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Estimating Default Frequencies and Macrofinancial Linkages in the Mexican Banking Sector

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Abstract

The credit risk measures we develop in this paper are used to investigate macrofinancial linkages in the Mexican banking system. Domestic and external macro-financial variables are found to be closely associated with banking soundness. At the aggregate level, high external volatility and domestic interest rates are associated with higher expected default probability. Though results vary substantially across individual banks, domestic activity and U.S. growth, and higher asset prices, are generally associated with lower credit risks, while increased volatility worsens credit risks. The expected default probability is also found to be a leading indicator of traditional financial stability indicators.

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I. Introduction

This paper assesses vulnerabilities of the Mexican banking sector using a variant of the Merton framework (1973, 1974) to capture volatility and non-linearities in credit risk indicators. The study constructs a set of credit risk indicators, for a period covering the last 10 years. We also examine the impact of potential shocks on the various risk indicators. In contrast to the Merton framework, which uses market valuation data to capture the collective views and expectations of market participants, this analysis uses book value data from balance sheets due to the absence of market data for most major banks in Mexico. The approach still incorporates volatility into the estimations, a key feature of the Merton framework for capturing non-linearities in the credit risk indicators, especially during periods of distress.

The credit risk indicators seem to capture well recent trends in the banking sector. A trend decline in the riskiness of Mexican banks is observed. The risk measures also seem to respond to the economic recession of 2001–02 and the uncertainty preceding the 2006 presidential election, and have picked up slightly in recent quarters (a time when traditional financial indicators suggest some deterioration in credit quality).

The credit risk measures we develop are used to investigate macrofinancial linkages in the Mexican banking system. Domestic and external macro-financial variables are found to be closely associated with banking soundness, with some heterogeneity across banks. At the aggregate level, high external volatility—as captured by the VIX index—and domestic interest rates are associated with higher average expected default probability. When looking at individual banks, results vary substantially, with different business models. Generally, domestic activity and U.S. growth, and higher asset prices, are associated with lower credit risks, while increased volatility worsens credit risks. The impact of funding costs variables is unclear, and somewhat counterintuitive—this may be due to banks' abundant liquidity.

The *expected default probability* (EDF) is shown to be a leading indicator of traditional financial stability indicators (FSIs). EDF is shown to Granger cause NPLs, while the two variables are closely associated in regression analysis. Despite their limitations, this suggests that our estimated credit risk indicators may be useful complements to other measures of financial soundness—used as indicators rather than as direct estimates of default probabilities. The data limitations are due to lack of market data and of high frequency data, which restricts the amount of volatility that is captured by the indicators. Further, our sample period (1998–2008) is characterized by a strong trend component and historically low volatility, possibly imparting a downward bias to the estimated risks.

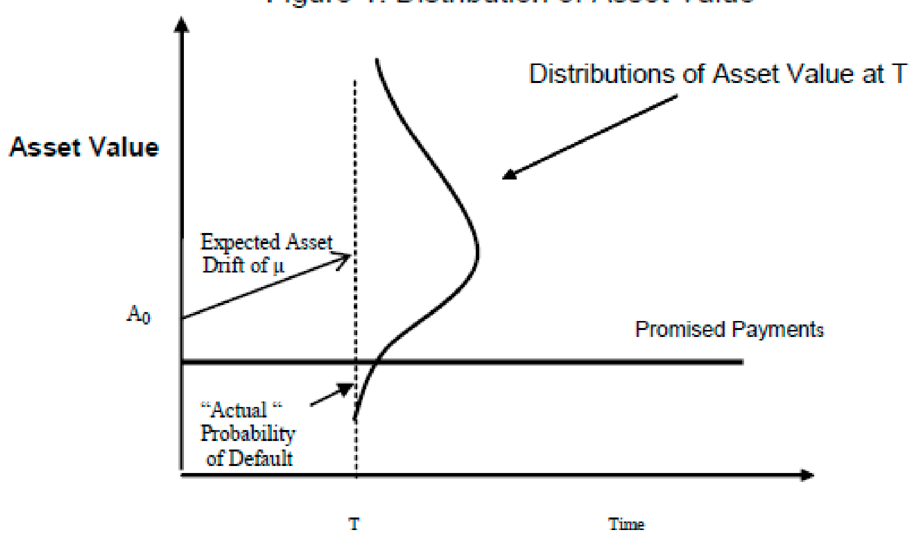
The paper is organized as follows. Section II presents the theoretical underpinnings behind the construction of book value credit risk indicators. Section III provides background on the form of key stylized facts about the Mexican banking system. Section IV discusses the data used in the analysis and presents the main results. Section V summarizes and concludes.

II. The Merton Framework Using Book Value Data

The contingent claims approach (CCA) provides a methodology to combine balance sheet information with widely used finance and risk management tools to construct marked-to-market balance sheets that better reflect underlying risk. The risk adjusted balance sheets use option pricing tools to value the liabilities which are modeled as claims on stochastic assets. It can be used to derive a set of risk indicators that can serve as barometers of risk for firms, financial sector vulnerability, and sovereign risk. Contingent claims analysis is a generalization of the option pricing theory pioneered by Black-Scholes (1973) and Merton (1973).

Credit risk and probabilities of defaults are directly related to balance sheet risk. When assets are insufficient to cover debt service payments, default ensues—the value of assets falls below a distress barrier comprising the total value of the firm's liabilities. Uncertain changes in future asset value, relative to promised payments on debt, is the driver of default risk. Figure 1 (from Dale and Walsh, 2008) illustrates the key relationships. At time horizon T, the value of assets may be above the promised payments indicating that debt service can be made, or below the promised payments leading to default. The uncertainty in asset value is represented by a probability distribution.

Figure 1. Distribution of Asset Value



The analysis models banks' equity as a contingent claim on the residual value of its assets. In the event of default, the firm's assets are used to pay debt holders (assumed to be senior claimants), with equity holders receiving the remainder or nothing. This payoff structure is essentially the same as for a call option on the residual value of the firm's assets. With information on the market value and volatility of equity and on the value of debt, it is possible to estimate the implied value for assets and assets volatility through the Black-Scholes option formula. With the total value of assets and assets volatility, it is then possible to estimate a set of credit risk indicators: expected default frequency (EDF), credit spread, distance-to-distress, and expected losses.[1]

Incorporating volatility explicitly into credit risk indicators offers clear advantages over traditional vulnerability analyses. It allows capturing nonlinear changes in risk, especially during times of stress when small shocks can trigger systemic repercussions. Further, since it uses market-based information, it incorporates collective views of all market participants, to the extent that all relevant information is already priced by the market.

Our application of the CCA framework uses book value data[2] to estimate the credit risk indicators. Most (large) banks are not listed in the Mexican equity market and market data are not available. While this reduces to some extent its forward-looking nature and the ability to capture the collective view of market participants, our approach still retains a key characteristic, the inclusion of asset volatility.[3]

Credit risk indicators are constructed directly from observed book value asset volatility. This information is used to construct four credit risk indicators: the distance-to-distress, the default probability,[4] credit spread, and expected losses given default (for technical details, see Appendix A). This approach has been used successfully in at least two occasions: for the banking sector of Uruguay (Souto, 2008) and for Brazilian banks (Souto, Tabak, and Vazquez, 2008). To measure book value asset volatility, we follow Souto, Tabak, and Vazquez (2008) and place a focus on downside risk volatility—recognizing the greater relevance of downside risks in assessing bank vulnerability. This measure also implies that steady asset growth is not treated as a source of risk.[5] Technically, volatility is estimated as:

[1] *EDF* is the expected probability that the firm may default within one-year (ahead) period. *Credit spread* is the premium an investor would be charging in order to be willing to bear the risk of the firm's default. *Distance-to-distress* is a measure of how far total assets are from the distress barrier, and it is scaled by total assets volatility. Finally, since there is a probability that total assets may fall below total debt, expected losses measures the potential losses debt holders may face, in the event of firm's default.

[2] For the sake of tractability, we assume book value assets to follow a geometric Brownian motion.

[3] It is important to emphasize that, since we are not deriving implied values for assets and assets volatility from market equity and equity volatility, using the Black and Scholes option formula, changes in the distress barrier have a much less pronounced effect in the estimation of the expected default frequency, as it is no longer used in the calculation of the implied assets volatility.

[4] This is the risk-neutral expected default frequency. It is important to appreciate that the risk-neutral valuation is merely an artificial device for obtaining solutions to the Black-Scholes differential equation. The solutions that are obtained are valid in all worlds, not just those where investors are risk neutral. When we move from a risk-neutral world to a risk-averse world, two things happen. The expected growth rate in the stock price changes and the discount rate that must be used for any payoffs from the derivative also changes. It happens that these two changes always offset each other exactly (Hull, 2005).

[5] Using this measure of volatility can potentially lead to wide changes in the estimated credit risk indicators. For example, during a period of sustained increase in assets (with no observed decline in asset value), the estimated distance-to-distress would be infinite, as downside volatility would be estimated to be 0. For computation purposes, these situations were smoothed out using the average of previous and next period.

$$\sigma = \sqrt{\sum_{t=1}^{N} Min\left(\ln(V_t) - \ln(V_{t-1}), 0\right)^2} \ ,$$

where V_t is the book value of total assets at time t, N represents a rolling window of 4 consecutive periods (quarters), equivalent to 1 year, and σ is the downside volatility measure. When estimating the expected default frequency, we annualize σ by multiplying it by $\sqrt{4}$.

III. Background: A few stylized facts about the Mexican Banking System

A few characteristics of the Mexican banking sector are important background to bank soundness analysis. They allow reflecting on how credit risk characteristics may affect individual banks, the banking sector as a whole, and affect its sensitivity to macrofinancial variables.

Levels of financial intermediation are low, with bank credit to the private sector substantially lower than in comparator countries. Moreover, an important share of banks' assets is devoted to holdings of public sector debt instruments.

The banking sector has experienced a fast expansion in recent years. This was notably driven by consumer and mortgage lending, with consumer lending increasing on average by over 40 percent each year from 2002 to 2007. More recently, consumer lending has slowed greatly, while credit to firms picked up in the last 2 years.

Traditional financial sector indicators (FSIs) reflect the strength of Mexican banks, despite some emerging risks. Banks are well capitalized—significantly above minimum regulatory requirements set at 8 percent of risk-weighted assets—and highly profitable. The banking system overall has benefited from the upswing in the economic cycle, which boosted credit demand while contributing to a steady improvement in banks' asset quality. Credit expansion has been funded mostly through an expansion of the deposit base, and reliance on external financing is limited. NPLs are at low levels, around 3 percent overall, although in some categories they have increased sharply recently.

The banking sector is highly concentrated and dominated by foreign-owned banks. The six largest banks[6] account for more than 80 percent of total banking sector assets and more than 75 percent of branches. Of these banks, 5 are foreign-owned.

[6] The six largest banks are BBVA Bancomer, Banco Mercantil del Norte, Banco Nacional de México, Banco Santander, HSBC y Scotiabank Inverlat.

The rest of the banking sector may be classified into three other main types, with different business models.[7] The panorama has evolved rapidly in recent years, with new entrants and greater competition—these have focused especially on previously under-banked segments of the population.[8]

- Small and medium-sized banks (17) manage 10.5 percent of total banking sector assets, lending mostly to SMEs. This group comprises of banks with small operations at the national level, regional banks and banks specialized on specific niche markets.[9]

- Small subsidiaries of foreign banks (14) account for 5.3 percent of banking sector assets and operate mostly as investment boutiques. Their credit activities are relatively limited, except for two subsidiaries focusing on consumer lending.[10]

- Banks associated with commercial and retail groups (BACCs) (5) focus on consumer lending. These banks[11] account for only 1.6 percent of assets.

Banks have different exposure profiles to the various credit markets, depending largely on their business strategies. Assets of the six large banks are now allocated about equally to households (19.5 percent) and enterprises (18.6 percent); a large share of their assets is in government securities. Small and medium-size banks focus on commercial credit (36.5 percent of their assets). Small subsidiaries of foreign banks hold mostly bonds, equity, and derivative products, and credit to the private sector represents a minor part of their assets (15.8 percent). Finally, banks associated with retail business groups concentrate their business on consumer credit (twice as much as any other type of banks), notably for the acquisition of durable consumer goods.

These stylized facts guide the analysis into an investigation of the vulnerabilities of banks in the current financial turmoil, in particular: what do credit risk indicators suggest,

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[7] We follow the same definition for group of banks as in the Financial Stability Report (2007) that is published by the Central Bank of Mexico.

[8] Since 2006, twelve new banks were licensed by the Ministry of Finance.[8] Among them, five are banks owned by major retail business organizations or financial groups owned by retail business organizations. This type of firm's incursion into the banking business, started in Mexico in 2002 with Banco Azteca, is supported by the authorities to encourage competition in the sector, particularly in the consumer credit market and increase the share of the population with access to formal banking services.

[9] There are 17 small and medium-sized banks: Banca Afirme, Banca Mifel, Banco del Bajío, Banco Inbursa, Banco Interacciones, Banco Invex, Banco Regional de Monterrey, Banco Ve por Más, Bansi, Ixe Banco, Banco Compartamos, Banco Monex, Banco Autofin, Banco Amigo, Banco Regional, Banco Multiva, y Consultoría Internacional Banco.

[10] Subsidiaries of foreign banks (14) are ABN AMRO Bank, American Express Bank, Banco Credit Suisse, Banco J.P. Morgan, Bank of America, Bank of Tokyo-Mitsubishi, Deutsche Bank, GE Money Bank, ING Bank, Barclays Bank, Prudential Bank, UBS Bank y Volkswagen Bank.

[11] Banco Azteca, Banco del Ahorro Famsa, Banco Fácil, Bancoppel, and Banco Wal-Mart Adelante.

in particular in light of the recent deterioration in credit quality, what is the expected sensitivity to potential shocks, and which types of banks may be more affected by such shocks?

IV. Estimating Credit Risk Indicators for the Mexican Banking Sector

A. Data and Methodological Assumptions

We construct credit risk indicators for Mexican banks using quarterly data starting in Q4 1997. Derivation of CCA risk indicators can be done at any frequency, but, due to data limitations, this paper uses quarterly data. Quarterly balance sheet data for the various banks were obtained from published data from the Superintendency of Banks (CNBV), for the December 1997–June 2008 period for 27 banks. We also restrict the banks in the sample to the ones for which we have consistent data during the sample period, to avoid issues of mergers and acquisitions.

Some judgment is used in estimating the default barrier and interest rate used in the calculations.

- The default barrier is calculated as the sum of short-term debt and 50 percent of long-term debt. Since longer-term debt can often be restructured, practitioners do not generally set the default barrier equal to the total book value of a company's debt.[12]

- Lacking information on the maturity of term deposits, we assumed that 95 percent of term deposits in Mexico have a term shorter than 12 months. The choice of this parameter naturally has some impact on the results, but this effect is generally minor.[13]

- The choice of interest rate is also not straightforward. The assumption under the Black-Scholes model is of a risk-free rate. In the Mexican context, where the sovereign is not AAA-rated and thus no bank is either, the choice of risk-free rate is not straightforward. For the purpose of our analysis, we use the 3-month treasury bill

[12] In addition, we follow Moody's-KMV in setting the distress barrier, as they use this definition for distress barrier, to calibrate their model and obtain an estimated default frequency that is as close as possible to the historical default probabilities.

[13] As noted in Gray and Walsh (2008), a more serious concern about the choice of default barrier is whether the threshold of interest is in fact default. Banks rarely default, and regulators are likely to be interested less in the probability of such an event than they are in the possibility that bank assets will fall below a level at which the authorities might be expected to intervene, or at which depositors might panic. However, such a "distance to distress" measure would require another assumption about what level assets would have to reach to warrant distress. One such assumption would be to estimate the level of assets implied by the CCA consistent with a minimum level of regulatory capital.

(MBono) rate for the construction of local currency risk indicators and the CPP rate for US$ risk indicators.[14]

Finally, we use data in both local currency and U.S. dollars. Given the low exposure of Mexican banks to foreign currency positions, using balance sheet data in local currency has the benefit of capturing the volatility of assets clean of exchange rate volatility. However, we also used indicators based on U.S. dollar balance sheet data, for comparability purposes and robustness checks, as most practitioners, including the KMV database, report U.S. dollar indicators.

B. Credit Risk Indicators

Figures 4 to 8 show time series for the four main banking risk indicators that we construct for the Mexican banking system, from December 1998 to March 2008, along with a 4-quarter moving average. The analysis is done at the level of individual banks; for conciseness of presentation, Figure 4 shows asset-weighted averages of all banks. Asset-weighted averages are also presented for each of the four main groups of banks (Figures 5–8): large banks, small- and medium-size banks, BACCs, and small subsidiaries of foreign banks. Both local currency and U.S. dollar rates are depicted in the panels.

For all credit risk indicators, a trend reduction in vulnerability is noted since 2000, paralleling improvements in traditional financial sector indicators.

Episodes of stress in the Mexican economic and political system seem also to be well captured by the credit risk indicators. The EDF measure suggests that risks increased substantially in 2001 and 2002, during the last economic slowdown experienced by Mexico, and, to a lesser extent, during the period preceding the Brazilian presidential elections in the third quarter of 2002. Since then the Mexican banking system has substantially reduced its risk—despite a slight pick-up in risk which coincided with the 2006 presidential election. The distance-to-distress indicator[15] is more volatile but provides a similar picture: two periods are particularly noticeable, during which the distance to distress contracted substantially (reflecting higher risks for banks), corresponding to the 2001–02 and 2005–06 periods previously identified.

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[14] CPP Index is the average cost of Funds for Mexican banks making large transactions. It includes all maturities of debt. The CPP dollar indicator measures the cost for banks issuing U.S. dollar-denominated deposits. This indicator does not include interest rates obtained from convertible bonds issued by financial institutions nor loans granted by export-import banks, the commodity credit corp., or other similar financial institutions. The central bank releases the indicator between the 8th and 12th of every month.

[15] The last two indicators of banking risk confirm the reading of the two indicators reviewed above—a gradual decline in risks for the Mexican banking sector, with two period of higher vulnerability, coinciding with the 2001–02 economic recession and the domestic turbulence associated with 2006 presidential election. They also confirmed the patterns for each of the four groups of banks. Small and medium-sized banks generally follow the same trend as large banks; small subsidiaries of foreign banks have a higher risk than other banks; BACCs have sharply reduced their risk level since coming into existence.

The evolution of credit risk indicators for the four groups of banks has been contrasted. Large banks, which largely dominated the sample, drive the aggregate trend describe above. Small and medium-size banks follow the same pattern as large banks, though an increase in credit risk is noted in late 2007–early 2008, with EDF picking up recently. Small subsidiaries of foreign banks also experienced a decline in the risk indicators, but from a much higher level—probably explained by their business model, i.e., mostly focused on securities investment, leading to a higher volatility of assets. Finally, credit risks for the BACCs has been declining steeply to reach low levels in 2008, though shortness in time series and small sample limits the validity of the results.

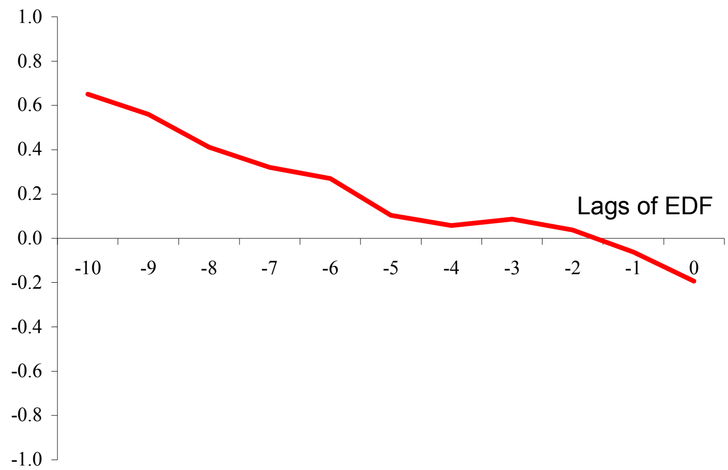
Estimates for credit risk indicators seem to be robust, whether using market-based data or a different measure for volatility. To check for the robustness of our estimates for the credit risk indicators (more specifically, the expected default frequency), we have used market-based data for a couple of banks for which this data was available. We find that there is a significant degree of correlation (around 60 percent) between the book value and the market-based indicators. In addition, we also compare the dynamics of the expected default frequency (EDF) using the downside-risk volatility and another process for volatility that put same weights for both positive and negative shocks. Again, the degree of correlation between the two estimated EDF's is fairly large for the aggregated banking system (around 80 percent).

C. Book-Value Credit Risk Indicators and Other Measures of Banking Risk

An interesting question is whether risk measures derived from book value balance sheet data provide additional information beyond what is contained in other measures of banking risk. As illustrated in Figure 2 the contemporaneous correlation between EDF and NPL is relatively close. Further, in simple OLS regressions, NPL is found to be significantly associated with EDF.

Empirical results suggest that book value credit risk indicators may be useful predictors of NPLs. Figure 2 presents the correlations between various measures of systemwide bank risk and the leads and lags of banking system expected default probability. The measure of NPLs is strongly correlated with increasing expected default probability estimates from a few months previous—that is increasing expected default probability predicts rising NPLs a few months later.

Figure 2. Mexico: Correlation Between EDF and NPL



Source: Staff calculations.

Further, EDF is shown (see Table 1) to Granger cause NPLs—whereas evidence of the reverse causality is absent.

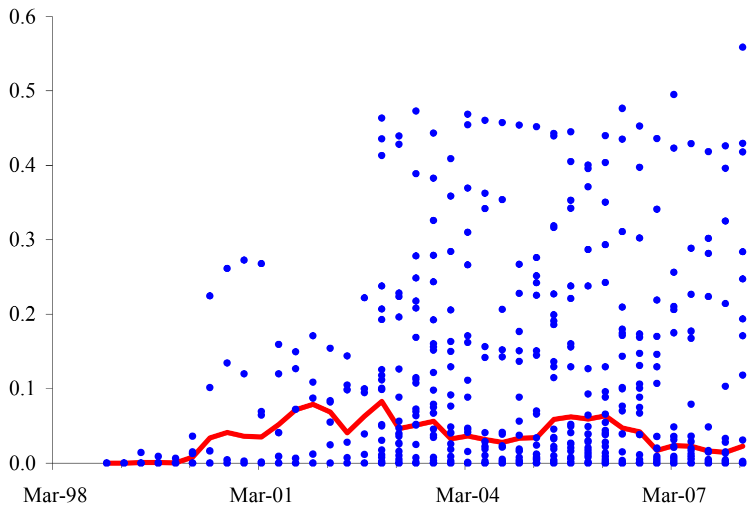
Table 1. Granger tests for the aggregated banking system.

Equation	Excluded	Chi2	Prob > Chi2
EDF	NPL	8.817	0.003
EDF	ALL	8.817	0.003
NPL	EDF	0.125	0.724
NPL	ALL	0.125	0.724

Note: 1-lag VAR, with EDF and NPL as the variables only.

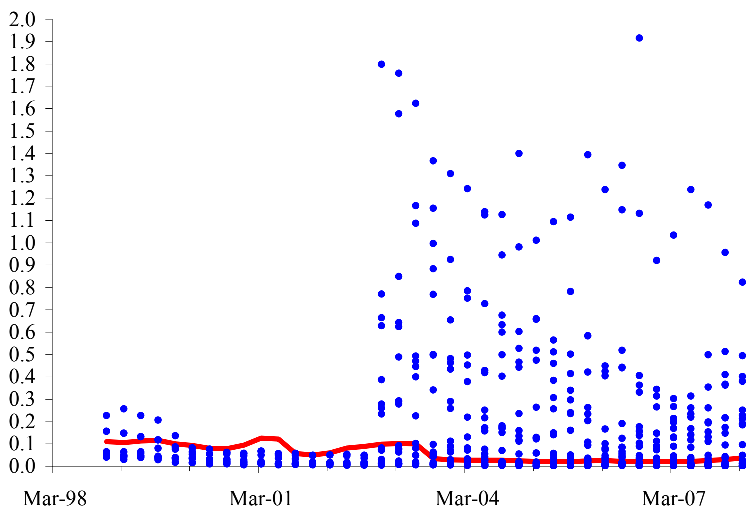
An additional benefit of using book value risk indicators is that they are potentially able to better discriminate across banks, especially in periods of stress, as they incorporate nonlinear effects. This is illustrated in Figures 3a and 3b.

Figure 3a. Mexico: Distribution of EDF (LCU)



Source: Staff calculations.

Figure 3b. Mexico: Distribution of NPL
(in % of TA)



Source: Staff calculations.

V. Assessing Macrofinancial Linkages

Providing some sense of the vulnerability of the banking system to macroeconomic and financial variables is important for the forward-looking monitoring of bank stress, especially when adverse shocks to the macrofinancial environment are forecast. The range of variables that may affect bank soundness and the probability of default is wide, especially given the heterogeneity of banks and business models—suggesting that a relatively large set of explanatory variables be considered. A stepwise regression process with backward elimination is used to filter out the variables of least significance for each individual banks, and also at the aggregate and bank group level—until a small set of explanatory variables of statistical significance remains[16]:

$$EDF_{it} = \alpha_i + \overline{\beta}_i \, .X_{it} + \varepsilon_{it} \, ,$$

where EDF_{it} is the time series of expected probability of default for bank *i* (or the weighted average for all banks in the sample), α_i is a constant, and $\overline{\beta}_i$ is a vector of coefficients for the set of explanatory variables X_{it}.

The variables chosen cover domestic real sector developments, foreign spillovers, and financial-market developments. We attempt to select those with relatively low correlation:

- **Domestic real sector developments**: Two activity indicators are included, the IGAE, an aggregate indicator of economic activity, and Mexican industrial production.
- **Foreign spillovers and linkages/External variables**:
  - **Real sector**: Given close linkages between Mexico and the U.S., we include U.S. industrial production, which is traditionally considered a good leading indicator of Mexican economic performance.
  - **Financial**: The VIX index[17] is included as a measure of financial stability/volatility in global financial markets. A complementary measure is stock market performance in U.S. markets, proxied by the average price changes in the S&P 500. Financial tightness is captured by including the 1-year Treasury bill rate and the 10-year Treasury bond rate, and the yield curve.

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[16] The stepwise regression with backward elimination starts with all explanatory variables and keep eliminating the ones, one-by-one, that are least significant, until ending with a set of factors that are all significant at least at the 10 percent level.

[17] The VIMEX and VIX index are highly correlated (from March 2004 to December 2008 (daily data), correlation in the levels of VIMEX and VIX is over 88 percent). Thus, results should not vary much, whether using VIMEX or VIX for capturing volatility.

- **Domestic financial variables**: Domestic financial conditions are proxied by the stock market price index (IPC) and the domestic interest rate, Cetes (IR).

- **Exchange rate**: A measure of exchange rate expectations is included, the forward foreign exchange rate.

Domestic and external macro-financial variables are found to be closely associated with banking soundness, with some heterogeneity across banks. The explanatory power of the regressions is high, ranging from 13 percent to 79 percent, with an average of 44 percent.

At the aggregate level, volatility in financial conditions and domestic interest rates are significant determinants of the average expected default probability. Greater volatility is associated with a deterioration in credit risk indicators—result which is robust for both EDF and DD. When NPLs are included as an explanatory variable, they are positively correlated with book value measures of credit risk. In addition, the domestic interest rate is statistically significant, though the sign of the coefficient is somehow counterintuitive—with higher interest rates being associated with lower risk. Potential explanations for this result may be the abundant liquidity of banks, and the possible pass-through to lending rates of higher funding rates.

Table 2: Stepwise regression for the aggregated banking system.

Panel A: Using estimated EDF as the dependent variable and NPL as one of the possible covariates.

Variables	Coefficients	
Constant	-0.0000314	
	-0.91	
NPL	0.0003854	**
	2.23	
CETES	-0.0049919	*
	-1.72	
R^2	0.1737	
F-Stat	2.94	*

Note: *, **, and *** mean that the coefficient is statistically different than zero at the 10%, 5%, and 1% significance levels respectively.

Panel B: When NPL is not one of the possible covariates.

Variables	Coefficients	Variables	Coefficients
VIX	0.000318 *	VIX	-1.69 *
	1.71		-1.72
R^2	8.8%	R^2	11.8%
F-Stat	2.91 *	F-Stat	2.96 *

Dependent variable: EDF   Dependent variable: Distance-to-Distress

Note: *, **, and *** mean that the coefficient is statistically different than zero at the 10%, 5%, and 1% significance levels respectively.

When looking at individual banks, results vary substantially, perhaps reflecting their different business models.[18] Generally, domestic activity and U.S. growth, and higher asset prices, are associated with lower credit risks, while increased volatility worsens credit risks. Positive coefficients reflect an increase in the expected default probability. External conditions are significant for most banks in the sample. The U.S. interest rate enters positively for most banks, but domestic interest rates are consistently negatively associated with default probabilities. The impact of funding costs variables is unclear, and somewhat counterintuitive—as mentioned above, this may be due to banks' abundant liquidity.[19] External demand is also significant for most banks, with greater U.S. industrial production generally associated with lower EDFs. Our variables do not show strong patterns across banks, possibly suggesting some degree of resilience for Mexican banks to exchange rate movements and external volatility. This may reflect the low net external positions of Mexican banks as well as the role of domestic deposits in funding recent credit growth.

The above results provide a complementary picture to the one presented in the 2006 FSAP Update. The FSAP Update used a series of stress test results to assess banks' resilience to a variety of shocks. The shocks were based on historical stress scenarios, periods of heightened volatility, and historical distributions of key macro variables for peer economies. The stress tests suggested that the banking system is resilient to shocks including

[18] We intend to investigate in future research about the factors that are driving these heterogeneities, for which detailed data on individual bank's balance sheet and portfolio composition may be necessary.

[19] It is possible that banks may be earning higher net interest margins, as interest rates increase, and this gain could be more than offsetting the losses that would potentially come from an increase in NPLs (resulting from higher interest rates). An alternative explanation might have to do with monetary policy and responses to inflationary pressures that can be coming from both supply and demand shocks at different times in the period of the analysis. It becomes more difficult to examine the effect of interest rates under such circumstances, without additional controls.

Table 3. Determinants of Individual Banks' EDFs: Results of Stepwise Regressions [1/ 2/ 3/]

Bank	Domestic Industrial Production	Domestic Consumer Prices	Domestic Nominal Interest Rate	Economic Activity	Forward Exch. Rate (Peso/Dollar)	VIX	US Nominal Interest Rate	US Industrial Production	R-Square
1	-1.00	…	-0.68	…	-0.24	…	0.00	…	0.40
2	10.61	0.04	…	…	0.15	…	0.00	…	0.49
3	…	…	…	…	…	…	0.01	…	0.19
4	…	…	…	…	…	…	-0.01	…	0.23
5	…	-0.43	2.14	…	…	…	…	-0.01	0.46
6	…	-0.47	…	…	…	…	0.03	-0.02	0.66
7	…	…	…	…	…	…	0.00	…	0.22
8	…	…	…	…	…	…	-0.06	…	0.53
9	…	-1.46	…	-1.94	…	-0.67	…	…	0.43
10	6.99	…	…	…	…	…	-0.12	0.04	0.52
11	…	…	…	…	…	…	-0.03	0.01	0.43
12	…	…	…	…	…	…	-0.06	…	0.73
13	…	…	-2.95	…	…	…	0.02	-0.01	0.63
14	…	0.51	…	…	…	…	-0.06	0.01	0.79
15	-1.27	…	…	…	…	…	…	0.00	0.32
16	-3.69	…	…	…	0.81	…	…	0.02	0.79
17	0.38	…	…	…	…	…	…	…	0.42
18	…	…	-7.30	…	…	…	…	…	0.17
19	-4.15	…	…	…	…	…	…	…	0.38
20	…	…	…	…	-1.58	…	…	…	0.13
21	…	…	-6.32	…	…	…	-0.03	…	0.58
22	…	…	-4.25	…	-0.73	…	…	-0.01	0.64
23	…	…	-0.09	…	…	…	0.00	…	0.62
24	10.61	…	…	…	…	…	…	…	0.21
25	…	…	…	…	4.57	…	…	…	0.25
26	…	…	…	…	…	…	…	-0.02	0.67

1/ The stepwise regression uses backward elimination. It starts with all explanatory variables and keep eliminating the ones, one-by-one, that are least significant, until ending with a set of factors that are all significant at least at the 10 percent level.
2/ We report results using EDFs computed using local currency balance sheet data. Results using dollar-measured EDFs, and using both measures for distance-to-distress are comparable.
3/ Table is presenting the coefficient results for the last stepwise regression for each bank. Last colimn presents the R-Square for each regression.

exchange rate movements, shifts in the term structure of interest rates, a sovereign risk shock, and a drop in domestic equity prices. The results suggested that, as of December 2005, exchange rate risk and sovereign risks did not have an appreciable impact on the system soundness while a sharp upward parallel shift in the yield curve was a greater source of vulnerability.

A panel regression, with pooled individual bank data, provides further support to the above findings. In order to use all available information for Mexican banks, we ran a linear dynamic panel-data model with 1 lag of the dependent variable as covariates and fixed panel-level effects, based on the Arellano and Bond (1991) GMM estimator. The results (Table 4) show that the individual banks' EDFs will deteriorate (increase): (i) when the EDF for the aggregate system increases, highlighting the importance of the systemic risk component; (ii) when the Mexican stock index decreases, consistent with the idea that a decrease in equity (which parallels with a decrease in the distance to the distress barrier) will increase borrowers' credit risk, impacting the bank credit risk indicator negatively; and (iii) when global activity declines. There is also some evidence, although weaker, that EDF will rise when the forward exchange rate increases.

Table 4: Panel regression results.

Bank EDF lag 1	0.64	***
System EDF	0.46	***
Mexican stock index	-0.80	**
Global activity	-0.24	***
Forward FX rate	0.16	*
Constant	0.03	***

Note: *, **, and *** mean that the coefficient is statistically different than zero at the 10%, 5%, and 1% significance levels respectively.

Our findings are comparable with similar studies undertaken for other emerging markets in Latin America. Using market data, Dale and Walsh (2008, on Chile), Souto, Tabak, and Vazquez (2008, on Brazil) and Abrego and Souto (2008, on Colombia) find that bank soundness is significantly related to macro-financial variables, while also finding evidence of heterogeneity between banks. Using book-value data, Souto (2007) finds that CCA indicators capture well the episodes of bank stress in Uruguay.

VI. Summary and Conclusion

This paper uses credit risk indicators estimated using book value data to assess vulnerabilities of the Mexican banking sector and non-linear responses in periods of distress. Our set of credit risk indicators are shown to be leading indicators of FSIs, in particular NPLs, thereby potentially providing useful early warning signals. External and domestic financial variables, as well as activity indicators, are found to be significant determinants of financial sector soundness.

The Merton contingent claims framework (1973, 1974) offers clear advantages over traditional balance sheet vulnerability analyses, including by incorporating volatility explicitly. Nonlinear changes in risk are especially important in times of stress when small shocks can trigger systemic repercussions. A set of credit risk indicators can be estimated, including the expected default probability and the distance-to-distress. In the case of Mexico, book value data are used to estimate the credit risk indicators, because most large banks are not listed in the Mexican equity market. While limiting the forward-looking nature and the incorporation of market information, the approach still captures asset volatility.

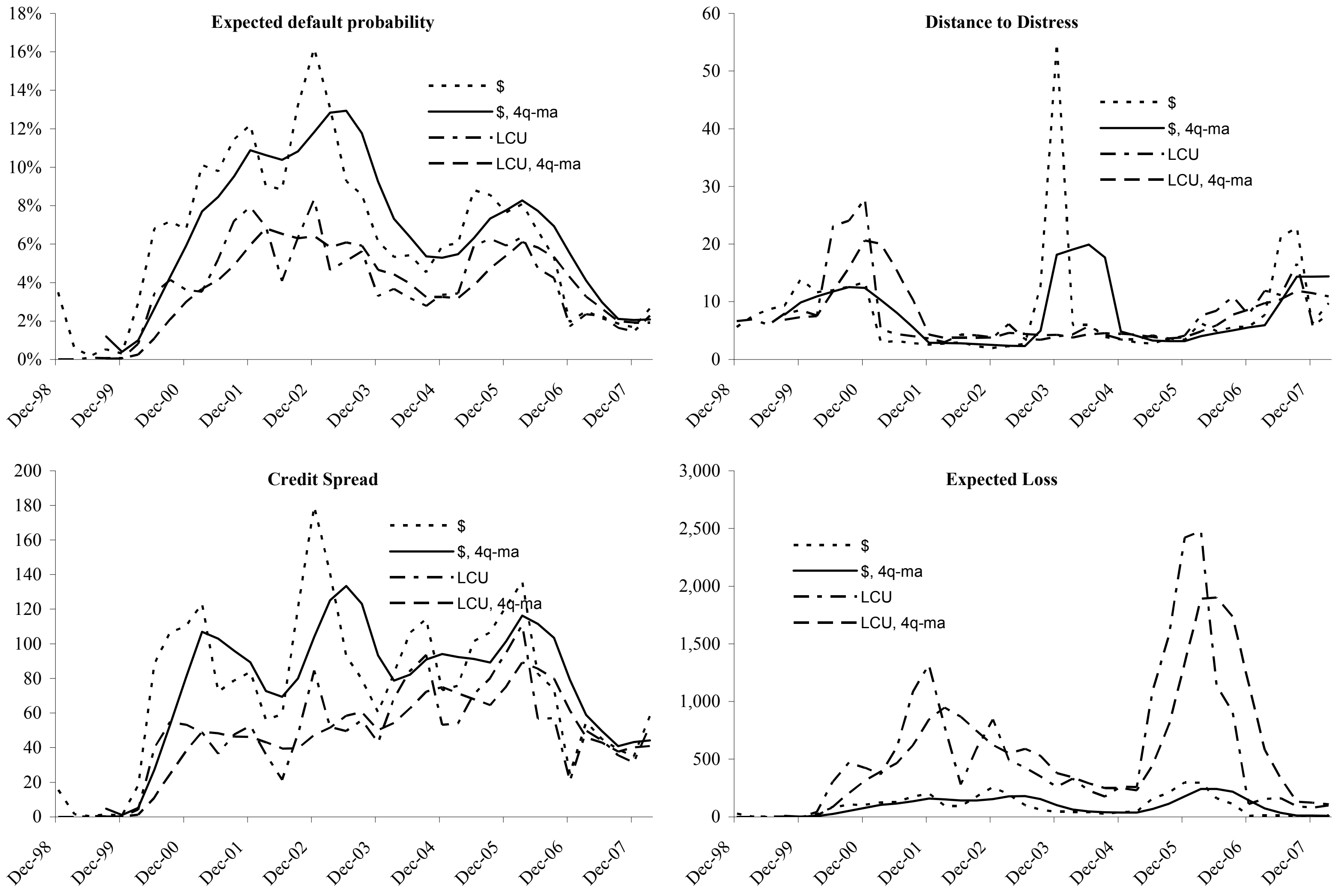
The credit risk indicators seem to capture well recent trends in the banking sector. Historically, a trend decline in the riskiness of Mexican banks is observed. The risk measures capture the economic recession of 2001–02 and the uncertainty preceding the 2006 presidential election, and have picked up in recent quarters with the deterioration in credit quality. Domestic and external macro-financial variables are found to be closely associated with banking soundness, with some heterogeneity across banks. At the aggregate level, volatility—as captured by the VIX index—and domestic interest rates are significant determinants of the average expected default probability. When looking at individual banks, results for estimated sensitivities to macro-financial variables vary substantially, perhaps reflecting their different business models. Generally, domestic activity and U.S. growth, and higher asset prices, are associated with lower credit risks, while increased volatility worsens credit risks. The impact of funding costs variables is unclear, and somewhat counterintuitive—maybe due to banks' abundant liquidity.

Our findings complement recent stress testing exercises (for example, undertaken in the 2006 FSAP Update) and are comparable with similar studies undertaken for other emerging markets in Latin America. Using market data, Dale and Walsh (2008, on Chile), Souto, Tabak, and Vazquez (2008, on Brazil) and Abrego and Souto (2008, on Colombia) find that bank soundness is significantly related to macro-financial variables, while also finding evidence of heterogeneity between banks. Using book -value data, Souto (2007) finds that CCA indicators capture well the episodes of bank stress in Uruguay.

Given their limitations, we suggest that our CCA-type indicators be considered as a complement to other measures and assessment of financial soundness. We interpret them as indicators rather than as direct estimates of default probabilities, for example. Data limitations (lack of market and high frequency data) restrict the amount of volatility that is captured by the CCA indicators. Furthermore, the 1998–2008 period is characterized by a strong trend component and historically low volatility, possibly imparting a downward bias to the estimated risks.

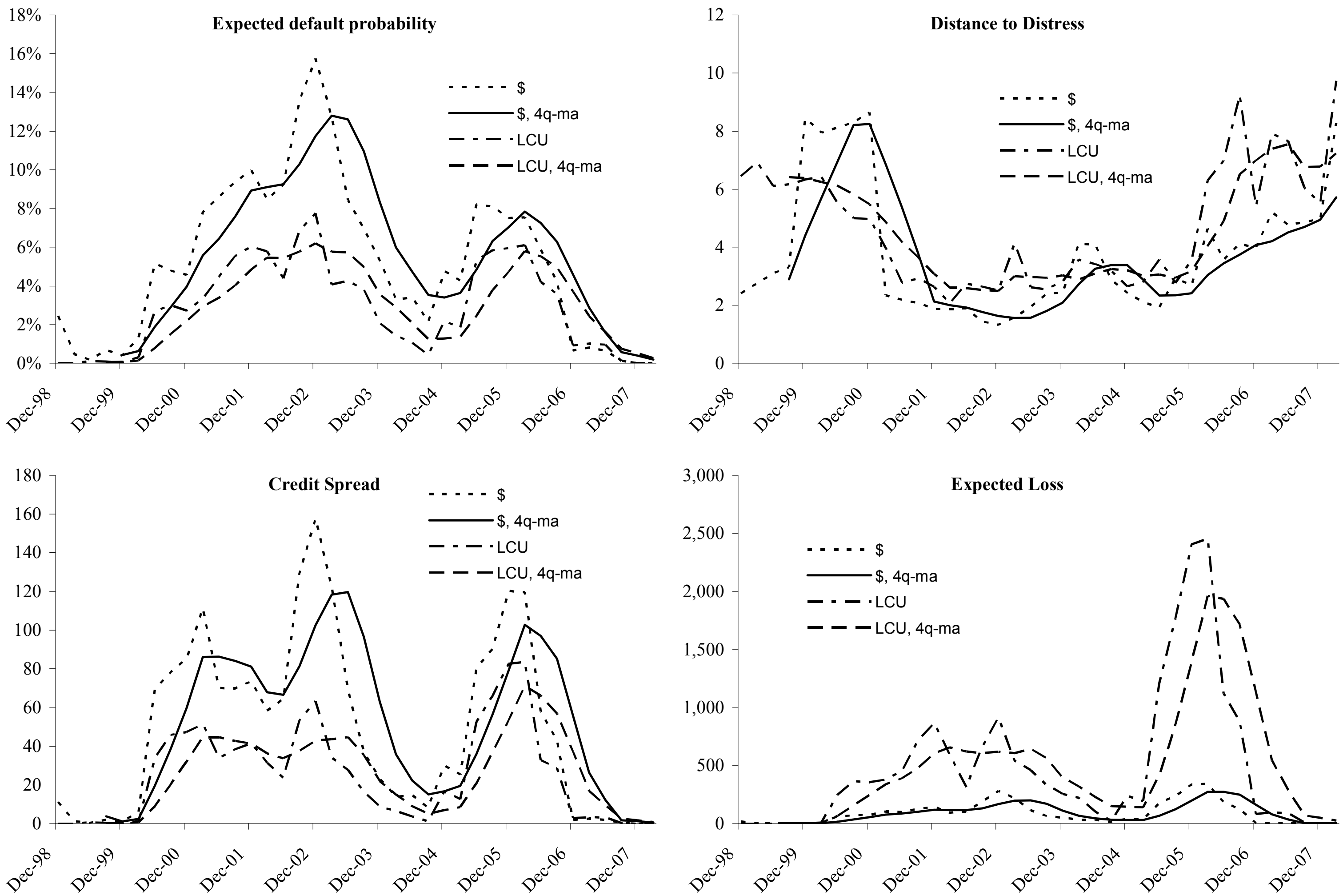
This work could be extended in numerous directions. First, the estimates of credit risk could be refined: using higher frequency data would better capture asset volatility, for example. Second, the credit risk indicators presented here are a potentially useful tool to assess the impact of shocks in the explanatory macrofinancial variables on bank soundness, within a stress test framework.

Figure 4. Mexico: Banking Risk Indicators, December 1998 - June 2008



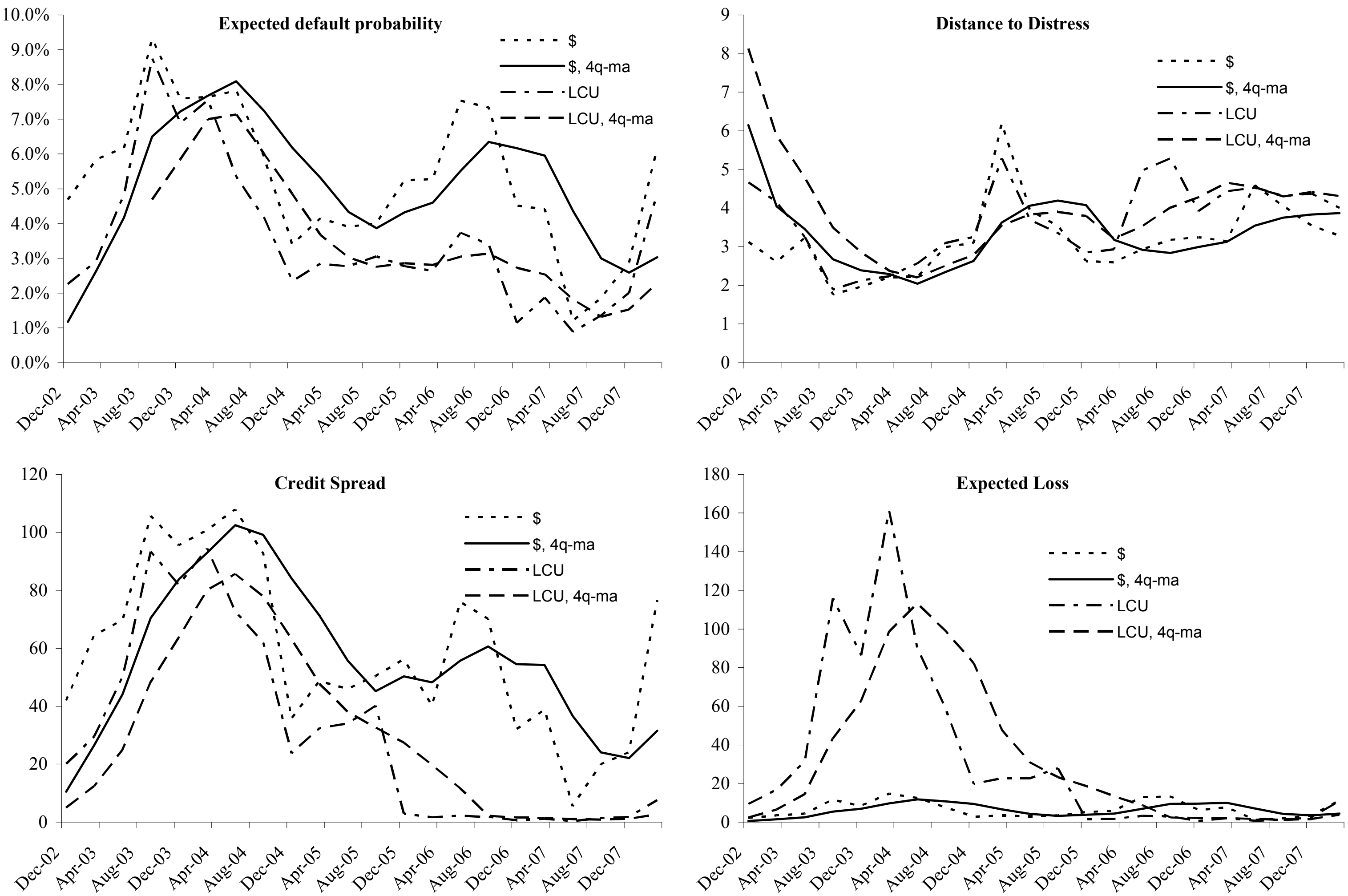
Source: Staff calculations.

Figure 5. Large Banks: Banking Risk Indicators, December 1998 - June 2008



Source: Staff calculations.

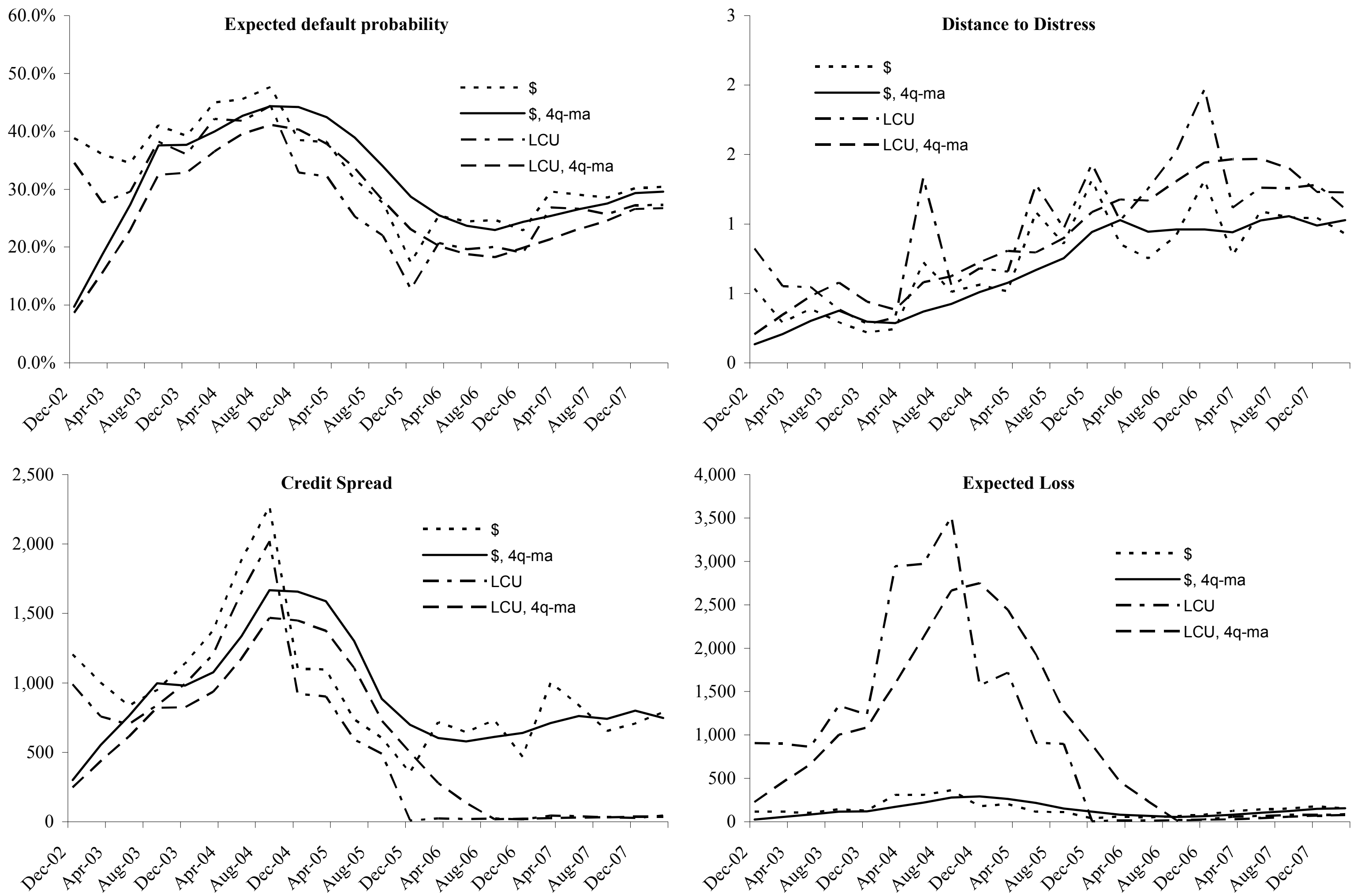
Figure 6. Small- and Medium-Size Banks: Banking Risk Indicators, December 2002 - June 2008 1/



Source: Staff calculations.

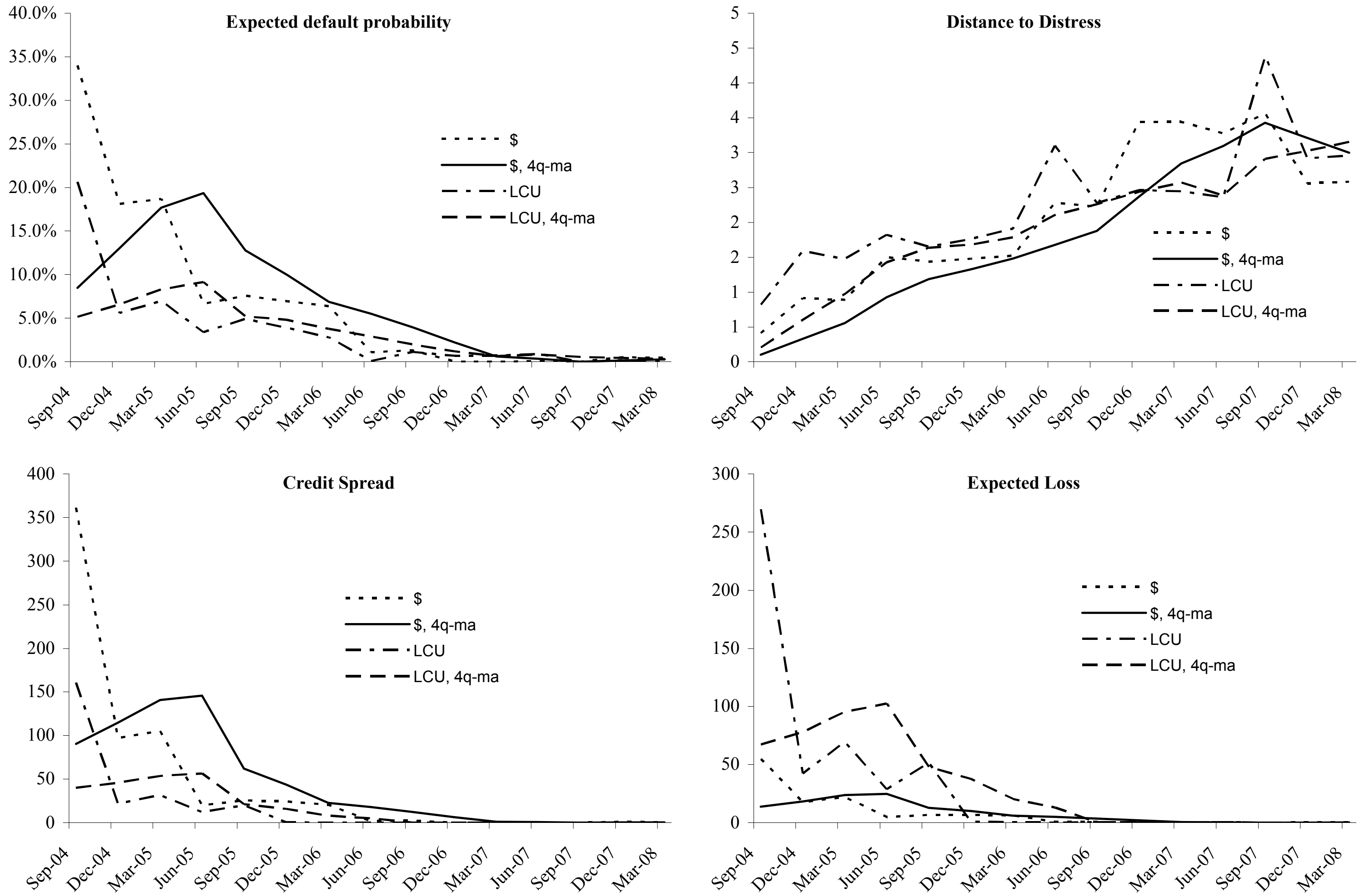
1/ Time series start in December 2002 - Before that date, data availability was limited to one bank.

Figure 7. Small subsidiaries of foreign banks: Banking Risk Indicators, December 2002 - March 2008



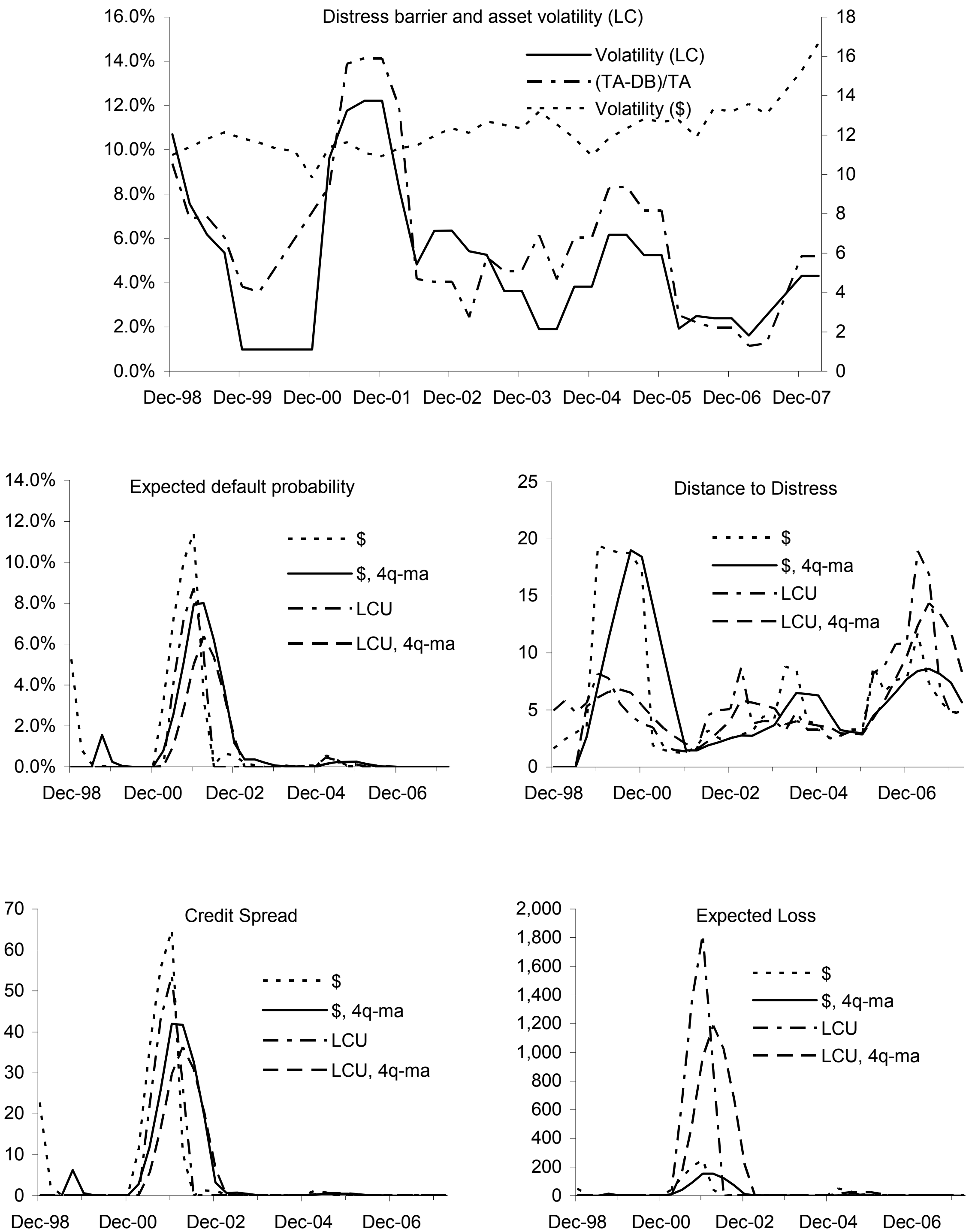
Source: Staff calculations.

Figure 8. BACC: Banking Risk Indicators, December 1998 - June 2008 1/



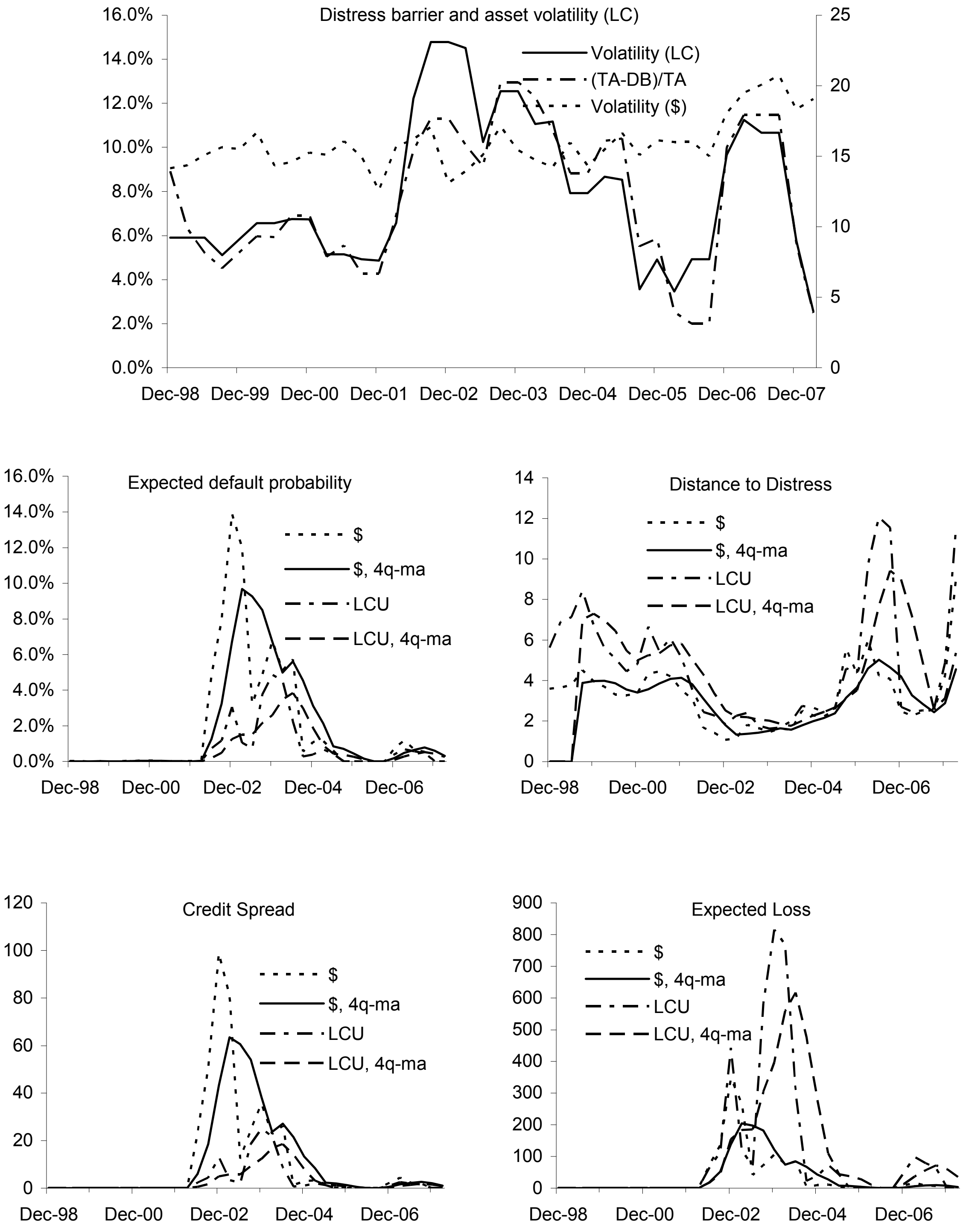
Source: Staff calculations.
1/ Historical data are only available for one bank - the results presented here may not be fully representative.

Figure 9. Bank 1: Banking Risk Indicators, December 1998 - June 2008



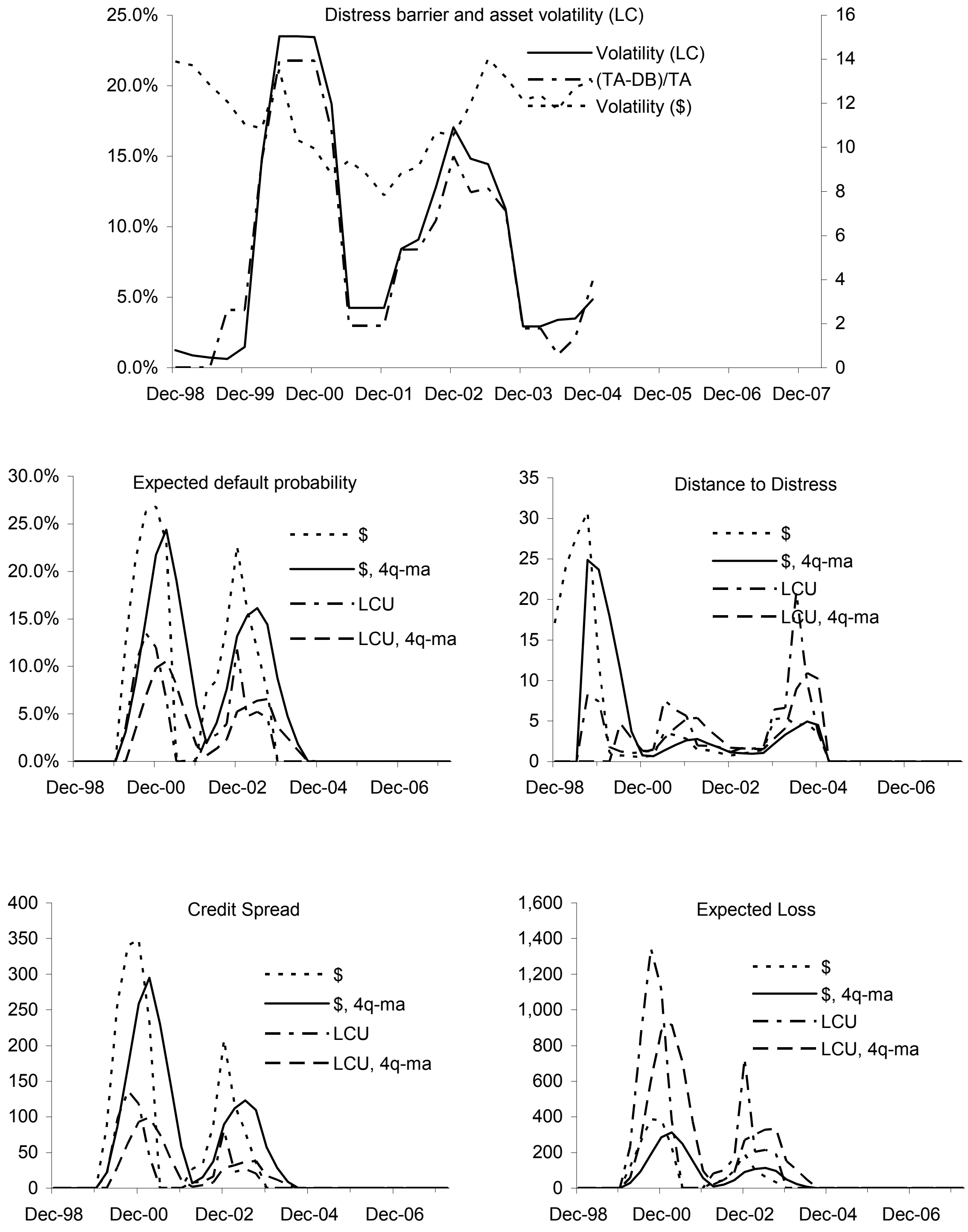
Source: IMF staff calculations.

Figure 10. Bank 2: Banking Risk Indicators, December 1998 - June 2008



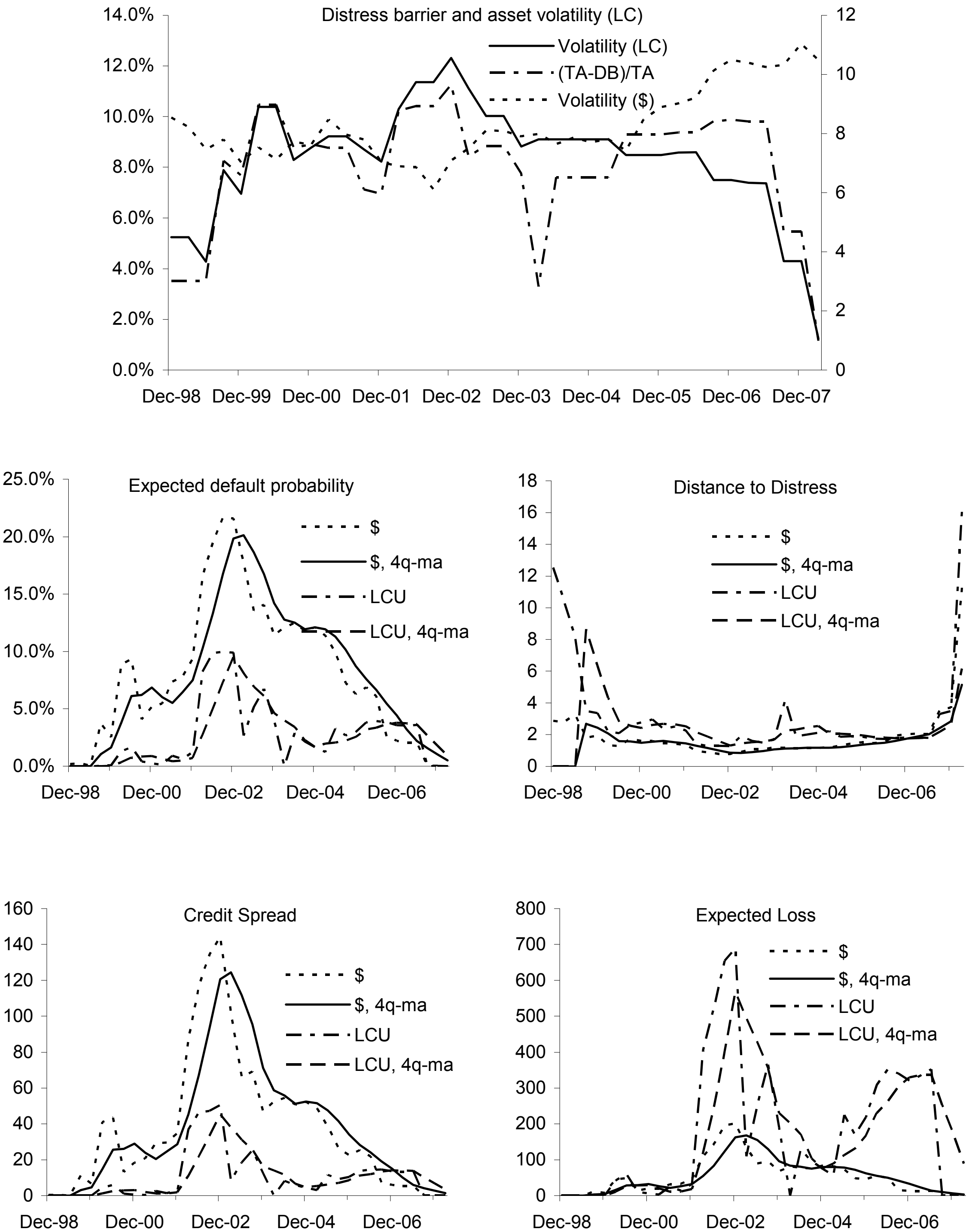
Source: IMF staff calculations.

Figure 11. Bank 3: Banking Risk Indicators, December 1998 - June 2008



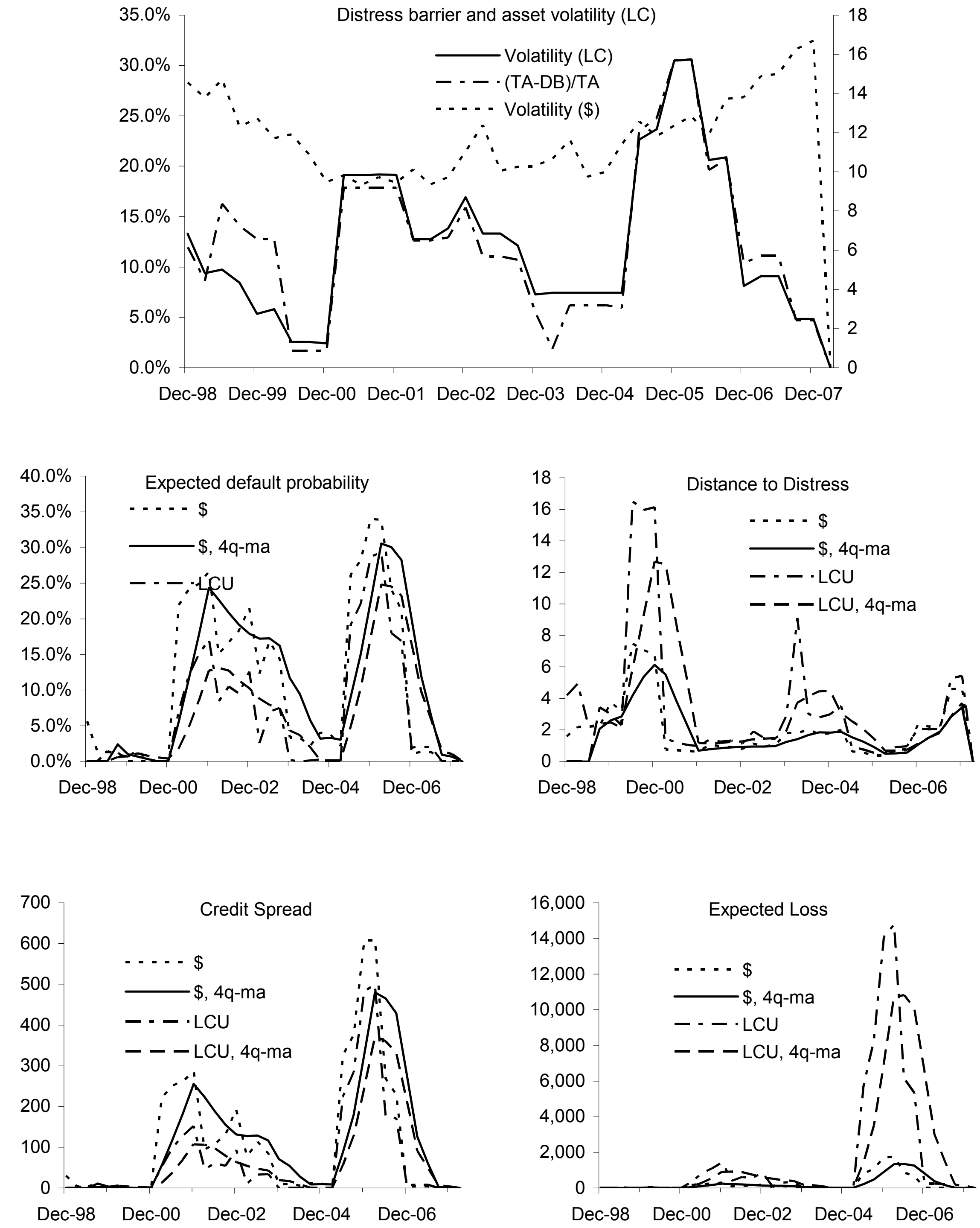
Source: IMF staff calculations.

Figure 12. Bank 4: Banking Risk Indicators, December 1998 - June 2008



Source: IMF staff calculations.

Figure 13. Bank 5: Banking Risk Indicators, December 1998 - June 2008



Source: IMF staff calculations.

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Appendix A: The CCA Framework

Overall, with information on the market value and volatility of sovereign debt and the value of base money, it is possible to estimate the implied value for sovereign assets and volatility, through the simple Black and Scholes option formula. After determining the distress barrier, the sovereign is assumed to default whenever the value of its implied assets fall below this distress barrier. An mentioned before, we define the distress barrier (DB) as:

$$DB = STD + \alpha \cdot LTD + IPTM \ , \tag{A.1}$$

where STD represents the short-term liabilities (maturity $\leq$ 1 year), LTD represents the long-term liabilities (maturity $>$ 1 year), α is a parameter between 0 and 1 (usually around 0.5), and IPTM corresponds to the interest payments on the liabilities due at the first year. We can, then, estimate assets and volatilities through:

$$V\sigma = D\sigma N(d_1) \text{, and} \tag{A.2}$$

$$D = VN(d_1) - De^{-rT} N(d_2) \ , \tag{A.3}$$

where V and σ are the implied value of asset and volatility, respectively, D is the value of the distress barrier, r is the risk-free interest rate – assumed constant, and d_1 and d_2 are the known terms from the Black and Scholes option formula as defined below:

$$d_1 = \frac{\ln\left(\frac{V}{D}\right) + \left(r + \frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}} = \frac{\ln\left(V \exp\left(\left(r + \frac{1}{2}\sigma^2\right)T\right)\right) - \ln(D)}{\sigma\sqrt{T}} \ , \tag{A.4}$$

and

$$d_2 = \frac{\ln\left(\frac{V}{D}\right) + \left(r - \frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}} = \frac{\ln\left(V \exp\left(\left(r - \frac{1}{2}\sigma^2\right)T\right)\right) - \ln(D)}{\sigma\sqrt{T}} \ . \tag{A.5}$$

Once the total assets value and volatility have been determined, it is possible to estimate a set of credit risk indicators as below:

(1) Distance to distress ($D2D$): which gives the number of standard deviations that the asset value is away from the distress barrier (D):

$$D2D = \frac{\ln(V) + \left(r - \frac{1}{2}\sigma^2\right)T - \ln(D)}{\sigma\sqrt{T}} \ . \tag{A.6}$$

(2) Risk neutral default probability ($RNDP$):

$$RNDP = N(-D2D)\,. \qquad \text{(A.7)}$$

(3) Credit default spread ($spread$):

$$spread = \frac{-1}{t}\ln\left(\frac{V}{De^{-rt}}N(d_1) + N(d_2)\right). \qquad \text{(A.8)}$$

(4) Expected losses given default (P):

$$P = De^{-rt}N(-d_2) - VN(-d_1)\,. \qquad \text{(A.9)}$$