IMF WORKING PAPER





WP/96/142

INTERNATIONAL MONETARY FUND

Monetary and Exchange Affairs Department

# Banking System Fragility: Likelihood Versus Timing of Failure--An Application to the Mexican Financial Crisis

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December 1996

## Abstract

This paper tests empirically the proposition that bank fragility is determined by bank-specific factors, macroeconomic conditions and potential contagion effects. The methodology allows for the variables that determine bank failure to differ from those that influence banks' time to failure (or survival rate). Based on the indicators of fragility of individual banks, we construct an index of fragility for the banking system. The framework is applied to the Mexican financial crisis beginning in 1994. In the case of Mexico, bank-specific variables as well as contagion effects explain the likelihood of bank failure, while macroeconomic variables largely determine the timing of failure.

**JEL Classification Numbers:**
C41, E44, G21.

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1/ Robert Billings is an economist in the Department of Finance Canada. The authors wish to thank John Green, Malcolm Knight, Alfredo Leone, Sunil Sharma, MAE seminar participants, and especially William E. Alexander for useful comments. As well, the authors are grateful to staff at the Federal Reserve Bank of Dallas, especially Susan Tetley, and to Federico Rubli Kaiser and Alejandro Díaz de León at the Bank of Mexico for providing valuable information and comments. Kiran Sastry provided able research assistance.

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**SUMMARY**

This paper proposes an empirical methodology to gauge the factors determining the fragility of banks and the banking sector. A framework is suggested to construct an operational index of banking sector fragility. While the framework is applied to the Mexican financial crisis that began in late 1994, it can be more generally extended to other countries.

The paper examines empirically the proposition that bank soundness is determined by bank-specific factors and macroeconomic conditions. When externalities or contagion effects exist in the system, aggregate banking sector variables play a role in determining the probability that individual banks will fail. The empirical methodology allows for the possibility that the factors influencing the likelihood of bank failure may be different from those determining the time of failure.

These propositions are examined for the case of Mexico's financial crisis that began in 1994. The empirical results suggest that bank-specific indicators as well as banking-sector variables (proxying for contagion effects) explain the likelihood of bank failure, while macroeconomic variables largely determine the time of failure. Moreover, the explanatory power of the model is greatly increased by extending the basic model comprising only bank-specific variables to include macroeconomic and aggregate banking-sector information.

An index of fragility for the overall banking system is derived based on the estimated degree of fragility of individual banks. In the case of Mexico, a threshold level of nonperforming loans to total loans shows clear signs of increasing banking system fragility much before the currency crisis actually unraveled the banking crisis.

## I. INTRODUCTION

Recently interest has grown in the implications of fragile banking systems with regard to monetary policy, capital account liberalization, and Fund financial surveillance. In this connection, a fundamental question is what factors determine the fragility of banks and the overall banking sector. As well, in the context of financial surveillance, it is paramount to gauge what determines the degree of fragility of banking systems and how to construct an operational index of banking sector fragility. The objective of this paper is to propose an empirical methodology to address these issues. While the framework is applied to the case of the Mexican financial crisis that began in late 1994, it can be more generally extended to other countries.

While the vast literature on early-warning systems of bank failure has mainly relied on bank-specific variables for clues about the soundness of individual banks, analyses of the role that macroeconomic factors--affecting all banks--can play in determining the soundness of individual banks have been generally lacking. Similarly, while policymakers have long been preoccupied with systemic risk, or contagion effects to banks which would be otherwise fundamentally sound, no empirical early-warning model of bank failure to our knowledge has accounted for those potential effects. This paper examines empirically the proposition that bank soundness is determined by bank-specific factors and macroeconomic conditions. Also, when externalities or contagion effects exist in the system, then aggregate banking sector variables play a role in determining the probability that individual banks will fail. The contagion effects can work through two different channels: (i) through information asymmetries affecting depositors' behavior, and/or (ii) as a result of banks' "herding behavior" in their risk-taking. The theoretical framework supporting these potential links is discussed in González-Hermosillo (1996).

We examine these propositions for the case of the Mexican financial crisis that began in 1994. The sample studied includes 31 commercial banks, of which a large number received some kind of direct financial assistance from the Government at different stages of the crisis (either through recapitalization schemes, acquisition of bad loans, assisted mergers, or liquidity support). We look at the contribution of certain bank-specific indicators, as well as aggregate banking sector and macroeconomic variables in explaining the one-step-ahead probability that Mexican banks would receive some kind of financial assistance from the Government.

The empirical methodology which we follow allows for the possibility that the factors that influence the likelihood of bank failure may be different from those that condition the time to failure. 1/ The empirical results in the case of Mexico suggest that bank-specific indicators as well as banking sector variables (proxying for contagion effects) are important in explaining the likelihood of bank failure, while macroeconomic variables largely determine the time to failure. Moreover, we find that the explanatory power of the model is greatly increased by extending the basic model comprising only bank-specific variables (akin to a basic CAMEL-type model) to include macroeconomic and aggregate banking sector information. These findings are expected and intuitive; however, to the best of our knowledge, have not been formally demonstrated in earlier literature. Furthermore, use of such models in a larger sample may help identify certain empirical regularities and early warning signals.

The paper is structured as follows. Section II briefly reviews certain events associated with the Mexican financial crisis that set the stage for this study. Section III presents the empirical methodology. Section IV discusses the data used in this study. The results of the empirical analysis are discussed in Section V. Section VI discusses how these results can be used to drive an index of overall banking sector fragility. Finally, Section VII provides some concluding remarks.

## II. MEXICO'S FINANCIAL CRISIS

The Mexican economy was shaken by the collapse of the peso in December 1994, with interest rates rising manyfold and economic activity severely contracting in the aftermath of the currency crisis. The authorities directed the infusion of capital and change of management for two banks--apparently largely due to fraud--a few months prior to the currency crisis . But, it was following the peso collapse that more than one half of all the banks comprising the domestic banking sector (excluding foreign banks) received some kind of financial support from the Government. No banks were liquidated during the crisis (indeed, in Mexico's modern history). By the end of 1995, banks accounting for more than 80 percent of the total assets of the banking system had received financial assistance from the Government through one or more of the various support programs introduced by the authorities. 2/ The authorities estimate the total cost of bank support at about 7.5 percent of GDP--though private estimates are much higher.

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1/ Similar approaches have been adopted in some of the most recent contributions to the literature of early-warning systems of bank failure. See, for example, Cole and Gunther (1993), Wheelock and Wilson (1994), and Lane, Looney and Wansley (1986).

2/ Interestingly, all the banks which had been privatized in the early 1990s received some sort of support from the Government.

Several programs were introduced during 1995 and early 1996 to support Mexican banks; some provided direct capital infusions or short term liquidity to banks, while other mechanisms were designed to assist certain groups of specific bank debtors. 1/

Among the direct assistance extended to banks, three principal mechanisms of support were adopted. The first type of bank intervention was characterized by financial support from FOBAPROA accompanied by changes in the banks' management. 2/ While the Mexican authorities have typically referred to these cases as the only banks that have been subject to direct "intervention," we define intervention more broadly. Specifically, bank intervention, or bank "failure," is said to occur when a bank receives financial assistance, other than short-term liquidity support, from a third party (such as the Government). 3/ The second type of financial assistance granted to Mexican banks by the Government, or intervention in our definition, was through the program of temporary recapitalization (PROCAPTE) that became effective in March 1995. Beginning in the Summer of 1995, a third type of intervention, the sale of bad loans to the Government, became the most common form of Government assistance to banks in distress. By December 1995, nearly Mex$81 billion in loans--on a gross basis--representing over 10 percent of the gross loans of the banking sector, had been purchased at a discount by the Government from several banks.

Prior to the peso collapse in December 1994 there were already indications that the banking sector was becoming increasingly fragile. Nonperforming loans of the whole banking sector relative to total loans jumped from 5.5 percent at end-1992 to 7.3 percent at end-1993 and 8.3 percent at end-September 1994. 4/ Similarly, the banking sector's riskiest assets relative to the system's capital jumped from 56.3 percent at end-1992 to 69.6 percent in September 1994. However, it was following the currency shock that the fragility of the banking system became evident. By September 1995, the banking sector's riskiest assets

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1/ For a detailed description of these programs, see Banco de Mexico (1996) and International Monetary Fund (1996).

2/ The Fondo Bancario de Protección al Ahorro (FOBAPROA), the deposit guarantee fund, is financed by contributions from banks proportional to their "captación directa" (which includes various types of deposits and Bankers' Acceptances). Mexico has a system of implicit full deposit guarantees.

3/ Cole, Cornyn and Gunther (1995) also suggest a broader approach. In their framework, "failure" includes not only those cases where institutions are declared equity insolvent but also those for which regulators mandate prompt corrective action.

4/ Reported nonperforming loans, in accordance with Mexican accounting rules, only include unpaid interest (not principal) and hence underestimate the magnitude of the nonperforming loans. Mexican banks are expected to report nonperforming loans according to the U.S. Generally Accepted Accounting Principles (GAAP) by March 1997.

accounted for over 120 percent of the system's capital, while aggregate nonperforming loans jumped to 10.3 percent of total loans. 1/

## III. EMPIRICAL METHODOLOGY

Using survival analysis, and quarterly data over the period 1991-95, the empirical analysis in this paper focuses largely on the determinants of bank failure (or intervention) and the factors affecting time until failure.2/ A full exposition of survival models is beyond the scope of this paper and we only provide a brief summary of the specific model used for estimation purposes. 3/

The estimation involves a two step procedure. First, the one-step-ahead probability of failure and the factors that affect the likelihood that a bank will fail are determined. In the case of bank intervention, we treat the regulators' decision to intervene a bank as a discrete variable which can take the value of one (intervention) or zero (no intervention), and this forms the dependent variable. The one-step-ahead probability of failure is estimated as a function of a set of explanatory variables using a logit model in panel data context, which is used in estimation models with qualitative dependent variables. 4/

Next, we conduct survival analysis to determine the factors that explain the duration of a given state; in our case, the state of no failure. Whereas the specification for the probability of failure focusses on the unconditional probability of an event taking place, survival models emphasize conditional probabilities, that is the likelihood that the event will end in "the next period" given that it has lasted as long as it has. Intuitively, the question that we try to answer through survival analysis is: given that a bank has survived until time t, what is the probability that it will fail during "the next period"? The survival analysis reveals information about the period leading up to intervention, including an estimate of the probability that a given bank will survive long enough to operate in any period under study, the probability that it will fail after reaching that period, and the expected time before a bank will fail.

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1/ The latter ratio on aggregate nonperforming loans to total loans also likely underestimates the actual size of the banking system's fragility because the Sistema de Información Estadistica (SIES) generally excludes data for banks after they have received financial support.

2/ While the main interest is predicting the probability that an institution will require financial assistance from third parties, empirical analyses, in practice, are typically limited to predicting the probability that a bank will receive financial support (intervention in our definition) because the observed state variables correspond to whether in fact a bank received such support.

3/ For a comprehensive discussion of survival models see Greene (1990), Kiefer (1988), Lancaster (1990) and Lee (1992).

4/ See Chamberlain (1980) for a discussion of fixed-effects logit models for panel data.

Survival times are data that measure the time to a certain event such as failure, death, response, the development of a given disease, or divorce. These times are subject to random variations and they form a distribution which is generally characterized by three equivalent functions: the survival function, the probability density function and the hazard function. These three functions are mathematically equivalent, that is if one function is given the other two can be derived. In the context of this study, the survival function, denoted by S(t), is defined as the probability that a bank survives longer than time t. The survival time has a probability density function defined as the probability of failure within a small interval of time. The hazard function of survival time gives the probability that a bank fails in a very short time interval, given that it has survived until the beginning of the interval.

The standard survival model assumes implicitly that each bank will ultimately fail, potentially resulting in mispecification if only a limited number of banks actually fail. The model described by equation (1) below modifies this assumption by allowing the probability of failure to be less than one. 1/

The likelihood function of the survival model can be written as:

$$L = \Pi_{i=1}^{N} \left[ \Pi_{t=1}^{T} \left[ P_{i,t} f(t_i) \right]^{Q_{i,t}} \left[ (1 - P_{i,t}) + P_{i,t} S(t_i) \right]^{1-Q_{i,t}} \right] \tag{1}$$

where P is the probability of failure, f(t) is the density function of the time to failure and S(t) is the survival function. Q is a variable which assumes the value of one for an uncensored observation and equals zero otherwise. Here, censored observations correspond to banks that survived over the sample period. N denotes the number of banks in the sample.

The probability of failure, P, and the factors that affect the likelihood that a bank will fail can be denoted as follows:

$$P = \frac{1}{(1 + e^{\alpha' X_{it}})} \tag{2}$$

where the coefficient vector $\alpha$ indicates the relationship between given characteristics and the probability of failure.

1/ This specification is suggested in Schmidt and Witte (1989), and is also applied in Cole and Gunther (1993).

The survival analysis presented in this paper focusses on the logistic functional form, which implies a hazard function that first increases, reaches a peak and then declines. 1/ The logistic specification is given by:

$$S(t) = \frac{1}{1+(\lambda t)^{\pi}}$$

$$f(t) = \frac{\lambda\ \pi(\lambda t)^{\pi-1}}{[1+(\lambda t)^{\pi}]^{2}} \tag{3}$$

$$\lambda = e^{-\mu' X_{it}}$$

where, $\pi$ and $\lambda$ are parameters that govern the shape of the survival curve, and the coefficient vector $\mu$ indicates the relationship between given (time-varying) characteristics and the survival time.

Thus, the parameters of the probit model ($\alpha$) and those of the logistic survival model ($\pi$, $\lambda$ and the vector $\mu$) are estimated in two stages. As described above, first, the value for P is estimated using a logit model. The dependent variable for the probit model takes on the value of one if the bank is intervened (failure) and zero otherwise. The estimated value for P is then substituted into equation (1) and the maximum likelihood function is then estimated using the specification for the survival function S(t) described above. The dependent variables for the survival model are the truncation vector Q (which denotes whether the bank has survived over the sample period or not) and the (log) time of survival of individual banks (the number of quarters before actual intervention).

## IV. THE DATA

The bank-specific data used in this study is derived from the bank-by-information contained in the Sistema de Información Estadistica (SIES) released by Mexico's Comisión Nacional Bancaria y de Valores. 2/ The appendix provides a description of the data and the sources. The sample examined comprises 31 banks (excluding foreign banks and some

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1/ We tested several other functional forms, including those based on the Weibull, normal and exponential distributions. We found that the logistic distribution best describes the banking difficulties in Mexico during the period of study. Similarly, Cole and Gunther (1993) also find that the logistic distribution best describes the banking difficulties in the United States during the period 1985-1992.

2/ Banks' balance sheet data are in a consolidated basis that includes foreign currency assets and liabilities.

domestic banks for which data were incomplete). Banking sector data was derived from the same source, while macroeconomic data was collected from the IMF International Financial Statistics. The data frequency is quarterly and corresponds to the period 1991:Q4 to 1995:Q3. The timing and type of financial support received by banks were compiled from public and official sources.

This paper empirically tests the proposition advanced in González-Hermosillo (1996) that the probability of failure depends on several variables; those which are bank-specific, those that characterize the banking sector through externalities or contagion factors, and macroeconomic factors that affect all banks. Equation (1) is estimated under different data proxies to predict the likelihood of failure (or, conversely, the likelihood of survival) and expected survival time. These variables are summarized in Table 1 and discussed in detail below. As noted in Cole and Gunther (1993), while some of the variables associated with the banks' balance sheet and income statements may decrease the likelihood of survival, certain peculiarities of banking and some institutional arrangements could work to extend, rather than reduce, the expected survival time of a bank, even though the bank ultimately would fail.

The predictive power of the data is explored by lagging the regressors one period (i.e., one quarter). However, we found useful to lag some of the (time-varying) macroeconomic regressors--specifically, interest rates and the change in the exchange rate--by three periods because of the overshooting that those variables exhibited during part of 1995, while accounting for possible lagged effects.

## 1. Bank-specific data

We examine several bank-specific indicators--some of which turn out to be akin to those used in the CAMEL rating system (i.e., evaluating capital adequacy, asset quality, management, earnings and liquidity). Table 2 provides sample means for the bank-specific variables over the entire sample period as well as the period immediately prior to the financial crisis.

As the risk-adjusted capital asset ratio (CA) serves as a cushion to absorb shocks, this ratio is expected to be negatively related to the likelihood of failure and positively related to the expected survival time. The mean CA for intervened banks is significantly lower than that of the non-intervened banks, although even the problem banks have a CA that is above the minimum BIS standard of 8 percent.

Credit risk is proxied by the ratio of nonperforming loans to total loans (NPLL). 1/ Banks with large troubled assets must provide for losses on a significant portion of those

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1/ Similarly, Grenadier and Hall (1995) proxy credit risk by the actual amounts of bank loans gone bad.

assets, reducing net earnings and, ultimately, capital. Thus, a high ratio of nonperforming loans to total loans would be positively related to the likelihood of failure and negatively related to the expected survival time. The mean NPLL of intervened banks is about three times higher than that of the non-intervened banks for the entire sample period.

Market risk is proxied by the riskiness and concentration of a bank's portfolio (often included as part of asset quality or management in CAMEL). In general, a large exposure to a vulnerable sector would be positively related to the likelihood of failure and negatively related to the expected survival time. 1/ On average, unsecuritized loans (NSTLOAN), residential mortgages (HOUSE) and agricultural loans (AGR) account for a significantly larger share of the loan portfolio of the intervened banks. In contrast, consumer loans (CONS) account for a relatively larger share of the loan portfolio of the non-intervened banks.

In general, sustained high levels of profitability would enable the bank to boost capital and improve its economic viability, thus being negatively related to the probability of failure and positively to the expected survival time. However, because exceptionally risky projects could also be associated with outstanding rates of return, a high degree of profitability for a certain given period may be actually positively related to the probability of failure. Different measures of profitability were examined: return on assets (ROA), return on equity (ROE), net interest margin (NIM) and profit margin (PROFMARG). The mean values for ROA and ROE are higher for the intervened banks for the entire sample period. In contrast, in the period prior to the crisis these ratios drop markedly for the intervened banks. On average, PROFMARG is markedly higher for the non-intervened banks over both periods.

Deposit runs, from the public or from other banks, would be positively related to the likelihood of failure and negatively to the expected survival time. However, it may be that a problem bank searching for additional funds to stay afloat is able to tap the interbank market, at least temporarily and possibly at a higher premium (particularly if information about the true state of banks is imperfect). Thus, an increase in interbank deposits may be positively related to the likelihood of failure. On average, the share of public deposits in total loans (DEPLOAN) is significantly higher for the non-intervened banks. In contrast, intervened banks have a higher share of interbank deposits in total loans (IBDLOAN). Interbank activities of intervened banks increase sharply prior to the crisis.

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1/ It is worth noting that the effect of the lending variables on bank survival time may be ambiguous in certain circumstances, even though these variables are expected to be positively related to the likelihood of eventual bank failure. One such situation would occur if banks with a particular class of loans find it easier to restructure their troubled loans. For example, widely available programs to promote certain categories of bank loans to be restructured (e.g., Mexico's debt relief programs to bank debtors which included, inter alia, restructuring of mortgage loans and consumer loans) could extend banks' survival time.

Table 1: Explanatory Variables

| Variable | Expected Sign: Failure | Expected Sign: Survival Time |
|---|---|---|
| 1. Bank-specific variables: | | |
| Capital-asset ratio (CA) | - | + |
| Non-performing loans to total loans (NPLL) | + | - |
| Non-securitized loans to total loans (NSTLOAN) | + | +/- |
| Mortgage loans to total loans (HOUSE) | + | +/- |
| Consumer loans (CONS) | +/- | +/- |
| Agriculture related loans to total loans (AGR) | +/- | +/- |
| Profit margin (PROFMARG) | +/- | + |
| Public deposits to total loans (DEPLOAN) | - | + |
| Interbank deposits to total loans (IBDLOAN) | +/- | + |
| Expenditures to total assets (EXPA) | + | - |
| Liquid assets to total assets (LIQUID) | - | + |
| Bank assets to total banking sector assets (SIZE) | +/- | +/- |
| | + | - |
| 2. Banking sector variables: | | |
| Total banking sector loans to GDP (LOANSH) | | |
| Banking sector fragility (TOTRISK) | + | - |
| Deposit fund (TFOBAP) | +/- | + |
| 3. Macroeconomic variables: | | |
| Exchange rate depreciation (DELEX) | + | - |
| Real interest rate (REALTB) | + | - |
| Economic activity (DELIPROD, DELGDP) | - | + |
| Unexpected inflation (CPI, INFL) | + | - |

Table 2. Means of Explanatory Variables

| | Entire sample period (1991:Q4 to 1995:Q3) | | Immediately prior to the financial crisis (1994:Q4) | |
|---|---|---|---|---|
| | Non-Intervened Banks | Intervened Banks | Non-Intervened Banks | Intervened Banks |
| CA | 36.0 | 8.6 | 25.6 | 9.3 |
| NPLL | 2.7 | 6.7 | 1.5 | 8.4 |
| NSTLOAN | 53.9 | 71.1 | 55.9 | 68.3 |
| HOUSE | 2.1 | 11.5 | 1.5 | 14.7 |
| CONS | 1.1 | 5.5 | 0.5 | 3.1 |
| AGR | 1.4 | 3.6 | 0.5 | 2.9 |
| ROA | 4.5 | 5.0 | 5.0 | -0.5 |
| ROE | 19.8 | 26.0 | 18.6 | -3.9 |
| NIM | 4.7 | 2.9 | 5.2 | 2.4 |
| PROFMARG | 15.4 | 5.3 | 10.9 | -7.2 |
| DEPLIAB | 78.7 | 60.3 | 68.5 | 51.3 |
| IBDLIAB | 7.3 | 9.1 | 7.1 | 14.6 |
| DEPLOAN | 115.1 | 74.2 | 106.2 | 76.1 |
| IBDLOAN | 12.8 | 32.8 | 23.1 | 97.7 |
| EXPA | 2.8 | 2.9 | 2.2 | 2.0 |
| LIQUID | 1.6 | 3.0 | 1.0 | 2.3 |
| SIZE | 0.6 | 6.3 | 0.5 | 6.7 |

Source: Sistema de Informacion Estadistica (SIES), Comisión Nacional Bancaria y de Valores.

A large volume of liquid assets would allow a bank to meet unexpected deposit withdrawals, and hence would expected to be negatively correlated with its likelihood of failure and positively with its survival time. On the other hand, high levels of liquidity may actually be associated with problem banks (or banks with a low franchise value). 1/ Intervened banks have a higher ratio of liquid assets to total assets (LIQUID) compared to non-intervened banks.

A bank-specific cost parameter which can also be representative of relative efficiency is operating expenses over total assets (EXPA), often used as a measure for quality of management. Higher costs are expected to be positively related to failure and negatively related to survival time. The mean value for EXPA is about the same for both intervened and non-intervened banks.

Finally, the size of the bank, in terms of assets, relative to the banking sector (SIZE) is used to assess whether relatively large banks are more likely to survive because, for example, they are better able to diversify risk. An easier access to short-term financing may extend their expected survival time, even if they are eventually intervened. Moreover, "too large to fail" policies would extend the survival time of larger banks. However, in the case of Mexican banks the average size of the intervened banks is significantly higher than those which have not been intervened.

## 2. Banking sector variables

In this study, we focus on the ratio of the banking sector's nonperforming loans to total loans (TOTNPLL) and on the share of loans classified as riskiest to total capital (TOTRISK) as proxies for the fragility of the overall banking sector. As a proxy for how extended the banking sector may be, we look at the share of total bank loans to GDP (LOANSH). Experience shows that banking crises are often associated with a rapid rise in loans relative to GDP, often in connection with rapid financial liberalization. 2/

As a proxy for the actual endowment of resources available to Mexico's deposit guarantee fund, FOBAPROA, we look at the ratio of the contribution of resources by all banks to this fund relative to the banking sector's nonperforming loans (TFOBAP). 3/ A higher endowment supporting the deposit fund would make the deposit guarantees more credible and would hence act to avert deposit runs. However, a period of banking crisis may also be associated with required new infusions of capital to the deposit fund, resulting in a positive correlation with the likelihood of failure.

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1/ See Rojas-Suárez and Weisbrod (1995) for a detailed discussion.

2/ See Sundararajan and Baliño (1991), and Drees and Pazarbaşıoğlu (1995).

3/ Given that Mexico borrowed more than US$20 billion in resources from abroad, part of which was directed toward the program of support offered to ailing banks, the actual endowment supporting the deposit guarantee fund was likely much higher than the banks' contributions to it.

### 3. Macroeconomic variables

In this study, the role of several macroeconomic variables in the Mexican banking crisis is analyzed. 1/ Specifically, we examine the role of the nominal and real foreign exchange rate--as an index (NER) and (RER) respectively, and their quarter-over-quarter change (DELEX) and (DELEXR) respectively--in predicting the probability of bank survival and the expected survival time. Following Mendoza and Calvo (1996), we also examine the ratio of foreign-currency denominated M2 over international reserves (M2RES) as a proxy for exchange rate fragility. Interest rates are also examined under different specifications: the nominal interest rate on 28-day Treasury bills or Cetes (TBRATE); the real interest rate on Cetes (REALTB); 2/ the margin between the nominal rate of return on Cetes and the short term rate on U.S. Treasury bills (TBGAP); and the volatility of the nominal and the real Cetes rate, (VOLNOM) and (VOLREAL) respectively. 3/ The effects of the Mexican currency crisis, and the associated hike in domestic interest rates, are expected to have a significant negative effect over banks. In addition, we look at changes in industrial production (DELIPROD) and in real GDP (DELGDP), as well as inflation (INFL) and the level of the consumer price index (CPI). Unexpected inflation and recessionary conditions are expected to impact negatively banks' performance.

## V. EMPIRICAL RESULTS

This section provides the findings from the estimation of equation (1) based on quarterly data for the period 1991:Q4-1995:Q4. 4/ The empirical analysis is based on the one-step-ahead probability of occurrence of direct intervention to banks comprising, in the case of Mexico, the three types of intervention described in Section II. 5/

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1/ The data used is compiled from IMF, International Financial Statistics database.

2/ Real interest rates are constructed by subtracting the year-over-year inflation rate from the current annual nominal rate of return.

3/ While the interbank interest rate is viewed as being more representative of domestic liquidity pressures, we were unable to obtain data on this variable for the earlier years of this study.

4/ The beginning of this period roughly corresponds to the onset of the program of privatization of Mexican banks. It is worth noting that several new banks obtained licenses to operate at different times during the period of study. Thus, from an empirical standpoint, banks' "beginning of life" roughly corresponds to the time when they were privatized, while new banks entered the system in later periods.

5/ When more than one type of direct intervention occurs for the same bank at different the groups of banks according to the different types of intervention. The means and the standard deviations of the different groups of banks also revealed no significant differences.

The empirical findings are reported in Table 3. 1/ The signs of the estimated coefficients correspond to the expectations in all cases for which the signs are unambiguous. The results of the full model (specification (1) in Table 3) suggest that bank-specific variables and banking sector variables are important determinants of the likelihood of failure. With respect to bank-specific variables, higher values for the share in total loans of nonperforming loans, and unsecuritized loans as well as higher interbank deposits are associated with a higher probability of failure. In contrast, the higher the share of agricultural loans in total loans the lower the likelihood of failure. In terms of banking sector variables, an increase in the share in GDP of loans, as well as in the contributions to the deposit insurance fund are positively correlated with a higher likelihood of failure. As regards to the predictive power of the model, this specification is quite robust, particularly with regard to type II error. The probability of committing type I error is 38 percent, while that of committing type II error is close to zero. 2/

It is worth noting that the results indicate that the factors which determine the likelihood of failure differ significantly from the factors which determine the timing of failure. In particular, the macroeconomic factors play a pivotal role in influencing the time to failure. High real interest rates as well as a depreciation of the exchange rate imply a decrease in the survival time of a bank. Similar to the findings on the likelihood of failure, an increase in the ratio of nonperforming loans to total loans decrease survival time. According to the estimation results, the higher the share of housing loans in total loans the higher is the survival time of a bank (possibly due to the loan restructuring programs). Size has a positive coefficient, implying that the larger the bank the longer is the probability of survival.

With regards to banking sector variables, an increase in the riskiness of the banking sector as a whole (a proxy for contagion effects) decreases the survival time of an individual bank. Similarly, an increase in the ratio of loans extended by the banking sector to GDP decreases banks' probability of survival.

We conducted a similar analysis using only bank-specific variables (a CAMEL-type approach). Specification (2) in Table 3 summarizes those empirical findings. Similar to specification (1), a higher ratio of nonperforming loans and unsecuritized loans to total loans increases the likelihood of failure. In addition, profit margins and the share of housing loans in total loans seem to be important determinants of the likelihood of failure. That is, banks with higher profit margins and a lower share of housing loans in total loans are less likely to fail. The predictive power of the CAMEL-type model is significantly lower than the

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1/ As discussed in the data section, alternative proxies were used for some of the variables. In this section, we report the variables which give the "best fit", that is the best predictive power for the model. The use of alternative variables do not change the results qualitatively and can be made available upon request.

2/ Type I error occurs when the null hypothesis is rejected when it is, in fact, true (i.e., predicting no failure when a bank, in fact, fails). Type II error occurs when the null hypothesis is accepted when it is, in fact, false (i.e., predicting failure when a bank, in fact, does not fail).

## Table 3. Regression Estimates 1/

| | (1) | | (2) | | (3) | (4) |
|---|---|---|---|---|---|---|
| | Intervention | | Intervention | | NPLL > NPLL* | Liquidity Support |
| | (Likelihood of failure) | (Survival time) | (Likelihood of failure) | (Survival time) | (Likelihood of failure) | (Likelihood of failure) |
| Constant | -39.84* | 2.02* | -14.13* | 1.29* | -1.28 | -6.60 |
| | (12.99) | (0.12) | (3.59) | (0.11) | (2.60) | (13.12) |
| CA | -0.15 | -0.02 | -0.19 | -0.02* | -0.51 | -0.29* |
| | (0.17) | (0.04) | (0.16) | (0.00) | (0.40) | (0.11) |
| NPLL | 1.21* | -0.73* | 0.52 | -0.43* | -- | 0.30 |
| | (0.44) | (0.35) | (0.15) | (0.07) | | (0.21) |
| PROFMARG | -0.18 | 0.07 | -0.22* | 0.01 | -0.66** | -0.16 |
| | (0.14) | (0.11) | (0.07) | (0.02) | (0.39) | (0.10) |
| LIQUID | -0.49 | 0.62 | -0.19 | 0.43* | -0.17 | -0.19 |
| | (0.36) | (0.46) | (0.16) | (0.09) | (0.72) | (0.23) |
| NSTLOAN | 0.13** | -0.01 | 0.15* | -0.02 | -0.02 | 0.07** |
| | (0.08) | (0.07) | (0.05) | (0.01) | (0.17) | (0.04) |
| HOUSE | 0.11 | 0.56* | 0.18* | 0.15* | 0.19* | 0.16* |
| | (0.11) | (0.17) | (0.06) | (0.03) | (0.04) | (0.09) |
| AGR | -0.27* | 0.11 | -0.08 | 0.16* | 0.41* | -0.05 |
| | (0.13) | (0.17) | (0.07) | (0.03) | (0.13) | (0.11) |
| SIZE | -0.06 | 0.42* | | | 0.26 | -0.25* |
| | (0.12) | (0.21) | | | (0.38) | (0.11) |
| DEPLOAN | -0.04 | 0.01 | | | -0.12 | 0.03* |
| | (0.03) | (0.02) | | | (0.10) | (0.01) |
| IDBLOAN | 0.03* | -0.01 | | | -0.13 | -0.01 |
| | (0.01) | (0.01) | | | (0.16) | (0.03) |
| TOTRISK | 0.01 | -0.68* | | | 0.19* | 2.48 |
| | (0.06) | (0.14) | | | (0.03) | (7.11) |
| REALTB | 0.11 | -2.00* | | | 0.93* | 1.50 |
| | (0.07) | (0.19) | | | (0.50) | (15.57) |
| DELEX | -0.06 | -0.46* | | | 0.29 | -0.99 |
| | (0.04) | (0.10) | | | (0.23) | (1.83) |
| LOANSH | 0.58* | -0.92* | | | 0.82 | 10.28 |
| | (0.23) | (0.33) | | | (0.69) | (39.46) |
| TFOBAP | 1.27* | 0.64 | | | 0.44* | 5.06 |
| | (0.64) | (0.94) | | | (0.15) | (89.87) |
| Type I error (in percent) | 38 | | 75 | | 18 | |
| Type II error (in percent) | 0 | | 0 | | 0 | |

1/ The standard errors are given in parentheses. * and ** denote, statistical significance at the 5 percent and 10 percent levels, respectively.

full model, while the probability of committing type I error is almost twice as high as the full model. This result confirms our hypothesis that bank fragility is not only determined by the condition of that particular bank, but also by the condition of the banking sector as a whole and the macroeconomic environment in which the banks operate. 1/

The results of the duration analysis for the CAMEL-type model indicate that the survival time is higher for banks with a higher share of liquid assets in total assets, as well as housing and agricultural loans in total loans. A lower share of nonperforming loans in total loans increases the survival time.

We also compared the results of the full model with an alternative model using a different state-variable derived from estimating a threshold level of the ratio of nonperforming loans to total loans. The threshold range, which prevailed before the first wave of bank interventions, was identified as 6 to 8 percent. We thus grouped the banks into two sets: those with nonperforming loans to total loans higher than the threshold and those with lower ratios. We then estimated the factors which affect the probability that a bank would reach the threshold level (specification (3) in Table 3). The results suggest that banks with higher profit margins, lower ratios of housing and unsecuritized loans to total loans are less likely to reach the threshold level of nonperforming loans. An interesting finding is that banking sector variables seem to be important determinants of whether a bank reaches the threshold. That is, the likelihood of an individual bank exceeding the threshold increases with the fragility of the banking sector as a whole.

We also examine the one-step-ahead probability that banks will receive temporary liquidity support. The results are presented under specification (4) in Table 3. The results indicate that banks with lower capital asset ratios, a higher share of housing and unsecuritized loans in total loans, as well as those with a higher share of public deposits in total loans are more likely to receive liquidity support. The size of the bank seems to be negatively related to the likelihood of receiving liquidity support. It is comforting to note that nonperforming loans to total loans is not an important determinant of the probability of receiving liquidity support. This may imply that the authorities did not extend liquidity support to banks in need of solvency support.

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1/ Clearly, this constitutes a "bare-bones" CAMEL-type of model. In practice, bank supervisors examine an array of other financial indicators for clues about the financial condition of banks. However, this simple CAMEL-type specification is useful because it sheds light on the marginal contribution of macroeconomic and banking sector variables in explaining banks' likelihood of survival and expected survival time.

## VI. INDICATORS OF FRAGILITY OF THE BANKING SYSTEM

Until now we have focused on the fragility of individual banks, although we argue that this can be influenced by the fragility of the overall banking system. Arriving at an indicator of the degree of fragility of the banking sector would be the next logical step.

The methodology proposed in this paper can be extended to provide an indicator of the fragility for the banking sector. One simple approach to develop an indicator of system-wide fragility is the use of a weighted average probability of failure of individual banks based on the probability of failure or the survival model. As a first step, we weight individual bank's estimated degree of fragility (or probability of failure, given the regressors) by its size (measured by the relative size of their assets relative to the entire banking system) to derive the estimated fragility of the overall banking sector.

To arrive at an estimate of the probability of failure of individual banks, the coefficients of the regressors, based on the logistic model, are multiplied by the explanatory data associated with each bank. 1/ This results in an estimated probability of failure for each individual bank in each period. The weighted average of the estimated degree of fragility of individual banks can be used to derive the estimated fragility index of the overall banking system. Chart 1, panel 1 depicts the estimated index of fragility of the Mexican banking sector, based on the probability of failure model discussed in Section V (specification 1). 2/ The index of banking sector fragility, based on the probability of bank intervention, was fairly low until 1994:Q4 when it jumped significantly. This, of course, mimics the fact that this specification models precisely the probability of intervention and most banks were actually intervened during 1995.

A similar exercise can be derived using the results obtained from the survival model. Chart 1, panel 2 depicts the index of banking sector fragility based on the estimated hazard function (capturing the probability that banks will exit the survival state, or nonintervened state, given that they have not yet exited such state). Interestingly, the function suggests that the likelihood that nonintervened banks will receive financial support increased slowly, but progressively, during most of the period under study up until 1994:Q4. It increased

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1/ The coefficients in logistic regressions cannot be interpreted as elasticities (as is the case of linear models). The contribution of a given factor can only be determined by applying the regression coefficients to a change in the values of a specific factor while holding the other factors at their average values.

2/ Because banks, once they have been intervened, are no longer part of our sample (given the information availability in SIES), the overall index of the system would improve immediately after several banks have been intervened (i.e., fragile banks are treated as "removed" from the system). In the case of Mexico, given that there were several "waves" of intervention, the index nonetheless deteriorated again after the some of the interventions in the early part of 1995.

significantly at the time of the currency crisis at end-1994 and it continued to rise during the first part of 1995, only to decline slightly toward the end of the sample period. 1/

It should be emphasized that the two fragility indices described above are ex-post measures of banking sector fragility, akin to ex-post forecast model testing. In contrast, Chart 1, panel 3 depicts an *ex-ante measure of banking sector fragility*, based on the probability of banks surpassing the threshold of non-performing loans to total loans, $NPLL > NPLL^{*}$. It is particularly interesting to note that this measure suggests that the Mexican banking system showed clear signs of increasing fragility since early 1993, much earlier than the other two measures of overall banking sector fragility based on the probability of actual intervention.

## VII. CONCLUDING REMARKS

The paper argues that the degree of soundness of banks, or their probability of failure, is determined by bank-specific factors as well as macroeconomic conditions, and by the overall fragility of the banking system when systemic risk is present. Bank-specific variables are largely conditioned by the microprudential guidelines applicable to banks, while the state of the economy and the shocks affecting it define the macroprudential setting in which banks operate. Thus, while microprudential risks are reduced by an appropriate legal framework and adequate banking supervision capabilities, macroprudential risk is minimized by the maintenance of transparent, predictable, and stable macroeconomic policies.

As noted earlier, while a macroeconomic shock would not discriminate among banks, the effects on individual banks would be commensurate to their exposure to the specific macroeconomic shock. The Mexican experience suggests that a negative macroeconomic shock may put the stability of the financial system at risk. Our findings give support to the view that rapid growth in bank lending may make the banking sector increasingly exposed to destabilizing shocks. Furthermore, the results suggest that adverse macroeconomic shocks will shorten the survival time of fragile banks (i.e. those with a deteriorating financial condition) and that contagion effects can play an important role in influencing both the likelihood and timing of failure.

It is also shown that the estimated degree of fragility of individual banks (or probability of failure) can be used to derive an index of fragility for the overall banking system. Of particular interest is the finding that a threshold level of non-performing loans to total loans shows clear signs of increasing banking system fragility much before the currency crisis actually unraveled the banking crisis (the latter can be characterized as the period in which significant Government support was provided to banks in distress).

The agenda for future research includes the application of the framework developed in this paper to other episodes of banking crises to ascertain empirical regularities over a larger sample. Such analyses may help identify stylized (ex-ante) early warning signals of systemic banking fragility.

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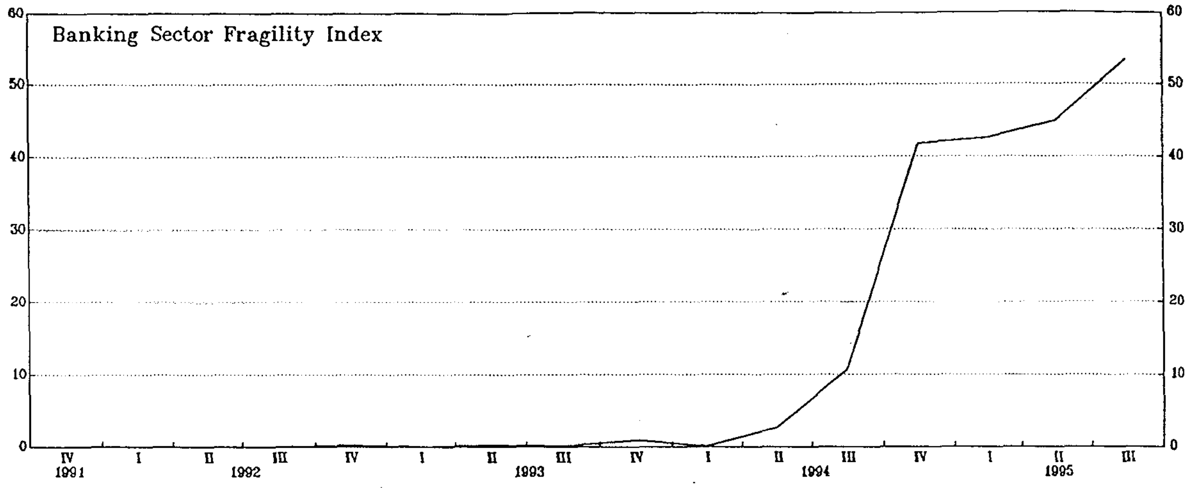
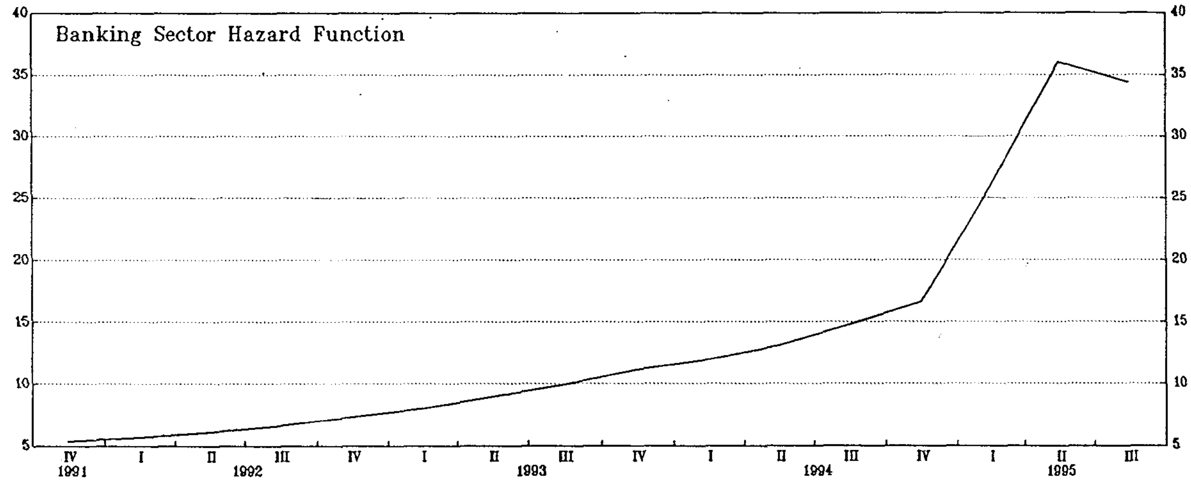
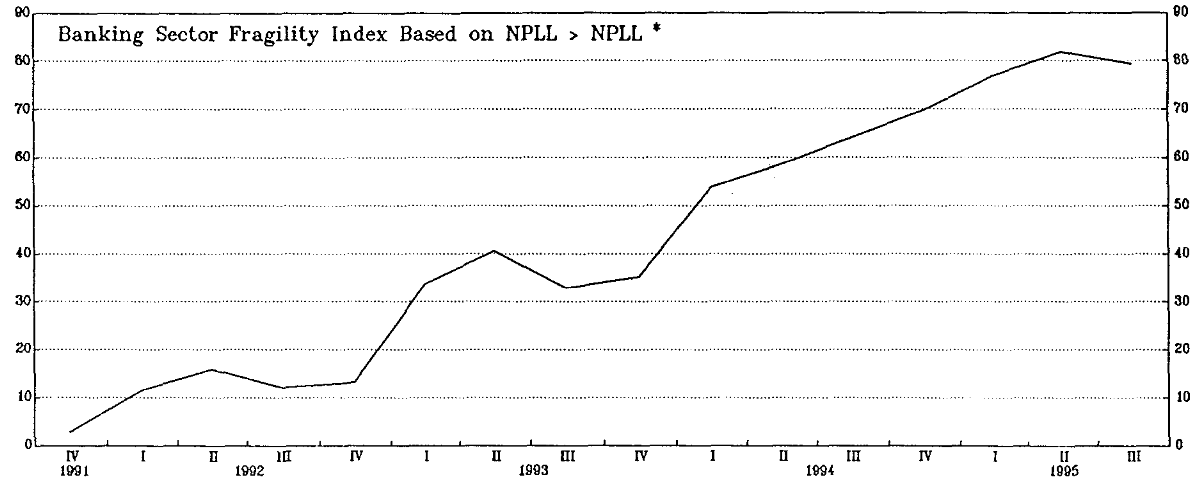
1/ The shape of this function is not surprising, given that the data best fit a logistic survival function with a hazard function that has precisely this shape. However, the model is useful in identifying the turning points in the Mexican case.

CHART 1

# INDICES OF BANKING SECTOR FRAGILITY




Source: Sistema de Informacion Estadistica.

Appendix

## DATA SOURCES

The bank-specific data used in this study is derived from the *Systema de Información Estadistica* (SIES) released by Mexico's Comisión Nacional Bancaria y de Valores.

CA Risk-adjusted capital-asset ratio ("indice de capitalización").

NPLL Non-performing loans to total loans ("indice de morosidad").

NSTLOAN Non-securitized loans to total loans ("prestamos quirografarios" plus "creditos simples y creditos cuenta corriente" over "cartera de credito total").

HOUSE Mortgage loans to total loans ("prestamos para la vivienda" over "cartera de credito total").

CONS Consumer credit to total loans ("creditos personales al consumo" over "cartera de credito total").

AGR Agriculture-related and other loans secured by inventories to total loans ("prestamos de habilitacion o avio" over "cartera de credito total").

ROA Return on assets ("rentabilidad sobre activos").

ROE Return on equity ("rentabilidad del capital").

NIM Net interest margin ("margen de interes neto").

PROFMARG Profit margin ("margen de utilidad").

DEPLOAN Public deposits to total loans ("captacion directa" over "cartera de credito total").

IBDLOAN Interbank deposits to total loans ("captacion interbancaria" over "cartera de credito total").

DEPLIAB Public deposits to total liabilities ("captacion direct" over "pasivos totales").

IBDLIAB Interbank deposits to total liabilities ("captacion interbancaria" over "pasivos totales").

EXPA Operating expenses to total assets ("costo de operacion" over " activos totales").

LIQUID Liquid assets to total assets ("disponibilidades" over "activos totales").

SIZE Bank assets to total banking sector assets ("activos" over "activos totales del sistema bancario").

| | |
|---|---|
| TOTRISK | Banking sector's riskiest assets to capital ("activos de mayor riezgo del sistema bancario" over "capital contable del sistema bancario"). |
| TOTNPLL | Banking sector's non-performing loans to total loans ("indice de morosidad del sistema bancario"). |
| TFOBAP | Contribution of banks to Fobaproa to banking sector's non-performing loans ("aportacion de bancos a Fobaproa" over "cartera vencida bruta"). |

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