*, Vol. 45, pp. 1–48.

Kim, S.-J., and M. Stone, 1999, "Corporate Leverage, Bankruptcy, and Output Adjustment in Post-Crisis East Asia," Working Paper 99/143 (Washington: International Monetary Fund)

Krainer, J., and J.A. Lopez, 2003, "How Might Financial Market Information be Used for Supervisory Purposes?," *Economic Review*, pp. 29–45 (San Francisco: Federal Reserve Bank of San Francisco).

Liang, X., and Zeger, X., 1986, "Longitudinal Data Analysis using Generalized Linear Models," *Biometrika*, Vol. 73, pp. 13–22.

Lyden, S., and D. Saraniti, 2000, "An Empirical Examination of the Classical Theory of Corporate Security Valuation" (unpublished; San Francisco: Barclays Global Investors).

Merton, R.C., 1974, "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates," *Journal of Finance*, Vol. 29, pp. 449–70.

_____, 1973, "Theory of Rational Option Pricing," *Bell Journal of Economics*, Vol. 4, pp. 141–83.

Ogden, W., 1987, "Determinants of the Ratings and Yields on Corporate Bonds: Tests of the Contingent Claims Model," *Journal of Financial Research*, Vol. 10, pp. 329–39.