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Determinants of Ex-Ante Banking System Distress: A Macro-Micro Empirical Exploration of Some Recent Episodes

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Abstract

This paper empirically analyzes the contribution of microeconomic and macroeconomic factors in five recent episodes of banking system problems in the U.S. Southwest (1986–92), Northeast (1991–92), and California (1992–93); Mexico (1994–95); and Colombia (1982–87). The paper finds that a low capital equity and reserve coverage of problem loans ratio is a leading indicator of bank distress, signaling a high likelihood of near-term failure. Distress is shown to be a function of the same fundamental macro-micro sources of risk that determine bank failures. Focusing on distress has the advantage that the fragility of the banking system can be assessed before a crisis actually occurs.

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I. Introduction

Although financial crisis have a long history, in the past two decades many countries have experienced episodes of significant financial sector distress.[2] Several recent periods of banking system distress have been associated with currency crises. Perhaps the most acute among the recent experiences are the financial problems encountered by some emerging markets. The current banking system problems that begun in the mid-1990s in Asia (including Thailand, Indonesia, and Korea) have also made apparent the possibility of regional contagion. In Latin America, severe banking crises also occurred in Mexico, Argentina and Venezuela in the first half of the 1990s, and in Chile and Colombia in the 1980s. But banking crises are not events reserved only for emerging economies. Episodes of significant banking system distress have been evident in Japan since the mid-1990s, in the Nordic countries during the early 1990s, and in the United States during the mid-1980s and early 1990s. Although with less intensity, banking problems have also recently afflicted countries like France and Italy.

These recent events have led to an explosion in the past few years in the number of studies that have taken different angles to try to explain the factors that contribute to financial crises. Clearly, finding basic early-warning systems of banking crisis and understanding its dynamics are critical, particularly in the current context of financial globalization in which countries can be affected by the financial problems in other countries. The current empirical literature seems to be largely divided into two camps: studies which primarily focus on the role of bank-specific data (largely in the context of CAMEL variables)[3] to explain bank failures, and studies focusing on the contribution of macroeconomic variables to explain banking crises.

Despite the clear advances in the literature of banking failures, many issues remain to be resolved. For example, why is it that, despite the fact that all banks in a country are hit by the same macroeconomic shock, not all banks fail? Do banks that fail have different characteristics than non-failed banks? If so, are some of those characteristics different several periods before actual failure? Are there some indicators that act akin to a pressure gauge through which near term failure is being signaled? Can these latter indicators be used to assess the degree of distress in the banking system before the crisis actually occurs? How to measure "moral hazard"? How does bank contagion occur? Are banking crises fundamentally different in advanced economies vis-à-vis developing countries?

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[2] See Kindleberger (1978), for example, for a historical perspective. More recent surveys of banking crises include Lindgren, Garcia and Saal (1996), and Caprio and Klingebiel (1996).

[3] The so-called CAMEL process is often used by bank regulators to rate the health of banks. The CAMEL rating given to a financial institution results in a single composite number based on five criteria of soundness. These criteria are related to capital, assets, management, earnings, and liquidity considerations. The scoring of each individual criteria for each institutions is computed relative to all the other institutions (i.e., individual performance being significantly above or below the industry's average).

This paper attempts to contribute to the literature of banking failures and banking system crises by analyzing the role of both micro and macro factors in the context of a simple model of bank failures based on market, credit and liquidity risks. By focusing on these notions of risk, rather than on actual definitions of variables, the analysis of different episodes of banking problems can be made broadly comparable despite the fact that specific circumstances and accounting systems usually vary among countries. The paper also attempts to examine some potential sources of contagion. By analyzing the experiences of five recent episodes of banking system distress in an advanced economy and in some developing countries—specifically, in the United States: the Southwest (1986–92), the Northeast (1991–92), and California (1992–93); in Mexico (1994–95); and in Colombia (1982–87)—it proposes a basic method by which to asses the ex-ante fragility of the banking system, before the bank failures actually occur. The main objective of this paper is to find parsimoniously the common factors across these different episodes of banking system distress.

The paper is organized as follows. Section II critically reviews the recent advances in the literature of bank failures and banking crises, and discusses the main issues still unresolved. Section III reviews the macroeconomic background for the episodes of banking system distress examined. It also examines the micro characteristics of banks that failed vs. banks that did not fail. Section IV discusses the basic theoretical framework in which bank fragility is a function of market, credit and liquidity risks (which can be associated with macroeconomic factors) and can be influenced by contagion factors. The different stages in the typical life cycle of bank failures and the main variables examined are also discussed. Section V briefly reviews the empirical methodology used to estimate the probability of failure and the time of failure. The empirical results for each episode are discussed in Section VI. The section begins by proposing an ex-ante measure of bank distress based on the ratio of capital equity plus loan reserves minus nonperforming loans to total assets (coverage ratio). The results suggest that the framework proposed captures reasonably well the episodes of bank fragility in all the cases examined. For completeness, a simple traditional CAMEL model with and without capital and nonperforming loans (the latter is a typical proxy for asset quality) was estimated.The results from this exercise suggest that capital and nonperforming loans account for a significant amount of the explanatory power in traditional CAMEL models. Based on the different models, the predicted values for each individual bank are then aggregated (and weighted by their relative asset shares) to arrive at estimates of fragility for the overall banking system—both based on (ex-post) failure and (ex-ante) distress. Section VII concludes and reviews some of the empirical regularities across regions that most clearly emerge from the analysis. In particular, market risk and liquidity risk were generally important in determining bank distress and eventual failure. Contagion seemed to be present in some cases but its impact was usually small. In addition, a high ratio of nonperforming loans to total assets and a low ratio of capital to total assets seemed to be strong indicators of bank distress.

II. Review of the Literature and Current Issues

Although the literature on bank failures and banking crises is indeed extensive, there seem to be two separate broad streams in the empirical literature: the "micro" and the "macro" camps.[4] First, the "micro" approach typically focuses on individual banks' balance sheet data, possibly augmented with equity price data, to predict bank failures. This literature was particularly prevalent in the 1980s, but many studies have also been published in the 1990s. Most studies have been in the context of U.S. banks. Typically, these studies use different empirical methodologies and financial ratios to produce an evaluation of the condition of banks consistent with the CAMEL rating system often used on-site by regulators. The list of variables that has been suggested is quite extensive and often involves complex accounting. (Appendix I provides a summary of the variables used in some representative studies.) A few of those studies have introduced some macroeconomic/regional factors as explanatory variables, but usually without a formal link to the rest of the analytical framework.

The second stream in the empirical literature, one which has seen significant growth in recent years, focuses on macroeconomic (sometimes, including institutional) variables to explain banking crises.[5] These studies typically focus on a large sample of countries which are known ex-post to have had a banking crisis during a certain period. The macroeconomic factors associated with episodes of banking sector problems highlighted in this literature include cyclical output downturns, adverse terms of trade shocks, declines in asset prices (e.g., in equity and real estate markets), rising real interest rates, boom-bust cycles in inflation, credit expansion, losses of foreign exchange reserves, and capital inflows. Interestingly, some of the studies that have recently attempted to examine the macroeconomic causes (only) of the current banking crises in Asian countries find that these models would have largely missed these crises (Demirgüç-Kunt and Detragiache (1998b), and Hardy and Pazarbasioglu (1998)).

Often, the argument by the "macro" camp is that, while it would be useful to include individual bank data in the analysis, bank balance sheet data are typically difficult to obtain as no single source of data exists to date. Furthermore, such data are often based on complex accounting principles that vary among countries. These factors can make cross-country

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[4] Although there seems to be a growing recognition that both micro and macroeconomic factors can contribute to banking crises (for example, Gavin and Hausman (1996), and Goldstein and Turner (1996)), the empirical literature continues to largely focus on either micro or macro determinants. Some notable exceptions are González-Hermosillo, Pazarbasioglu, and Billings (1997), and Honohan (1997).

[5] Among these studies are Kaminsky and Reinhart (1996), Demirgüç-Kunt and Detragiache (1998a, 1998b), and Hardy and Pazarbasioglu (1998).

comparisons difficult, particularly if some of the typical variables used in most (full-fledged) CAMEL studies were to be constructed for cross-country comparisons.[6]

What is needed? First, an integrated approach of the micro" and "macro" camps. The macro approach has the advantage that many countries can be easily analyzed at once—partly because the data are centralized and are usually readily comparable, but also because dealing with bank-specific data requires a fair amount of institutional knowledge (e.g., accounting practices in that country, timing of failures, etc.). However, the macro approach is based on the ex-post knowledge that there was a crisis, the period in which it began and when it ended.[7] Even if the timing and the duration of crises could be pinpointed precisely, studying a new episode of banking crisis would need to await for the actual crisis to occur—as there is no generally accepted measure of fragility that can be analyzed prior to the actual crisis.[8] Therefore, the second element that is needed is some measure by which to gauge bank fragility, in an ex-ante basis, before the actual failure. Even so, perhaps the major shortcoming of the macro approach is that, by not including individual banks in the analysis, it does not explain why it is that almost without exception not all banks fail even if hit by the same macro shock.[9] What makes some banks survive the shock? What are the channels through which macro shocks affect banks? By recognizing that there are generally two types of banks, sound and unsound, the micro approach focuses on the characteristics of these two groups of banks.

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[6] Hence the appeal of studies based on "simpler", more basic bank data that can facilitate comparisons across countries. An example is Rojas-Suárez (1998) in which banking problems in Mexico, Venezuela and Colombia are examined based on some basic bank-specific data only (no macro variables are included). The argument is that, in developing countries, basic variables such as deposit and lending interest rates, and growth in interbank deposits and loans, are better predictors of bank problems than other more traditional CAMEL ratios.

[7] These are not always straightforward questions. For example, most of the macro studies previously mentioned typically include the crisis of 1982 in Mexico as a "banking crisis" because the banking system was nationalized (a common definition of "intervention"). But the issue at heart in Mexico during that period was not whether banks were fragile and possibly insolvent, but that they facilitated the outflows of capital that contributed to the currency crash of 1982. The nationalization of Mexican banks was a (likely political) response to the currency crisis. Another example is Japan: formally, the banking crisis may have begun in early 1998 when the government announced that it would make resources available for undercapitalized banks. However, although it is difficult to pinpoint exactly when the Japanese banking crisis began, it is clear that it was some years ago.

[8] However, a few studies have used a given level of nonperforming loans to define periods of "crisis." For example, Demirgüç-Kunt and Detragiache (1998a) and Rojas-Suárez (1998).

[9] An exception may be banking crises associated with war or such other catastrophic events.

The micro camp, and specifically the studies based on CAMEL-type analysis, tend to produce satisfactory estimation results—in part because there are usually a significant number of potential proxies for the explanatory variables. However, this approach not only often fails to perform appropriately if economic conditions are changed,[10] but some of the explanatory variables that are typically used to predict bank failures are themselves endogenous. For example, a common variable used to measure asset quality is nonperforming loans, which itself is a *result* of poor loan decisions and/or deteriorated economic conditions.[11] Banks do not fail because they have a large portion of troubled loans, they fail because of their earlier investment decisions whose outcomes may be also influenced by changed economic conditions—a high level of nonperforming loans are the result of those same fundamental causes.[12] A similar argument can be made about capital. Minimum levels of capital (including credit risk-weighted capital-asset ratios) serve as a cushion to absorb shocks. However, ex-post (especially when the bank is in financial trouble), capital is the residual between its (market value) assets and the institution's nonownership liabilities.[13] Indeed, a bank is insolvent when the market value of its capital equity becomes negative. Measures of earnings also typically pose a problem in CAMEL models because, although low earnings are probably indicative of financial distress, soaring earnings do not necessarily mean that a bank is sound. As discussed below in what regulators have found to be the typical life cycle of bank failures,

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[10] This is recognized by the Federal Deposit Insurance Corporation (1997), p. 512, when it is pointed out in the conclusions of this recent massive study that "ongoing research at each of the federal bank regulatory agencies is warranted. Such research would include regional economic data in the current off-site monitoring models, thereby further enhancing our understanding of the causes of financial distress."

[11] This is equivalent to having a good forecasting record of patients' deaths based on high levels of fever as an *explanatory* variable. High fever is clearly a result of something else gone seriously wrong in the organism.

[12] The Federal Deposit Insurance Corporation (1997), for example, acknowledges that many prediction models of bank failures use measures of banks' current condition or ex-post risk (i.e., ratio of equity to assets, ratio of net income to assets, ratio of nonperforming loans to assets, and the ratio of equity plus reserves minus nonperforming loans to assets) and that, for the United States, their predictive power falls considerably for periods longer than a year. Instead, they emphasize the need to gauge ex-ante measures of risk.

[13] In this connection, Federal Reserve Chairman Greenspan recently made some interesting comments: "...the Basle Accord set a minimum *capital ratio*, not a maximum *insolvency probability*...In overseeing the necessary evolution of the Accord [...], it would be helpful to address some of the basic issues that have not been adequately addressed by the regulatory community. There are really only two questions here: First, how should bank "soundness" be defined and measured? Second, what should be the minimum level of soundness set by regulators?," Greenspan (1998).

often banks that eventually fail as a result of their high risk-taking were very profitable several periods before their actual failure. As is the case with the macro approach, there is clearly a need in the micro camp to develop generally robust measures of ex-ante bank fragility.

In addition, although there is some anecdotal evidence of banks' moral hazard behavior (or "looting" as described in Akerlof and Romer (1993)), the supporting empirical evidence seems to be generally lacking.[14] Finding proxies for moral hazard is obviously not an easy task. As well, none of the two empirical approaches seems to have been able so far to link bank failures with contagion effects, despite the importance of this source of systemic risk.[15] Finally, although it is often assumed that banking crises in developing countries are intrinsically different than in advanced economies, neither approach has provided a definitive empirical answer to this question. All these issues remain to be solved in the literature.

III. Banking System Problems in the United States, Mexico, and Colombia: The Macro-Micro Background

A. Banking System Problems in the United States (1980s to early-1990s)

During the 1980s and early 1990s, more than 1,600 commercial and savings banks insured by the Federal Deposit Insurance Corporation (FDIC) failed (i.e., were closed or received FDIC financial assistance)—far more than in any other period since the 1930s.[16] Most of the bank failures occurred between 1986 and 1992, peaking during 1987–89. Bank failures represented approximately 9 percent of both total bank assets, and of the total number of banks existing at the end of 1979 plus all banks chartered during the subsequent 15 years (Federal Deposit Insurance Corporation (1997)). Although unquestionably costly, perhaps at a national level this episode of banking system distress may not have been of "crisis proportions" relative to the size of the U.S. economy when compared, for example, to the recent banking crises in some emerging economies.[17]

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[14] One exception is Demirgüç-Kunt and Detragiache (1998a), in which the role of moral hazard is examined by introducing a dummy if countries had explicit deposit insurance programs. However, since the explanatory data are mostly contemporaneous, it is unclear whether crisis periods led to the introduction of explicit deposit insurance schemes.

[15] However, González-Hermosillo, Pazarbasioglu, and Billings (1997) attempt to address some potential sources of contagion (proxied by certain banking system variables) in Mexico.

[16] Banks are considered to have been intervened (failed) if they were liquidated or received assistance from the FDIC.

[17] Caprio and Klingebiel (1996), for example, classify this episode of banking failures in the
(continued...)

However, bank failures in the United States during this period were highly concentrated in a few states—some of which included the country's largest banking markets. In some of those states, bank failures accounted for a sizable proportion of the total assets of the state banking system and of the number of existing banks in the region. The states most affected by bank failures include Texas, Oklahoma and Louisiana in the Southwest; New Hampshire, Massachusetts and Connecticut in the Northeast; and California (Table 1). The figures at the state level would seem to be of comparable proportions to several other known episodes of banking crises.[18] Interestingly, commercial bank failures in these three U.S. regions—the Southwest, the Northeast, and California—largely occurred in different periods (Figures 1 and 2).[19] Prohibitions against interstate branching in several states during this period (including Texas, Colorado, Illinois, Kansas and others) limited the banks' ability to diversify geographically and made some of the state banking crises akin to sub-national banking crises within the United States.[20] "Geographically confined crises were translated into a national problem" (Federal Deposit Insurance Corporation (1997), p.13). These geographically confined crises are examined below.

The Southwest

The macro/regional setting

Commercial bank failures in the *Southwest* (defined here to comprise Texas, Oklahoma and Louisiana because the banking problems in the region were concentrated in those states) largely occurred during 1986–92, peaking in 1988–89. The banking problems in this region followed a decline in regional economic activity (Figure 3) which was largely associated with weak agricultural prices and plunging oil prices. The decline in oil prices since 1981, and their virtual collapse in 1986, represented a major shock for the energy-producing southwestern states (Figure 4). The regional real estate market had been booming as a result of the hitherto strong energy market. As oil prices began drifting downward in 1981, southwestern banks sought new investment opportunities in the then-booming real estate markets, particularly in

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[17](...continued)
United States, including failures in the savings and loans industry, as a "borderline" banking crisis.

[18] Caprio and Klingebiel (1996), Sundararajan and Baliño (1991), and Lindgren *et. al.* (1996) provide estimates of the magnitude of recent banking crises for several countries.

[19] In the remainder of the discussion on the United States, and in the empirical analysis, the focus is on commercial banks. For a discussion on the U.S. savings and loan crisis and the failures of mutual savings banks, see Federal Deposit Insurance Corporation (1997).

[20] Interstate branch banking restrictions in the United States were not phased out until the mid-1990s.

the commercial real estate market. Real estate markets began a prolonged decline in the mid-1980s with construction activity (Figure 5) and real estate prices plunging.[21]

Characteristics of failed banks vs. non-failed banks

Against a common macro/regional environment and shocks, not all banks located in the same area of distress are affected equally by those events and, indeed, not all banks typically fail. What makes banks that fall into crisis different from those that do not? Are some of those characteristics evident several periods before the actual crisis? Are other characteristics particularly apparent shortly before the crisis?[22]

In the case of southwestern banks, the main characteristics of banks which eventually failed relatively to the banks that did not fail (Figure 19 in Appendix II) and that were evident through much of the period of study include: banks that failed had a significantly higher ratio of commercial and industrial loans (which include loans to the energy sector) relative to total assets; a higher proportion of loans in the commercial and residential real estate sector, and in consumer loans; a higher ratio of loans to assets; a lower proportion of liquid assets and higher expenses; paid a higher average interest rate on deposits and received a lower average yield on loans. In contrast, the ratio of nonperforming loans to total assets (and relative to total loans) for banks that failed were somewhat higher at the beginning of the period than for banks that did not fail, but showed a dramatic deterioration as the crisis intensified. Similarly, equity capital ratios (and profitability) were somewhat lower at the beginning of the period for banks that failed, but deteriorated dramatically as the crisis intensified. The capital and reserve coverage of nonperforming loans (coverage ratio) of banks that eventually failed declined rapidly, becoming negative in 1987— just before the peak of the southwestern bank crisis in 1988–89.[23]

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[21] An excellent review of the banking problems encountered in the Southwest, the Northeast and in California—on which the description of the macro/regional settings in this section is largely based—are provided in Federal Deposit Insurance Corporation (1997), Chapters 9–11.

[22] Standard summary statistics (mean and standard deviations) of the main characteristics of banks that failed (uncensored) vs. those that did not fail (censored) in each region, for the entire sample period, are presented in Tables 9–13 in Appendix II. While indicative of overall major differences among the two groups of banks, these aggregate statistics do not capture how the banks' positions changed over time. To shed light on these questions, Figures 19, 21, 23, 25, and 27 in Appendix II plot the medians of the main characteristics of failed banks vs. non-failed banks over time for each region.

[23] U.S. bank data, including information regarding banks' intervention, come from the Federal Reserve Bank of Dallas. The bank balance sheet data is gathered in the Report of Condition and Income ("Call Report"). Macroeconomic and regional data for the United States comes

(continued...)

The Northeast

The macro/regional setting

The banking problems in the *Northeast* (defined here to comprise New Hampshire, Connecticut and Massachusetts, also because a large part of the bank failures in the region occurred in these states) became prominent during 1991–92. Supported by a strong regional economy, the real estate markets in the Northeast boomed during the 1980s. However, regional economic activity weakened late in the decade (Figure 6) as a result of a slowdown in military spending as the Cold War came to an end, and a decline in activity in the computer industry which was largely concentrated in New England. The real estate market boom of most of the 1980s turned into a bust. In the early 1990s, an oversupply of real estate projects led to a decline in construction activity (Figure 7) and real estate prices went into a sharp decline. The northeastern banks had been aggressive participants in the hitherto prosperous real estate markets of the 1980s.

Characteristics of failed banks vs. non-failed banks

Northeastern banks that eventually failed, relatively to banks that were not intervened, also exhibited certain characteristics several years before the period of distress (Figure 21 in Appendix II), including: higher shares of commercial and industrial loans, and of commercial real estate loans; a lower share of residential real estate loans and consumer loans; a higher loans to assets ratio; and a lower liquidity ratio. Nonperforming loans and equity capital between these two groups of banks were nearly undistinguishable (in fact, the ratio of equity capital to total assets was slightly higher for banks that eventually failed) several years before the period of distress surfaced, and it was not until the crisis escalated that nonperforming loans and equity capital deteriorated dramatically. Diminished profitability also seemed to be a late indicator of impending problems for those banks that eventually failed. The coverage ratio of banks that eventually failed declined sharply in 1990 when it became negative—about one year before the peak period of failures in 1991–92.

California

The macro/regional setting

California's banking problems were particularly prevalent during 1992–93, but there were some occurrences of failure beginning in the mid-1980s. Although many banks failed in this state, they were generally small (in contrast to the Southwest and the Northeast). The prosperous 1980s took a turn by the end of the decade as the California economy slowed

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[23](...continued)
from the U.S. Bureau of Economic Analysis, the U.S. Census Bureau and the IMF Financial Statistics database.

(Figure 8). Bank problems surfaced in precisely the sectors that had led to the economic boom of the 1980s: defense-related manufacturing associated with the Cold War, construction activity, and the real estate markets. During most of the 1980s, California had been also a major recipient of Japanese investments and these inflows of capital had contributed to a booming property sector. As the Japanese economy fell in recession in 1990, Japanese investors and banks (which themselves were beginning to face "a large portfolio of nonperforming assets, and pressures from financial markets and Japanese regulators to deal with these issues" (Federal Deposit Insurance Corporation (1997), p. 396)) significantly cut their lending and investments in U.S. real estate markets. California had been an important recipient of the Japanese investments in the U.S. property market. When Japanese investments declined, this also had an important impact on the California economy.[24] The real estate market and construction activity suffered a significant decline in California during the late 1980s and early 1990s (Figure 9).

Characteristics of failed banks vs. non-failed banks

Banks that eventually failed in California, relatively to those that did not fail, exhibited certain characteristics several years before the period of distress (Figure 23 in Appendix II), most notably: a higher loans to assets ratio; a lower liquidity ratio; and higher expenses. Nonperforming loans deteriorated sharply as the crisis intensified. Capital ratios (and profitability) also worsened as the crisis unfolded. The coverage ratio of banks that eventually failed declined sharply in 1991, approaching zero and becoming negative about one year before the peak period of failures in 1992–93.

What role did interest rates play?

At the national level, U.S. nominal and real interest rates generally declined from the mid-1980s to the early 1990s (Figure 10), which helped the condition of most banks by lowering the cost of funding and improving the creditworthiness of borrowers. The decline in interest rates was accompanied by an upward-sloping yield curve in the early 1990s which "increased the value of bank security portfolios and raised net interest margins on new loans, reducing the number of bank failures" (Federal Deposit Insurance Corporation (1997), pp. 410–411).

[24] Japanese investment in the U.S. real estate markets declined during 1990–92, becoming net sellers in 1993–94 (Federal Deposit Insurance Corporation (1997)).

B. Banking System Problems in Mexico (1994–95)

The macroeconomic setting

The recent Mexican financial crisis is regarded by many as the prototype of crisis that could threaten other emerging markets whose capital markets are becoming more integrated with global markets because of the evident connection between banking crisis and currency crisis, and also because of the apparent contagion to other economies.[25] The Mexican economy was shaken by the collapse of the peso in December 1994, with interest rates increasing manyfold and the economy contracting drastically in the months that followed (Figures 11 and 12).[26] Two relatively small banks received an infusion of capital and had their management replaced by the regulatory authorities, apparently in connection with fraudulent activities, during the third quarter of 1994. But it was not until after the currency collapse that several banks were intervened by the authorities.[27] By end-1995, more than ½ of all the Mexican banks had received financial support from the government, including the two largest banks which had a significant amount of their problem loans removed from their books and purchased by the authorities in the final quarter of 1995.

Characteristics of failed banks vs. non-failed banks

Banks that eventually failed in Mexico, relatively to those that did not fail, exhibited certain characteristics evident several periods before the crisis (Figure 25 in Appendix II), most notably: a higher proportion of residential loans; and lower profitability. Banks that eventually failed saw their level of nonperforming loans deteriorate rapidly prior to the crisis, while they

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[25] The Mexican financial crisis has been well documented, for example, in U.S. General Accounting Office (1996) and in International Monetary Fund (1995).

[26] Macroeconomic data for Mexico comes from the IMF Financial Statistics database.

[27] Although no banks were liquidated, there were several programs of government assistance to fragile banks, including: capital infusions and removal of management through FOBAPROA (the deposit insurance fund); assistance through the temporary recapitalization scheme PROCAPTE; and the purchase of banks' problem loans by the government. Bank's are considered to have been intervened (failed) if they received any of these types of government assistance.

had much lower capital ratios than was the case for banks that did not fail.[28] The coverage ratio of failed banks was also significantly lower than for non-intervened banks.

C. Banking System Problems in Colombia (1982–87)

The macroeconomic setting

The banking crisis in Colombia was spread over several years, with some banks failing in 1982 and during 1986–87. Although the number of banks that failed in Colombia was relatively small, especially when compared to more recent crises in other emerging economies, failed banks represented about 20 percent of the total assets in the banking system.

Most of the explanations available concerning the causes of Colombia's banking crisis point to the sudden end of the coffee boom of the late 1970s (for example, Rojas-Suárez and Weisbrod (1995)). In Colombia, economic conditions in the 1970s and early 1980s were heavily dependent on coffee exports. The price of coffee in international markets (based on Brazilian coffee) fell from over US$2 per pound in 1977 to 83 cents in 1981. Coffee prices recovered to US$1.90 per pound in 1986, before they fell again to 90 cents in 1987. Colombia's export prices followed closely this pattern (Figure 13).

Characteristics of failed banks vs. non-failed banks

Banks that eventually failed in Colombia, relatively to those that did not fail, showed certain characteristics (Figure 27 in Appendix II), including: declining ratios of liquidity and deposits from the public relative to total assets; rising average interest rates paid on deposits and interest received on loans; and increasing expenses. Nonperforming loans rose sharply prior to the period of failures in 1986–87. The capital equity ratios of failed banks were slightly lower than of non-failed banks before 1986–87, but they rose sharply at the time of the bank interventions—presumably in connection with some rehabilitation plans. The coverage ratio of failed banks declined sharply and became negative in 1984— two years before the 1986–87 wave of bank failures.[29]

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[28] Bank-specific balance sheet data for Mexican banks come from the Sistema de Informacion Estatistica (SIES), reported by the Comisión Nacional Bancaria y de Valores. According to the official data, the equity capital levels (including the risk-weighted capital-to-asset ratios (RISKCA)) of many of the banks which were not intervened were unusually high compared to most banks in other countries. This can be explained in part by the fact that most of the non-intervened banks were relatively new and had a modest asset base—overstating the ratio of minimum capital levels relative to the banks' (small) asset size.

[29] Bank-specific balance sheet data for Colombia, and information regarding bank interventions, were compiled by the Central Bank of Colombia and the Banking Superintendency.

(continued...)

IV. Model of Bank Distress and Main Variables

A. The Basic Framework

The literature on early-warning systems of bank failure has primarily relied on bank-specific variables for clues about the soundness of individual banks, while the analysis of macroeconomic factors has been essentially the domain of the literature on banking (and financial) crises. Relatively few studies have attempted to integrate these two approaches. One of those attempts is the basic framework proposed in González-Hermosillo (1996), which suggests that bank fragility is essentially a function of liquidity risk, market risk and credit risk.[30] In turn, those risks are conditioned by macroeconomic conditions and can be influenced by the overall fragility of the banking system. In particular, based on a simple two-period balance sheet framework,[31] the probability of an individual bank becoming unsound F_{z_i} can be expressed as a function

$$F_{z_i} = F\ (x,\ y,\ k) \tag{1}$$

where deposit flows during a given period are given by x (normalized by the stock of total deposits or assets), y constitutes the bank's (normalized) net asset income and k can be viewed as the bank's optimal (normalized) level of capital required to minimize the expected costs of insolvency. The values of x and y are known in period t but are only known in a probabilistic form for period t+1. In this framework, k is chosen by bank's management as the optimal level of initial capital (but could also be imposed by the regulatory authorities as the minimum level of capital)—however, the ex-post market value of capital is clearly the difference between (market value) assets and non-ownership liabilities.

Equation (1) is generalized to explore the fundamental sources of risk. Assuming a zero expected recovery rate of defaulted loans, the expected net asset income at the beginning of the period can be expressed as a function of market risk $\beta^* (\Gamma)\ i_m$ and default risk $\tau\ (\Gamma,\ i_m)$:

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[29](...continued)
Information on specific types of loans was not available. Macroeconomic data for Colombia come from the IMF Financial Statistics database.

[30] This section is essentially an abbreviated version of that study. Focusing on these risks has the advantage, over traditional CAMEL models, that off-balance sheet items (if data are available) could be also analyzed in a similar manner since they too are subject to the same types of risks.

[31] The framework assumes only two types of assets: reserves in the form of currency and risky earning assets. Liabilities constitute only deposits and capital.

$$y = y(\beta^*(\Gamma)\ i_m\ ,\ \tau(\ \Gamma,\ i_m)) \tag{2}$$

In particular, the realized net asset income of a bank at the end of the period will depend on: the realized (exogenous) market return i_m adjusted by the β^* $(\cdot)$ of the bank's asset portfolio $(\beta^*(\cdot) \geq 0)$ chosen by bank management;[32] and on the occurrence of default by the borrowers τ $(\cdot)$. The vector Γ is assumed to encompass macroeconomic variables related to the state of the business cycle (e.g., output growth, housing market activity, etc.). Assuming that borrowers are always willing (but sometimes unable) to pay, the likelihood of default by borrowers may change with the business cycle and with changes in the market interest rate.

This basic model can be augmented in two respects. First, if banks were assumed to follow a "herding" type of behavior vis-à-vis other banks, the choice of β^* $(\cdot)$ could also be a function of the fragility of the overall banking system F_T (which is essentially derived by aggregating the fragilities of individual banks, weighted by their asset shares). Thus, for example, in an effort to maintain market share, banks may increase their degree of risk-taking if they perceive that other banks are doing the same thing—particularly if there are deposit guarantees which would reduce the banks' potential costs of assuming such added risks. Second, banks can also encounter higher default risk (even if economic conditions are favorable) if borrowers are able, but not willing, to repay their loans. This may reflect poor credit controls by banks' management. Alternatively, this may be also the result of banks taking deliberate extreme credit risks (i.e., engaging in "looting" or, more generally, moral hazard) by extending loans "in circumstances in which no reasonable person would expect a future positive payoff in any future state of the world, but for which the present payoff was very high" (Akerlof and Romer (1993), pp. 28–29).

Depositors' behavior regarding their desired flows of deposits into, or out of, the bank(s) where their deposits are held can be viewed as a function or

$$x = x\ (\ u\ ,\ (F_{z_i}\ |\ \gamma^*(\gamma_{\max},\ e,\ F_T),\ \Omega\ ))) \tag{3}$$

where u refers to the depositors' exogenous and stochastic needs for bank deposit transactions (e.g., reflecting liquidity needs, payments requirements, savings decisions, etc.). F_{zi} is the expected probability that the bank in question (bank i in this case) will fail given the antici-

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[32]Such that highly cyclical investments would be characterized by a high β^*, while investments that hedge the market risk will have a β^* that approximates 0. Thus, for example, a $\beta^* = 0.5$ would denote that the return on the bank's portfolio is expected to be about half of the market's return.

pated effective level of deposit guarantees, γ^*, and given the information set available at time t, Ω, used to form expectations. In the case of explicit deposit insurance schemes, the level of γ^* is a function of the statutory maximum level of deposits per account covered by the deposit insurance program γ_{max}, the (exogenous) endowment available in the deposit insurance fund e, and the expected probability F_T that there may be a significant number of banks in the system also failing. If many banks fail during the same period, the endowment may not be sufficient to cover all the ailing banks. If depositors suspect that the bank where they hold their deposits is in trouble, they may withdraw their money from that bank and place it in another bank perceived to be sound. If they suspect that many banks are in trouble but they are unable to distinguish which banks are actually unsound (i.e., there is asymmetric information), and there is uncertainty as to whether the resources in the deposit insurance fund are sufficient to cover all losses, there may be deposit runs—even from banks that would be otherwise sound.[33] Sudden deposit withdrawals would increase liquidity risk for banks and could lead to failure if assets cannot be made readily liquid, while maintaining their market value, to cover for the deposit withdrawals. In the presence of asymmetric information, the fragility of the overall banking system can affect even sound banks if indiscriminate deposit runs develop—thus, contagion can occur.

B. The Life Cycle of Bank Failures

In practice, it is of course often difficult to determine what may constitute "excessive" risk-taking by banks because they are in the business of taking risks. Too much risk can result in financial distress, but too little may also threaten the bank's long-term viability. Excessive risks can be extremely profitable at first. Changed economic conditions following the initial investments frequently reveal (ex-post) the actual magnitude of those risks.

In interviews with U.S. regulators, for example, it was found that bank failures seem to have a life cycle which roughly corresponds to three phases (see Federal Deposit Insurance Corporation (1997)). In the first stage, there may be rapid loan growth, loan concentrations emerge, and lending is aggressive (internal controls in the growth area are weak, and underwriting standards are lenient). The increased lending may be funded by a volatile lending source. This growth could occur throughout the entire institution or within a specific asset type. The growth will generate added revenue from increased loan fees and interest income. In addition, because these are largely new loans, initially there are no delinquencies, so that the growth is almost always accompanied by growth in income and capital (assuming retained earnings). If the rapid growth draws the attention of the regulators, management usually points to the "excellent earnings" and contribution to capital that the growth has provided. In the United States, this stage of development seems to take up to two years.

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[33] The case of implicit deposit guarantees would be similar if the perceived risk is that the overall liabilities of the banking system would be monetized. See González-Hermosillo (1996) for an elaboration.

In the second stage, the institution has rising loan-quality problems. Associated expenses may far exceed the industry averages. Nonrecurrent sources of income are used to maintain the same level of profits that existed during the growth phase. Eventually profits begin to decline, and inadequate reserve levels become apparent. At this point the bank may have a high loans-to-assets ratio. Management may still believe that the problem is manageable. This stage may take an additional one to two years.

In the final stage, deteriorating asset quality is a serious problem. If the institution is large, the capital markets (if sufficiently developed) may have recognized that the institution has inadequate loan-loss reserves and are unwilling to provide fresh capital and funding. At this point, major changes in the banks' operations are necessary if they are to avoid failure. Dividends may be cut, expenses (mostly personnel) are slashed, and assets are sold to cover losses and expenses. This crisis phase may last up to a year and results either in failure of the bank or, if fundamental changes are made, in its eventual recovery.

Based on this analysis of the life cycle of bank failures, it would appear that different indicators tend to surface at different times in the cycle. In developing a procedure to identify the ultimate sources of risk for U.S. banks, research at the Federal Deposit Insurance Corporation (1997) attempted to separate "condition" or "ex-post risk" variables—as indicators of the current strength or weakness of a bank—from some of the fundamental sources of risk. They find that a bank in a weak condition would typically have low equity capital and net-income ratios, and high nonperforming loan ratios. On the basis solely of those condition variables, they found little evidence in 1982 to distinguish banks that failed from those that did not fail five years later. They then examined nine sources of (ex-ante) risk: loans-to-assets ratio; large deposits to total liabilities; return on assets; asset growth; loan growth; operating expenses to total expenses; salary expenses per employee; interest on loans and leases to total loans and leases; and interest and fees to loans and leases. Their study, covering all U.S. banks for the period 1980–88 and based on the explanatory power of individual variables using logit regression, showed that the best long-range predictor of failure is bank's loans-to-assets ratio.[34] However, the predictive power of most variables frequently changed across different periods. Furthermore, it is not clear from the study what were the criteria for choosing those particular variables (other than perhaps because of their individual predictive power), nor was the joint explanatory power of different variables put together apparently explored.

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[34] The empirical methodology adopted in the FDIC report is based on analyzing the information content of each individual factor separately. The variable with the highest predictive power for failure was determined by a Chi-Square test score. In contrast, the approach followed in this paper combines the information content of several variables combined to be consistent with the theoretical framework proposed.

C. Main Variables

In a similar spirit to the FDIC approach, this study also attempts to identify fundamental sources of risk, which are largely the result of bank management's behavior in the past, and proximate indicators of fragility (or bank "condition" in FDIC's terminology). However, the choice of variables here is consistent with the theoretical framework discussed above in which bank distress is a function of market risk, credit risk and liquidity risk, often related to economic conditions and the fragility of the overall banking system. Furthermore, the focus is on finding "common ground" across different episodes of banking system problems (rather than fitting models based on different idiosyncratic variables in each case but with the highest predicting power). Obviously, accounting systems are often different among countries and the relevant measurements of alternative types of risk may vary according to the circumstances specific to each episode. However, to the extent possible, an effort was made to maintain conceptual equivalences across the different episodes of banking crises examined.

Table 2 summarizes the indicators of bank failure and distress examined in this study, and their expected signs. The hypothesized proximate indicators of fragility are nonperforming loans, capital equity, and the combined equity capital and loan reserve coverage of nonperforming loans—which are similar to most of the FDIC's condition variables.[35] The proxies for the fundamental sources of risk were chosen based on the specific type of risks examined: market, default or liquidity risk. In general, high market risk would occur if a bank's loan portfolio is heavily concentrated on booming sectors that may be subject to boom-bust dynamics (including, for example, sectors vulnerable to foreign exchange fluctuations), in areas that are highly dependent on cyclical economic conditions (e.g., real estate, sectors dependent on commodity prices or the stock market), or in sectors with returns significantly higher that the market rate of return (investments with high β^*). The variables proxying for market risk are likely to vary depending on the specific circumstances in each region. For example, a high exposure to commercial and industrial loans was probably only an important factor in the case of banks in the U.S. Southwest because this category of loans includes loans extended to the energy-dependent sector.

There are several proxies for credit or default risk. In general, a high loan-to-assets ratio is probably associated with fast lending growth and weak internal credit controls. High yields paid on loans may indicate that the bank is originating high-risk loans, but low yields may also mean that risk is not priced properly. High interest rate spreads may also mean that the bank is taking risky loans; however, low interest rate spread may reflect the bank's efficiency. The sources of liquidity risk depend on whether some type of deposits are more volatile and

[35] Risk-weighted capital-asset ratios were not examined in the cases of the United States or Colombia because the period of study for these two countries began prior to the introduction of the Basle Accord in 1988. For consistency, risk-weighted capital-asset ratios were not reported in the case of Mexico, but they produced similar results to the other alternative measures of capital examined.

whether a bank has enough liquidity to respond to large deposit withdrawals. The variables include large deposits, interbank deposits and deposits from the public, liquid assets and the average interest rate paid on deposits. The proxies for moral hazard are two. First, insider loans because of their inherent potential conflict of interest (however, this data are only available for the United States). Second, the ratio of interest income on loans, fees and leases to total assets because—consistent with the observation made by Akerlof and Romer (1993) for the case of some financial institutions in the U.S. Southwest during the 1980s—moral hazard may be associated with banks loading up on up-front fees, commissions and high interest rates on loans extended even though the long-term viability of the loans is not expected to be favorable.[36]

The regional and macroeconomic variables were generally based on measures of economic activity and real interest rates. In addition, other variables representative of the specific circumstances of each episode of banking system distress were also included (e.g., oil prices in the case of the U.S. Southwest, currency depreciation in Mexico, and coffee-related export prices in Colombia). The banking sector variable, as a proxy for contagion based on the theoretical framework discussed above where contagion can occur through deposit runs and/or banks' hearding behavior, used was the ratio of total loans in the banking system of the country or region relative to output.[37] Banking system loans growing significantly faster than output would be generally associated with increased fragility. This may be the result of banks following "herding behavior" patterns in their lending. The increased fragility of the banking system could also lead to deposit runs if depositors are unable to distinguish which banks remain solvent. However, it may also be that banks may find some safety in large numbers if regulators are less able (or willing) to intervene additional banks as more banks run into financial difficulties.

Since all the variables chosen are essentially proxies, some additional bank-specific variables (including measures of profitability, cost efficiency, size and dummies for banks part of a holding company structure) were also included to explore their potential role in explaining bank failure and distress. Before discussing the empirical results, the empirical methodology is briefly reviewed.

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[36] Banks may be willing to lend to exceptionally risky projects in which the probability of a positive payoff in the future is very small but for which the present payoff is very high—often in the form of originating fees or in an extremely high interest rate on the loan—particularly if a third party is expected to born the future liabilities while the benefits in the near term can be appropriated by the bank.

[37] This variable is also often used as a proxy for financial liberalization because of the resulting rapid expansion of bank loans.

V. Empirical Methodology

The probability of bank failure was estimated based on the fixed-effects logit model for panel data suggested by Chamberlain (1980). Let $i = 1, 2, \ldots, n$ denote the groups (banks in this case) and $t = 1, 2, \ldots, T_i$ the observations for the ith group. Let y_{it} be the dependent variable taking on values of 0 or 1, and x_{it} be a row vector of explanatory variables in a model of the form

$$y_{it} = \alpha_i + \beta' x_{it} + \varepsilon_{it} \tag{4}$$

Although constant over time, the parameter α_i may be different for different cross-sectional units. To account for heterogeneity, let $y_i = (y_{it}, \ldots, y_{iT})$ be the outcomes for the ith group as a whole and $k_{1i} = \Sigma\, y_{it}$ (the summation from t=1 to T_i) be the observed number of ones for the dependent variable in the ith group. Fixed-effects logit regression maximizes a conditional likelihood function based on the probability of a possible value of y_i conditional on $k_{1i} = \Sigma\, y_{it}$ (the summation from t=1 to T_i).[38]

The (time-varying) survival time models estimated were based on monotonic hazards. Let T represent the duration of stay in the state of no-failure (time to exit) and t a realization of T. Assuming that the random variable T has a continuous probability density function $f(t)$, the cumulative probability distribution is given by

$$F(t) = \int_o^t f(s)\, ds = Prob(T \leq t) \tag{5}$$

the survival function is given by

$$S(t) = 1 - F(t) = Prob(T \geq t) \tag{6}$$

and the hazard function can be written as

$$\lambda(t) = \lim_{dt \to 0} \frac{Prob(t \leq T < t + dt \mid T \geq t)}{dt} = -d\ln S(t)/dt \tag{7}$$

which is the conditional probability that a bank that has occupied the state of no-failure for a time t leaves it in the short interval of length dt after t. Alternatively, the hazard function is the instantaneous rate of leaving the state of no-failure per unit of period at t.

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[38] See Hsiao (1986) for a full exposition.

Specifically, the hazard function can take the form

$$\lambda(t) = \lambda_0(t)\ e^{\beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k} \tag{8}$$

where λ_0 (t) is the baseline hazard (the individual heterogeneity). In the case of the proportional hazard model with time-dependent explanatory variables, first suggested in Cox (1972), the partial likelihood estimator provides for a method of estimating the vector β without providing a direct estimate of λ_0 (t).[39] The Weibull hazard assumes that $\lambda_0(t) = pt^{p-1}$, where p is the shape of the parameter to be estimated from the data. The exponential hazard model is a particular case of the Weibull function in which p=1, and hence λ_0 (t) = 1.[40]

VI. Empirical Evidence

A. "Distressed" Banks

From the informal examination of the broad characteristics of banks that failed vs. those that did not failed in the five episodes of banking system problems examined, it would appear that a notable increase in the nonperforming loans (relative to total assets and/or total loans, and adjusted or not for loan reserves) of fragile banks shortly preceded the period of banking crisis. Often, a decline in the capital equity ratios of fragile banks also preceded the period of crisis.[41] To allow for a general framework, the main indicator of distress was constructed by combining these elements: the ratio of capital equity and loan reserves minus nonperforming loans to total assets (coverage ratio).

Focussing on the coverage ratio as the main indicator of distress has several advantages. It allows for the possibility that two banks with an equally high ratio of nonperforming loans to

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[39] The estimator is somewhat similar to Chamberlain's estimator for the logit model with panel data in that a conditioning operation is used to remove the heterogeneity (see Greene (1997) for a discussion). The partial likelihood inference method used to estimate the Cox model depends only on survival data at the times at which at least one of the subjects in the sample failed—i.e., the covariates are only evaluated at the failure times.

[40] See Lancaster (1990) for a comprehensive examination of survival models. Kiefer (1988) provides brief survey of these models.

[41] At times, diminishing profitability also preceded a crisis. However, this factor is downplayed as a core indicator of crisis because of the inherent uncertainty about whether high levels of profitability may mean that a bank is sound or taking large risks that can be extremely profitable at first, but that would likely turn around if economic conditions changed.

assets would be in a different standing if one has set aside reserves to cover for a significant amount of the problem loans, or if it has a higher level of equity capital. In the cases examined, the coverage ratios of banks which were never intervened seemed to be generally bounded at the upper-end (usually at around 8–12 percent)[42] because equity capital, constituting resources that are expensive for a bank to maintain inactive, is usually not much higher than the minimum level required by the authorities. As the coverage ratio declines and approaches zero, the bank's own resources in the form of equity capital and loan reserves become increasingly insufficient to cover for nonperforming loans.[43] As this happens, a bank would be increasingly more fragile and likely to be in distress.

Banks were considered to be in "distress" if their coverage ratio was lower than a certain threshold.[44] In the case of U.S. banks the coverage ratio threshold was set at zero, so that banks were considered to be in "distress" when their coverage ratios were zero or negative because their own resources in capital equity and reserves for problem loans would be insufficient to cover for nonperforming loans. In the cases of Mexican and Colombian banks, the threshold would be expected to be higher because of the more narrow definition of

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[42] The main exceptions were some banks with a small asset base for whom coverage ratios were higher due to inflated ratios of minimum capital relative to assets.

[43] Ex-post, a portion of the bad loans may be eventually recovered, but it is simpler (and possibly prudent) to assume ex-ante that the recovery rate would be close to zero.

[44] Using a certain threshold for nonperforming loans would have had also some appeal because this seems to be the most clear indicator of near term failure. Indeed, crisis banks or crisis periods based on a certain threshold of nonperforming loans have been used in: González-Hermosillo, Pazarbasioglu, and Billings (1997), where Mexican fragile banks appear to be those with nonperforming loans of more than 6–8 percent of total loans; in Demirgüç-Kunt and Detragiache (1998a), where a "crisis" period is defined, inter alia, as one in which the nonperforming loans of the banking system are more than 10 percent of total assets; and in Rojas-Suárez (1998) where "crisis" banks are those whose nonperforming loans to total loans are greater than the average for the system as a whole during "tranquil" periods plus two standard deviations. However, besides the difficulty in making cross-country comparisons given different accounting systems, focusing on nonperforming loans alone ignores the role of potentially offsetting increases in reserves for problem loans and higher levels of capital.

nonperforming loans than in the United States.[45] Arbitrarily, the coverage ratio threshold for Colombia and Mexico was set at 1.5 percent.[46]

In general, the data examined suggest that banks which failed typically showed earlier signs of distress and often had multiple periods in which distress was apparent before the actual intervention. However, not all banks which became distressed were necessarily intervened—likely because of corrective actions that may have diminished the need for intervention or due to improving economic conditions. Intervention is an extreme one-time event and its timing is largely determined by the regulators. As discussed below, when aggregating the incidence of bank distress for the overall system (weighted by banks' asset shares) it was generally found that the rise in this indicator of fragility typically preceded and magnified the actual ex-post (asset weighted) incidence of failures in the banking system.

In order to compare the characteristics of failed and non-failed banks vs. banks classified as "distressed" or not, banks were regrouped based on whether they experienced episodes of distress or not. Banks' characteristics (based on their medians) are presented in Appendix II: Figure 20 refers to banks in the U.S. Southwest, Figure 22 to banks the U.S. Northeast, Figure 24 to California, Figure 26 to Mexico and Figure 28 to banks in Colombia. The figures suggest that the characteristics of distressed banks were broadly consistent with those of banks that eventually failed; and similarly for non-distressed and non-failed banks. (The figures related to the characteristics of failed and non-failed banks were previously discussed and can be also found in Appendix II).

To ascertain formally what were the predominant factors that determined the probability and timing of bank failure, and whether in fact those same factors would also explain bank distress, the following section focuses on the econometric analysis.

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[45] For the United States, nonperforming loans were defined in this study as loans past-due 90 days or more, plus nonaccrual loans and repossessed real estate loans. In Mexico, past-due loans data (prior to 1997) included any interest that was past-due 30 days (for loans repaid in multiple payments) plus only the corresponding installment of principal past-due, but not the entire principal balance of the loan. This significantly underestimated the level of nonperforming loans in Mexican banks. (In 1997, Mexican accounting rules changed to include the entire principal balance as past due.) In Colombia, nonperforming loans were considered to be loans past-due 180 days or more.

[46] Several different thresholds of coverage ratios were examined, but the 1.5 percent level proved to best represent the same population of banks that eventually failed. Some sensitivity analysis based on different thresholds showed no significant differences in the empirical results.

B. Probability of Bank Failure and Time of Failure

A set of models were estimated for each region with banking problems. The first simple models examined the individual explanatory power of the ratio of nonperforming loans to total assets (NPLA) and the ratio of equity capital to total assets (EQ) in determining the one-period ahead probability of intervention and time of intervention. Second, a model based on bank-specific variables (proxying for market risk, credit risk, liquidity risk and moral hazard), but excluding NPLA and EQ was examined. Third, the latter was augmented to include macro/regional variables, and a banking system variable (proxying for contagion).[47] The dependent variable takes the value of one if the bank was intervened at time $t+1$ and zero otherwise. The explanatory variables correspond to time t.

As discussed below, in almost every case, NPLA and EQ were fairly good predictors of bank failure—though NPLA was generally the best—which is consistent with the impression gathered from the figures examined that NPLA and EQ (or, more generally, the coverage ratio (COVR)) seem to be good proximate indicators of failure. In a second step, the same models based on bank-specific variables and the augmented full models were also estimated for the case in which banks became distressed. In this case, the (contemporaneous) dependent variable takes the value of one if a bank is distressed and zero otherwise.

As discussed earlier, the probability of failure is estimated based on a fixed effects logit model.[48] The timing of failure was estimated by fitting a non-parametric (time-varying) Cox proportional hazard model. A parametric (time-varying) Weibull distribution—and an exponential distribution if the maximum-likelihood estimator of p in the Weibull function was close to 1—with monotone hazard rates were also estimated.[49] The estimates based on the

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[47] Only the combined full model is reported in the tables due to space limitations, but the augmented macro/regional model was also estimated separately. The two models were generally very similar and are depicted separately in the figures based on the predicted (asset-weighted) probabilities of banking system failures and of banking system distress.

[48] It is worth noting that the empirical model does not formally ascertain the direction of causality and that there may be indeed important simultaneity among some of the variables (e.g., deposit runs may be a function of the perceived fragility of banks and banks may be fragile because of the deposit runs).

[49] The only routines currently available in Stata to estimate time-varying parametric survival models assume a monotonic hazard (not including, for example, log-logistic and log-normal models). When estimating models with time-varying covariates, Stata essentially estimates the hazard at the various intervals in which the covariates are assumed to be constant (e.g., between (12 and 24 months[, and then between (24 and 36 months], etc.). The data is cross-sectional time series as every bank has a record for each period in which it is not

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Cox proportional hazard model were generally consistent with those obtained from estimating a parametric Weibull hazard model and, hence, only the latter are reported.[50]

Empirical results for the U.S. Southwest

For the case of the three regions in the United States, the data is annual covering the period December 1985 to December 1992. The maximum survival time is (right) censored at 96 months.[51] In the Southwest, 2,946 commercial banks in the states of Texas, Oklahoma and Louisiana were examined, of which 647 banks were intervened during the period 1986–93.

The empirical findings for bank failures in the Southwest are reported in Table 3.1. In models (1) and (2), a higher ratio of nonperforming loans to total assets (NPLA) and a lower ratio of capital equity to total assets (EQ) are associated with a higher probability of failure and a higher hazard rate (or, equivalently, reduced survival time). The model χ^2 are high in both models, but the pseudo R^2 is higher in the case EQ.[52] However, the odds ratio (or exponentiated coefficient e^{β}) of NPLA is larger; such that a one percentage point rise in

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[49](...continued)
censored and, consequently, the observations would not be expected to be independent from each other. By using the Huber-White robust estimator of variance (Huber (1967) and White (1980)), the assumption of independence of the observations can be relaxed, producing "correct" standard errors (in the measurement sense) even if the observations are correlated. See Stata Statistical Software (1997), p. 235–39, for a detailed discussion of this procedure.

[50] The results from the Cox proportional hazard models are available upon request.

[51] Left-censoring can be a problem in the case of bank data because, except for the banks that opened for business during the period of study, it is generally not known how long banks have been in the state of no-failure prior to the beginning of the period of study. However, the associated statistical problems (e.g., large standard errors) would diminish with large data samples.

[52] The χ^2 test evaluates the null hypothesis that all the coefficients in the model, except the constant, equal zero:

$$\chi^2 = -2 (\ln L_i - \ln L_f)$$

where L_i is the log likelihood in the first iteration where the model has only a constant, and L_f is the final iteration's log likelihood. The pseudo R^2 reported in the fixed effects logit models is also used to compare the fit of different models for the same dependent variable and constitutes:

$$\text{pseudo } R^2 = 1 - \ln L_f / \ln L_i$$

NPLA would increase the probability of failure by more than 1 ½ percentage points, while a one percentage point increase in EQ would reduce the probability of failure by about ⅓ of a percentage point.[53] Similarly, a one-unit rise in NPLA would increase the hazard of failure (or reduce the survival time) by 1.14, while a one-unit increase in EQ would reduce the hazard (or increase the survival time) by 0.9.[54] The estimated p values greater than one for the Weibull hazard models indicate positive duration dependence; that is, the likelihood of failure at time t, conditional upon survival up to time t, is increasing in t.

Model (3) is based on bank-specific variables (proxying for market, credit and liquidity risks, and for moral hazard) and the full model (4) augments regional/macro variables and a banking sector variable (proxying for contagion).[55] In general, higher commercial real estate loans

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[53] The coefficients are transformed to odds ratios because this facilitates comparisons regarding relative effects. Standard errors and confidence intervals are similarly transformed. The odds ratio constitutes the exponentiated coefficient, e^{β}, and represents the amounts by which the odds favoring F (failure) = 1 are multiplied with each one-unit increase in that particular explanatory variable (if other explanatory variables stay the same). The asymptotic z statistics is analogous to the usual t-statistics in simple ordinary least squares regression.

[54] The coefficients in the hazard models are reported in a log relative hazard metric, in which the hazard ratios are exponentiated coefficients. In the charts below, the hazard models are transformed to a log expected time metric (and then to expected failure time) to compute the banks' predicted failure time. The instantaneous hazard rate function based on the log relative hazard parameterization takes the form:

$$\lambda\,(t) = \lambda_0\,(t)\;\; e^{\beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k}$$

where λ_0 (t) = 1 for the exponential regression, and $\lambda_0\,(t) = p\,t^{p-1}$ for the Weibull regression and p (or $\sigma = 1/p$) is the shape parameter to be estimated from the data. Alternatively, the equation could be rewritten to depict the log expected time parameterization:

$$\ln\,(T) = \beta^0 x + e$$

where e has an extreme value distribution scaled by σ and $\beta^0 = -\sigma\,\beta$. In this form the model is called the log expected time parameterization because $\beta^0 x$ is an estimate of the (log of) the failure time T. See Stata Statistical Software (1997), pp. 349, Vol. P-Z, for a detailed discussion on this metric transformation.

[55] Reported in the tables are only the estimation results based on the models with the best explanatory power after imposing some degree of parsimony to maintain tractability and reduce correlation. However, several other variables not reported were also examined in all

(continued...)

(LCOMRE) and residential loans (LRESI) increase the probability of failure, suggesting that these loans were quite risky. Higher commercial and industrial loans (LCI) reduce the survival time.[56] The existence of high credit risk is somewhat ambiguous. On the one hand, a higher average yield on loans (LNYIELD) is associated with a lower probability of failure and an increased survival time—suggesting that credit risk may have been priced properly. Although a higher loans-to-assets ratio (LAS) is correlated with a lower probability of failure, it is also associated with a reduced survival time (this latter effect would be consistent with high credit risk coming from a fast expansion of loans to assets). With respect to liquidity risk, the variables had most of the expected effects. In particular, an increase in interbank deposits (DEPIB), large deposits (DEPLGE) or in liquid assets relative to total assets (SEC) are associated with a lower probability of failure. However, although higher level of liquid assets is associated with increased survival time, higher levels of interbank deposits and large deposits seem to reduce banks' survival time—possibly because a higher ratio of these deposits relative to total assets leaves banks more exposed to sudden deposit withdrawals. There is no evidence that higher insider loans (INSL) increased the probability of failure or reduced banks' survival time in the Southwest. However, a higher ratio of interest income and fees to total assets (INTAS) had an significant positive correlation with a higher probability of failure and a reduced survival time—consistent with the hypothesis that moral hazard can be associated with high fees and current payments.

Model (4) introduces macroeconomic and banking sector variables (the latter as a proxy for contagion). As expected, an increase in regional economic activity (SPERYCH) would increase the survival time of banks. However, a puzzling result is that lower real interest rates (INTRS) seem to be consistent with a high probability of failure. The latter result may be reflecting the fact that U.S. interest rates generally declined throughout the entire period of study, largely as a result of a credit crunch.[57] Notwithstanding this puzzle, lower real interest rates are associated, as expected, with an increased survival time (interestingly with the largest hazard ratio). A lower price for oil increased the probability of failure, but high oil prices reduced the survival time—the latter may be associated with asset "bubbles" since the risk of a burst is higher as the boom stage develops further. Finally, although the coefficients are small, a higher ratio of banking system loans relative to the region's personal income (STLNPI) is correlated with a lower probability of failure, but also with a reduced survival time—the

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[55](...continued)
the models (including, for example, proxies for size, holding company dummies, and other balance sheet ratios). Those estimates can be made available upon request.

[56] LCI gives conflicting results in explaining the probability of failure as its sign changes in models 3 (a) and 4 (a).

[57] A potential explanation for this puzzle is that for a given schedule of savings and investment as a function of the real interest rate, the investment function shifted inwards (intersecting the savings function at a lower real interest rate) as a result of the credit crunch.

former may be consistent with regulatory forbearance (in the sense that having a large number of banks already in difficulty could reduce the probability that an additional weak bank would be also intervened) and the latter with possible contagion. Adding the macroeconomic and banking system variables greatly increases the explanatory power of the model compared to model (3) where only bank-specific variables are considered.

Models (5) and (6) repeat the same exercise just described, except that the dependent variable becomes bank "distress" instead of failure. The number of occurrences of distress during the 1985–92 period in the U.S. Southwest is nearly three times the number of actual bank failures and some banks experienced multiple occurrences of distress (i.e., a bank's coverage ratio may be below the threshold repeatedly during several periods). The results are broadly consistent with models (3) and (4) discussed above. The most notable differences are the following: higher commercial real estate loans (LCOMRE) and residential loans (LRESI) are now also associated with a reduced survival time (when examining bank failures, a higher level of these loans was associated only with a higher probability of failure); an increase in regional economic activity (SPERYCH) is now also correlated with a lower probability of distress (before it was only with an increased survival time); higher real interest rates (INTRS) are now associated with a higher probability of distress (before the relationship seem to be inversed and puzzling); and the signs for interbank deposits (DEPIB) are now conflicting in models (5) and (6) when explaining the banks' probability of distress.

The predicted probabilities of failure and survival time for each bank and in each period, based on the models described, were then aggregated and weighted by the banks' asset share relative to the whole banking system in the region for each period. This imposes a difficult test, because it is not only important to infer correctly the actual *number* of failures (specifically, the correct number of predicted zeros and ones), but also to predict the precise banks that failed in each period according to their relative size. The expected probability of failure based on the coverage ratio (ph_covr) would have overestimated somewhat the actual (asset-weighted) probability of banking failures in the Southwest, but it would have given a clear indication that the banking system was rapidly weakening one or two years before the peak of the banking crisis (Figure 14.1). The expected probability of failure based on the ratio of nonperforming loans to total assets (ph_npla), and based on the ratio of capital equity to total assets (ph_eq), would have predicted similar developments. The expected probability of failure based on bank-specific variables (ph_bs), and the models augmented by the regional/ macro (ph_rm) and the banking system variables (ph_f), would have shown a deterioration of more comparable magnitudes to the actual events; however, they would have predicted a new wave of crisis emerging at around the time when the actual crisis was dissipating.[58]

[58] This result is somewhat puzzling, but it can be explained in part by the deterioration (after having improved) of several of the risk characteristics of crisis banks at around that period; e.g., crisis banks saw their ratio of liquid assets to total assets decline and their ratio of residential loans to total assets increase in 1992 (Figure 19 in Appendix II). In addition, the

(continued...)

The predicted intervention times (based on a log expected time parameterization, as noted earlier) for individual banks were aggregated similarly by taking asset-weighted averages. The expected failure times are given in arbitrary time units, in connection with the arbitrary measurement of time and the maximum (right) censoring of banks. Hence, expected failure times should be interpreted with caution as more indicative of general patterns than of exact dates. In general, a higher degree of bank fragility would be associated with reduced time until failure or, equivalently, reduced survival time (failure would be expected to occur sooner). Based on the coverage ratio, the predicted (asset weighted) failure time for the banking system (et_covr), shows a significant decline prior to the peak of the crisis (signaling increased fragility) and an improvement as failed banks exit the sample (Figure 14.1). Models based on bank-specific variables (et_bs), augmented by regional/macro variables (et_rm) and a banking sector variable (et_f) appear to be much less foretelling of a forthcoming crisis—although, this may reflect in part the fact that the data does not go back far enough prior to the surfacing of the banking crisis. However, the (asset weighted) expected failure time does increase significantly as weak banks that fail are removed from the system.[59]

Lastly, the same exercise of predicting the fragility of the banking system by adding up the asset-weighted fragility of individual banks was performed based on the expected probability of distress and time of distress (Figure 14.2). The number of occurrences of distress during the 1985–92 period is nearly three times the number of actual failures. The asset-weighted distress occurrences seem to precede and magnify the asset-weighted incidence of failures; in other words, there were more incidences of distress than of failure, and the incidences of distress were generally apparent before the actual bank interventions. The estimated probability of distress based on the three models (ph_bs, ph_rm and ph_f) seem to capture reasonably well the degree of distress in the banking sector. The chief difference with the predicted probability of intervention is that the surge in the predicted probability of failure toward the end of the period is much more modest when focusing on bank distress. The expected time of distress' paths are also broadly consistent with the case of interventions, except that the expected failure time based on bank-specific variables (et_bs) is flatter when focusing on distress that when examining actual bank interventions.

Basic CAMEL approach: U.S. Southwest

How would these results compare with the standard CAMEL approach? To shed some light on this question, a simple model based on typical CAMEL proxies was estimated to predict bank interventions. For simplicity, the basic model relies only on one proxy for each variable

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[58](...continued)
nominal price of oil declined moderately during 1991–94 (Figure 4). Of course, changes in other variables with opposite effects may have also worked to partially offset these effects.

[59] Once banks are intervened, they no longer remain in the sample. However, banks that become distressed remain in the sample until they fail.

(many studies often use several proxies at the same time): the ratio of capital equity plus loan-reserves to total assets (CA) for capital adequacy; the ratio of nonperforming loans to total assets (NPLA) for asset quality; the ratio of loans to assets (LAS) for management quality; net income (NI) for earnings; and the ratio of liquid assets to total assets (SEC) for liquidity (model (1) in Table 3.3). In model (2), an experiment is performed in which NPLA and CA—the variables used here to define "distress"—are dropped.[60] While the fit of model (1) is reasonably good, it would seem that CA and NPLA indeed play a fairly significant role in explaining bank failures. The pseudo R^2 falls dramatically and the model χ^2 is significantly lower in model (2).

The predicted (asset-weighted) probability of banking system failure based on the full CAMEL model (model (1)) is depicted as ph_cam1, while model (2), excluding NPLA and CA, is represented by ph_cam2 in Figure 14.3. Model (1) seems to provide a clearer signal (though somewhat overstated) of impending crisis. The expected failure times are not significantly different in both models (et_cam1 and et_cam2).

Empirical results for the U.S. Northeast

In the Northeast, 261 commercial banks in the states of New Hampshire, Connecticut and Massachusetts were examined, of which 41 banks were intervened during the period 1986–93.

The empirical findings for bank failures in the Northeast are reported in Table 4.1. Consistent with the findings obtained for the U.S. Southwest, a higher ratio of nonperforming loans to total assets (NPLA) in model (1), and a lower ratio of capital equity to total assets (EQ) in model (2) are associated with a higher probability of failure and a higher hazard rate (reducing the survival time). A one percentage point rise in NPLA would increase the probability of failure by more than 3½ percentage points, while a one percentage point increase in EQ would reduce the probability of failure by about ⅓ of a point. Similarly, a one-unit rise in NPLA would increase the hazard of failure by 1.2, while a one-unit increase in EQ would reduce the hazard by 0.8. The estimated p values indicate positive duration dependence.

The results from model (3) based on bank-specific variables and the full model (4) suggest that a higher ratio of commercial real estate loans to total assets (LCOMRE) and residential loans to total assets (LRESI) are associated with a higher probability of failure, and that the former is correlated with a reduced survival time, suggesting (as was the case for Southwestern banks) that real estate loans were quite risky. A higher average yield on loans (LNYIELD) is associated with a lower probability of failure and an increased survival

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[60] As discussed earlier, nonperforming loans are clearly the result of earlier investment decisions and, possibly, changed economic conditions. Equity capital, being the difference between bank's assets and non-ownership liabilities (in this case based on book-values, but proper accounting to reflect market-values would make for a stronger case), is a residual. Provisions may be also thought of as being a function of expected losses.

time—suggesting that credit risk may have been priced appropriately.[61] A higher level of interbank deposits (DEPIB), large deposits from the public (DEPLGE) and a higher liquidity ratio (SEC) are associated with a lower probability of failure, and with an increased survival time in the cases of DEPIB and SEC. There is no evidence that higher level of insider loans (INSL) increased the probability of failure or reduced banks' survival time of banks in the U.S. Northeast. An increase in regional economic activity (SPERYCH) lowers the probability of failure and increases the survival time of banks. Lower real interest rates (INTRS), as was evident during most of the period of study, are again surprisingly consistent with a higher probability of failure. Although with a relatively small effect, a higher ratio of banking system loans relative to the region's personal income (STLNPI) is correlated with an increased survival time—possibly in connection with regulatory forbearance. Regional/macro variables appear to have a significant explanatory power.[62]

The expected probability of failure based on the coverage ratio (ph_covr), would have overestimated the actual (asset-weighted) probability of banking failures in the Northeast, but it would have given a clear indication that the banking system was rapidly weakening about a year before the peak of the banking problems (Figure 15.1). The overestimation seems to be largely due to the role of nonperforming loans (ph_npla). The expected probability of failure based on bank-specific variables (ph_bs) would have shown a moderate increase prior to the banking problems, but the augmented regional/macro (ph_rm) and banking system variables (ph_f) would have magnified this deterioration—albeit significantly overestimating the actual magnitude of the crisis.

The expected (asset weighted) failure time based on the coverage ratio (et_covr) shows a significant decline prior to the peak of the crisis and an improvement as banks that fail exit the sample, largely because of nonperforming loans (et_npla). Bank-specific variables (et_bs), and models augmented by regional/macro variables (et_rm) and by the banking sector variable (et_f), suggest similar developments (Figure 15.1).

The number of occurrences of distress during the 1985–92 period is more than three times larger than the number of actual failures. The results from the models based on bank distress (models (5) and (6)) are broadly consistent with the results from the models based on intervention. The chief differences are that an increase in residential loans (LRESI) lengthens the survival time, and the effect of the real interest rate (INTRS) is now not statistically

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[61] The number of variables estimated for the Northeast and California is smaller than in the Southwest because LCI and POIL were only appropriate for the latter case, and also because correlation among some of the other variables, given the smaller samples in the Northeast and California, did not allow for their inclusion.

[62] The full model 4 (a) did converge when estimating the probability of failure and, hence, the bank-specific, and the macro/regional and banking system components were examined separately.

significant. The full model seems to have a significantly greater explanatory power than the one based only on bank-specific variables.

The (asset-weighted) distress occurrences seem to precede and somewhat magnify the (asset-weighted) incidence of failures (Figure 15.2). The estimated probability of distress based on the three models (ph_bs, ph_rm and ph_f) seem to indicate increasing stress in the system before the emergence of the banking crisis, though the augmented models based on macro/regional variables (ph_rm) and the full model including proxies for contagion (ph_f) show a more pronounced deterioration. The expected distress time paths are also generally consistent with those results.

Basic CAMEL approach: U.S. Northeast

Using a simple CAMEL model, it appears that nonperforming loans (NPLA) and capital (CA) strongly influence banks' survival time (Table 4.3). The predicted (asset-weighted) probability of banking system failures with all CAMEL variables (ph_cam1) magnifies the results obtained from the model that excludes NPLA and CA (ph_cam2) (Figure 15.3). The expected failure times are not substantially different in both models.

Empirical results for California

In California, 562 commercial banks were examined, of which 55 banks were intervened during the period 1986–93. In contrast to the bank failures in the Southwest and the Northeast, most of the banks intervened in California were relatively small and interventions happened generally later.

The empirical findings for bank failures for California are reported in Table 5.1. As in the Southwest and in the Northeast, a higher level of nonperforming loans (NPLA) in model (1) and a lower level of equity (EQ) in model (2) are associated with a higher probability of failure and a reduced survival time, with the effect of NPLA being greater than that from EQ. In California, a one percentage point increase in NPLA would increase the probability of failure by almost 1½ percentage points, while a 1 percentage point increase in EQ would reduce the probability of failure by almost ½ of a point. Similarly, a one-unit increase in NPLA would increase the hazard of failure by 1.2, while a one-unit increase in EQ would reduce the hazard by 0.6. The estimated p values indicate positive duration dependence.

The results from model (3) based on bank-specific variables and the full model (4) suggest, as is the case with the other U.S. regions, that higher levels of commercial real state loans (LCOMRE) and residential loans (LRESI) are generally associated with a higher probability of failure. Also similarly to the other two episodes of banking problems in the United States, higher interbank deposits (DEPIB) and large deposits from the public (DEPLGE) are associated with a lower probability of failure, and a higher liquidity ratio (SEC) is correlated with an increased survival time. However, in contrast with the other two regions in the United States, a higher average yield on loans (LNYIELD) is associated with a decreased survival time—suggesting that credit risk was a problem in California. Also in contrast with the other regions, a higher level of insider loans (INSL), a proxy for moral hazard, is associated with a reduced survival time. The macro/regional effects are similar to the other U.S. regions. An increase in regional economic activity (SPERYCH) increases the survival time of banks while lower real interest rates (INTRS), evident during most of the period of study, are consistent with a high probability of failure. A higher ratio of banking system loans relative to the estate's personal income (STLNPI) is correlated with a lower probability of failure—albeit having a small effect. Introducing regional/macro and banking sector variables appear to significantly increase the explanatory power of the bank-specific model.

The expected probability of failure based on the coverage ratio (ph_covr), would have overestimated the actual (asset-weighted) probability of banking failures in California, but it would have shown a increase prior to the banking failures, largely on account of the predicted probabilities of failure based on nonperforming loans (ph_npla) (Figure 16.1). The expected probability of failure based on bank-specific variables (ph_bs), as well as the augmented regional/macro (ph_rm) and banking system models (ph_f), would have shown a sharp increase prior to the banking problems.

In terms of the (asset-weighted) expected failure time for the banking system, the coverage ratio (et_covr) shows a significant decline prior to the peak of the crisis and an improvement as banks that fail exit the sample. Bank-specific variables (et_bs), and models augmented by regional/macro variables (et_rm) and by a banking sector variables (et_f), suggest similar trends (Figure 16.1).

When comparing the results with bank distress (models (5) and (6)), the results are broadly consistent with those obtained from the failure models. The chief differences are that an increase in residential loans (LRESI) now reduces the probability of distress; a higher level of commercial real estate loans (LCOMRE) also reduces the survival time; a higher average yield on loans (LNYIELD) reduces the probability of distress (giving conflicting signals regarding credit risk vis-à-vis the results for intervention); and real interest rates (INTRS) and the ratio of total banking system loans to the state's personal income (STLNPI) are now not significant. The number of occurrences of distress during the 1985–92 period is more than four times the number of actual failures.

As in the previous cases, the (asset-weighted) distress occurrences seem to precede and significantly magnify the (asset-weighted) incidence of failures (Figure 16.2). The estimated probability of distress based on the three models (ph_bs, ph_rm and ph_f) seem to indicate increasing stress in the system prior to the peak of the bank failures. The expected distress time paths are also broadly consistent with those results.

Basic CAMEL approach: California

Based on a simple CAMEL model, it appears that nonperforming loans (NPLA) in particular, but also capital (CA), give some of the strongest signals of likely failures (Table 5.3). The predicted (asset-weighted) probability of failure with all CAMEL variables (ph_cam1) magnifies somewhat the results obtained from the model that excludes NPLA and CA (ph_cam2) (Figure 16.3). The (asset-weighted) expected failure times in both models show somewhat different paths: while et_cam1 based on the full model increases after declining briefly prior to the peak of the bank failures, et_cam2 which excludes nonperforming loans and capital is flatter throughout most of the period.

Empirical results for Mexico

In Mexico, 31 domestic commercial banks (excluding foreign banks) were examined based on quarterly data for the period 1992-Q1 to 1995-Q3, of which 16 banks were intervened by the authorities during 1994–95.[63] The banks' maximum survival time is (right) censored at 45 months.

The empirical findings for bank failures for Mexico are reported in Table 6.1. As in all the previous cases examined, a higher level of nonperforming loans (NPLA) in model (1) and a lower level of equity (EQ) in model (2) are associated with a higher probability of failure and a reduced survival time. In Mexico, a one percentage point increase in NPLA would increase the probability of failure by almost 2 percentage points, while a 1 percentage point increase in EQ would reduce the probability of failure by about ⅓ of a point. Similarly, a one-unit rise in NPLA would increase the hazard of failure by 1.2, while a one-unit increase in EQ would reduce the hazard by 0.6. As in the other cases considered, the estimated p values indicate positive duration dependence.

The results from model (3) based on bank-specific variables and the full model (4) suggest that higher residential loans (LRESI) and higher agricultural loans (LAGR) are associated with a reduced survival time. A higher ratio of loans to assets (LAS), a proxy for credit risk, is correlated with a higher probability of failure. Higher deposits from the public (DEPPUB) increase banks' survival time, while a higher proportion of liquid assets (SEC) reduces the probability of failure. Higher interbank deposits (DEPIB) seem to increase the probability of failure—this effect may be related to size, since the largest banks (which received government assistance toward the end of the period of study) presumably had the greatest access to the interbank market. The ratio of interest and fees to assets (INTAS), a proxy for moral hazard, was not significant. A depreciating domestic currency (an increase in DELEX) would reduce the banks' survival time, while real interest rates (INTRS) were not significant. A higher ratio of banking system loans relative to GDP (BSLNGDP) is associated with a reduced survival time and, in contrast with the previous cases examined, it has a fairly substantial effect—which

[63] Several banks were intervened by the authorities on different occasions (other than by providing banks with direct temporary liquidity support) during this period, but failure is assumed to occur at the time of the first intervention.

would be consistent with the hypothesis of contagion.[64] The model's statistics seem to improve significantly with the inclusion of macro and banking system variables.

The expected (asset-weighted) probability of banking system failures based on the coverage ratio (ph_covr) shows a gradual, but clear increase beginning in early-1993 (Figure 17.1)—close to two years before the actual crisis. Although ph_covr underestimates the actual (asset-weighted) bank failures, this effect occurs largely in 1995-Q4 when the two major Mexican banks received government financial support in the form of purchases of some of their bad loans. The predicted probabilities of failure resulting from nonperforming loans (ph_npla) seem to give a clearer signal than if based on equity capital (ph_eq). The expected (asset-weighted) probability of banking system failures based on the bank-specific model (ph_bs), as well as the augmented regional/macro (ph_rm) and banking system models (ph_f), would have shown a significant increase shortly before the banking crisis.

The expected (asset weighted) failure time based on the coverage ratio (et_covr) is quite flat during most of the period, largely due to the effect of equity capital (et_eq) since nonperforming loans (et_npla) alone would have shown a continuous decline throughout most of the period of study (Figure 17.1). Bank-specific variables (et_bs) and the model augmented by regional/macro variables (et_rm) show some deterioration prior to the actual crisis, but the decline is fairly steady if based on the full model (et_f) which includes the effects of possible contagion.

When compared with bank distress, the results (models (5) and (6)) are generally consistent with those from the failure models. The main differences are that an increase in residential loans (LRESI) also increases the probability of distress; a higher proportion of non-securitized loans (LNONSEC) appear to increase banks' survival time; loans to assets (LAS), public deposits (DEPPUB) and the exchange rate (DELEX) are no longer significant; and higher interest rates (INTRS) increase the probability of distress. The change in the effects coming from DELEX and INTRS is particularly interesting because bank failures seem to have been affected significantly by the currency depreciation, but not bank distress which was impacted more directly by high real interest rates. The number of occurrences of distress during the period 1992-Q1 to 1995-Q3 is close to four times the number of actual failures.[65]

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[64] While generally consistent, the empirical results in this paper for Mexico are not directly comparable to those reported in González-Hermosillo, Pazarbasioglu, and Billings (1997). In this study, the models estimated for Mexico are considerably more parsimonious (the covariates are chosen to facilitate cross-country comparisons while focusing on the role of nonperforming loans and capital) and, further, the empirical methodology is based on monotonic (time-varying) hazards supported by a different software program (Stata instead of Limdep).

[65] As noted earlier, banks are assumed to fail only once, but the can have multiple occurrences of distress.

As with the previous cases examined, the (asset-weighted) distress occurrences seem to precede and significantly magnify the (asset-weighted) incidence of failures (Figure 17.2). The estimated probability of distress based on the three models (ph_bs, ph_rm and ph_f) suggest increasing stress in the system prior to the banking crisis. The expected distress time paths are also broadly consistent with those results.

Basic CAMEL approach: Mexico

Based on a simple CAMEL model, it appears that nonperforming loans (NPLA) would have given the strongest signal of likely failures (Table 6.3). However, the overall fit of model (1) is only moderately better than model (2) which excludes capital and nonperforming loans. The predicted (asset-weighted) probability of failure with all CAMEL variables (ph_cam1) is similar to the probability predicted by the model that excludes capital and nonperforming loans (ph_cam2) (Figure 17.3). The expected (asset-weighted) failure times in both models show different paths: while et_cam1 which includes all the variables increases steadily, without nonperforming loans and capital et_cam2 is flatter and shows a moderate decline prior to the crisis.[66]

Empirical results for Colombia

In Colombia, 18 domestic commercial banks (excluding foreign banks) were examined based on annual data during the period 1980–88, of which 5 banks were intervened by the authorities during 1982–87. The maximum survival time is (right) censored at 108 months. The bank data available for Colombia is significantly less comprehensive than for the other cases examined (for example, there is no information about the composition of loans), while the number of observations (and failures) is notably smaller. Hence, arriving at meaningful estimators was not always a successful exercise. Nonetheless, the data was still able to shed some light on the determinants of bank failures and bank distress.

The empirical findings for bank failures for Colombia are reported in Table 7.1. Although nonperforming loans (NPLA) in model (1) and capital (CA) in model (2) are not significant when estimating the probability of failure, a higher NPLA and a lower CA are associated with a reduced survival time.[67] In Colombia, a one percentage point increase in NPLA has roughly the same effect (around 1.1) on the hazard of failure as a 1 percentage point decrease in CA. The estimated Weibull p values were close to 1 and, hence, and an exponential hazard was

[66] This is a puzzling result which suggests that et_cam2 (excluding NPLA and CA) was a better indicator of impending crisis than et_cam1. These results may be associated in part with the relatively high and stable levels of capital that Mexican banks (including banks that failed) appeared to have during the most of the period of study (Figure 25 in Appendix II).

[67] CA seemed to fit the models significantly better than EQ for Colombia, whereas EQ generally provided a marginally better fit than CA in the other cases examined.

estimated. In contrast with the previous cases examined, these results suggest that the hazard rate does not vary over time in Colombia: the likelihood of failure at time t, conditional upon survival up to time t, is constant and independent of t.

The results from model (3) based on bank-specific variables and the full model (4) suggest that a higher average yield on loans (LNYIELD) reduces the survival time—consistent with the hypothesis of high credit risk. A higher level of deposits (DEPPUB) seems to be associated with a reduced survival time—perhaps because banks with a larger deposit base are more exposed to potential deposit runs. A higher (implicit) average interest paid on deposits (INTDEP) is correlated with a decreased survival time—suggesting that banks in trouble tend to pay higher rates to maintain deposits. A higher ratio of interest income to total assets (INTAS) seems to be associated with increased survival time—while this proxy does not give support to the presence of moral hazard, the effect may be reflecting increased profitability resulting from a higher ratio of INTAS. The price of exports (PEXP),[68] and the ratio of total banking system loans to GDP (BSLNGDP) as a proxy for banking system contagion are not significant.[69] The hazard models seemed to generally fit the data better than the fixed-effects logit models—probably because the former rely on a larger number of observations while fixed-effects logit models drop all the observations for which there is no failure.

The expected (asset-weighted) probability of banking system failures based on the coverage ratio (ph_covr) shows a significant increase two years before the peak of the crisis in 1986–87 (Figure 18.1). The rise seems to be more the result of an increase in the probability of failures based on nonperforming loans (ph_npla) than because of capital (ph_ca). The expected (asset-weighted) probability of banking system failures based on the bank-specific model (ph_bs) would have also shown a significant increase before the peak of the crisis. In terms of the expected (asset weighted) failure time, the coverage ratio (et_covr) shows a significant decline prior to the peak of the crisis and an improvement following the exit of failed banks from the system. Generally similar paths are also depicted by the expected time of failure based on the three models (et_bs, et_rm and et_f).

The results from the models based on bank distress (models (5) and (6)) give a broadly similar picture to the failure models. However, there are several differences in the estimated parameters. A higher average loan yield (LNYIELD) lowers the probability of distress (which suggests that risk was not priced properly).[70] A puzzling result is that a higher level of interbank deposits (DEPIB) is associated with an increased probability of distress and a reduced

[68] INTRS is not included because the available interest rate data did not cover the entire period of study.

[69] The fixed-effects logit model based on bank-specific variables and augmented by PEXP and BSLNGDP did not converge. Hence, the components were estimated separately.

[70] This is consistent with results obtained for Colombia in Rojas-Suárez (1998).

survival time (possibly related to banks' size). Equally as puzzling is the fact that a higher level of deposits from the public (DEPPUB) is correlated with a higher probability of distress in the full model (potentially reflecting the possibility that banks with a larger deposit base are more vulnerable to deposit runs). Higher interest rates paid on deposits (INTDEP) now also increases the probability of distress. A higher ratio of interest income to total assets (INTAS) is now associated with a higher probability of distress. Higher export prices (PEXP) are associated with a lower probability of distress but also with a reduced survival time (similarly to the effect of POIL in the U.S. Southwest). Lastly, a higher level of banking system loans relative to GDP (BSLNGDP) is correlated with a higher probability of distress and a reduced survival time (consistent with contagion).

As in the previous cases examined, in Colombia the (asset-weighted) distress occurrences also seem to precede and significantly magnify the (asset-weighted) incidence of actual bank failures (Figure 18.2). The estimated probability of distress based on the three models (ph_bs, ph_rm and ph_f) indicate increasing stress in the system prior to the peak of the banking crisis. The expected distress time paths based on expected survival time resulting from et_bs and et_f are broadly consistent with those results—albeit less definitive.

Basic CAMEL approach: Colombia

Based on a simple CAMEL model, it appears that nonperforming loans (NPLA) would have given the strongest signal of expected survival time (Table 7.3).[71] The predicted (asset-weighted) failure time with all CAMEL variables included (et_cam1) shows a substantial drop prior to the peak of the crisis, while the decline is significantly less pronounced if nonperforming loans and capital are excluded (et_cam2) (Figure 18.3).

VII. Conclusions

The results obtained support the view that bank failures generally experience a life cycle. In particular, sound and unsound banks show different characteristics, largely the result of different risk-taking behavior, that can be observed several periods before the actual failures. However, soon before failure occurs, nonperforming loans and often equity capital ratios deteriorate rapidly—signaling growing distress. In general, the effect of a one-unit increase in the ratio of nonperforming loans to total loans increases the probability of failure and reduces the banks' survival time by more than an equivalent decrease in the ratio of equity capital to total assets (though in Colombia the impact was similar). Even though nonperforming loans generally seemed to be a better proximate indicator of failure than equity capital, focusing on the banks' coverage ratio (the ratio of capital equity and loan reserves minus nonperforming loans to total assets) has the advantage of allowing for a more general framework. In particular, it takes into account the possibility that two banks with an equal ratio of nonperform-

[71] The models based on fixed-effects logit did not converge.

ing loans to total assets would be in a different financial standing if one of the banks set aside significant reserves to cover its problem loans or if it increased its capital equity.

The models examined suggest that both macroeconomic and microeconomic factors are important in determining banks' fragility. The models based on bank-specific variables—built on different measures of market, credit and liquidity risks, and including proxies for moral hazard (but not including capital equity or nonperforming loans)—seemed to perform reasonably well in most cases. These variables would seem to capture the fundamental sources of ex-ante risk. The actual variables used in each episode of banking problems were sometimes different depending on the specific circumstances in each case. However, conceptual equivalencies were broadly maintained across regions—suggesting that the main conceptual elements of risk are transferable. This conceptual approach based on the different types of risk examined is particularly useful when attempting to make inferences about separate episodes of banking problems in which the circumstances or accounting systems are not the same in each case. The introduction of macroeconomic or regional variables improved significantly the predictive power of the models based on bank-specific data only. The models generally had high model Chi-Square statistics, suggesting that the joint explanatory power of the variables chosen was adequate.

Some of the empirical regularities across regions that most clearly emerge from the analysis include the observation that a high ratio of nonperforming loans to total assets and a low ratio of capital to total assets increase the probability of failure/distress and reduce the expected survival time of banks (Table 8 summarizes the empirical results across regions). The proxies for market risk and liquidity risk were generally important in determining bank distress and eventual failure, and in determining the expected survival time. In particular, problem banks had a significantly higher exposure than non-problem banks to sectors which were initially booming but that went bust shortly before the banking crises actually materialized. Problem banks also generally faced a liquidity problem (through deposit runs and/or low liquidity ratios). In contrast, proxies for credit risk and moral hazard gave somewhat conflicting results depending on the episode examined, as they were present in some cases but not in others, and sometimes the variable used was not unequivocal as to whether the risk was indeed present. Contagion, measured by the ratio of loans of the overall banking system to the region's GDP, seemed to be present in some cases but its impact was usually small (the main exception being Mexico).

In providing an answer to the question of how this framework compares with the traditional approach based on CAMEL variables, a basic CAMEL model was estimated for each episode based on frequently used proxies (including nonperforming loans as proxy for asset quality). When excluding capital equity and nonperforming loans, the fit was significantly poorer—suggesting that nonperforming loans and capital are responsible for a significant amount of the explanatory power in traditional CAMEL models.

Bank distress, as measured by banks' deterioration in their coverage ratio, was consistently evident prior to actual failure. Banking system fragility based on this measure of distress showed clear signs of deterioration prior to the actual crisis, and generally magnified the intensity of the (ex-post) crisis. Not all banks that were in distress failed—presumably because corrective measures were adopted or due to improved economic conditions. Nonetheless, banks that eventually failed typically showed signs of distress in repeated occasions prior to their actual failure. The advantage of focusing on distress, rather than on actual failure, is that the fragility of the banking system can be assessed before a crisis actually occurs. For policy makers, as well as researchers, this can be a useful tool.

Table 1. U.S. Bank Failures, 1980–94

	Failures as a Percent of Total Number of Banks	Failures as a Percent of Total Bank Assets
California	15.3	1.7
Connecticut	18.4	22.2
Louisiana	22.4	17.4
Massachusetts	10.6	12.9
New Hampshire	12.6	32.0
Oklahoma	22.0	23.9
Texas	29.4	43.8
United States	**9.1**	**9.0**

Source: Federal Deposit Insurance Corporation (1997).

Notes: FDIC-insured commercial and savings banks that were closed or received FDIC assistance during 1980–94. Based on the total number of banks at the end of 1979, plus banks newly chartered in 1980–94.

Table 2. Indicators of Bank Failure/Distress

Variable	Description	Probability of Failure/Distress Expected sign:	Survival Time Expected sign:	What the Variables Measure
A. Proximate indicators of fragility:				
NPLA	Ratio of nonperforming loans to total assets	+	-	High level of problem loans indicative of pervasive bank problems
NPLLRA	Ratio of nonperforming loans minus loan reserves to total assets	+	-	
NPLL	Ratio of nonperforming loans to total loans	+	-	
EQ	Ratio of equity capital to total assets	-	+	High level of capital represents a cushion to absorb shocks
CA	Ratio of equity capital plus loan reserves to total assets	-	+	
COVR	Ratio of equity capital plus loan reserves minus nonperforming loans to total assets	-	+	Bank's capital and loan reserve coverage of problem loans
B. Fundamental sources of risk:				
Market risk: β				
LCI	Ratio of commercial and industrial loans to total assets (US)	+/-	-/+	High market risk if concentration on boom sectors, in areas highly dependent on cyclical economic conditions, or in sectors with returns significantly higher than the market (high betas)
LAGR	Ratio of agricultural production loans to total assets (US, Mexico)	+/-	-/+	
LCOMRE	Ratio of construction loans plus loans secured by multifamily, nonresidential, and farm real estate to total assets (US)	+	-	Commercial real estate loans tend to be particularly risky because they typically have long gestation periods
LRESI	Ratio of loans secured by 1-4 family real estate to total assets (US). Ratio of housing loans to total assets (Mexico).	+/-	-/+	
LCON	Ratio of consumer loans to total assets	+/-	-/+	
LNONSEC	Ratio of unsecuritized loans to total assets (Mexico)	+/-	-/+	
Credit risk: τ				
LAS	Ratio of loans to total assets	+	-	The greater the ratio, the greater the bank's portfolio subject to default risk. High loan ratios may be associated with weak internal controls and underwriting standards
LNYIELD	Average yield on loans	+/-	-/+	High yields may indicate that the bank is originating high-risk loans. Low yields may indicate that risk is not priced properly
INTSPR	Difference between average loan yield and deposit interest rate	+/-	-/+	High spreads may mean that the bank is taking risky loans. Low spreads may mean that the bank is efficient
Liquidity risk : x (funding sources)				
DEPLGE	Ratio of large certificates of deposit to total assets (US)	-	+	Large deposits not insured may be volatile
DEPPUB	Ratio of deposits from the public to total assets (Mexico, Colombia)	-	+	Deposit runs would reduce the bank's liquidity
DEPIB	Ratio of fed funds purchased plus other borrowed funds to total assets (US). Ratio of deposits from other banks to total assets (Mexico, Colombia)	-	+	Interbank deposits. Peer banks may have better information about a bank's weak financial condition

Table 2. Indicators of Bank Failure/Distress (Concluded)

Variable	Description	Probability of Failure/Distress Expected sign:	Survival Time Expected sign:	What the Variables Measure
SEC	Ratio of investment securities to total assets	-	+	Liquid assets. Bank's ability to deal with deposit withdrawals
INTDEP	Ratio of interest expenditures to total deposits	+	-	High deposit rates to attract deposits may be indicative of liquidity problems or bank's perceived risk
Moral hazard proxies				
INSL	Ratio of insider loans to total assets (US)	+	-	Conflict of interest
INTAS	Ratio of interest income on loans, fees and leases to total assets	+	-	Banks loading up on commissions, up-front fees and high interest rates on projects unlikely to be sound. Consistent with "looting" (Akerlof and Romer (1993))
C. Regional/ macroeconomic				
POIL	Oil prices (US)	-	+	Regional terms of trade shock in the US Southwest, heavily dependent on energy
PEXP	Price of exports (Colombia)	-	+	Terms of trade shock in Colombia, heavily dependent on coffee exports
DELEX	Change in nominal exchange rate (Mexico)	+	-	Devaluation shock in Mexico (exchange rate defined as domestic price of foreign currency)
SPERYCH	Change in state personal income (US)	-	+	Economic activity by state in the U.S.
INTRS	Short-term real interest rate	+	-	Potential interest rate shock
D. Banking sector				
STLNPI	Ratio of total banking system loans by region to region's personal income (US)	+/-	-/+	Potential bank "herding" behavior or deposit runs; regulatory forbearance
BSLNGDP	Ratio of total banking system loans to GDP (Mexico, Colombia)	+/-	-/+	
E. Other bank variables:				
NI	Ratio of net income to average assets	+/-	-/+	Profitability. However, depending on the state of thebanking cycle, excesively risky projects can be very profitable at first
ROE	Ratio of interest income to average equity	+/-	-/+	
PROFMARG	Profit margin	+/-	-/+	
EXPW	Ratio of salaries and employee benefits to average assets	+	-	Proxies for efficiency
EXPP	Ratio of expenses on premises and fixed assets to average assets	+	-	
SIZE	Logarithm of total assets	-	+	Economies of scale; too large to fail

1/ Nonperforming loans are defined in the United States as the ratio of loans past due 90 days or more, plus nonaccrual loans and repossessed real estate loans; in Mexico (until 1997) as the ratio of loans past due 30 days or more (past due interest on that installment only, not including the entire unpaid principal balance); and in Colombia as the ratio of loans past due 180 days or more.

Table 3.1. Estimation Results—U.S. Commercial Bank Failures in the Southwest

	(1)		(2)	
	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio
Proximate Indicators of Fragility:				
NPLA	1.641* (16.013)	1.143* (17.225)	--	--
EQ	--	--	0.323* (-13.131)	0.887* (-13.462)
Model Statistics:				
Model χ^2	761.33*	296.69*	1145.64*	181.23*
Pseudo R^2	0.489	--	0.736	--
Log likelihood	-397.428	-1,454.579	-205.270	-1,525.744
p (Weibull)	--	1.429* (8.717)	--	1.298* (9.357)

Number of banks (1985): 2,946
Number of records (1985–92): 17,528
Number of failures (1986–93): 647

Table 3.1. Estimation Results—U.S. Commercial Bank Failures in the Southwest (Concluded)

	(3)		(4)	
	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio
Bank-Specific Variables:				
Market Risk				
LCI	0.967** (-1.956)	1.013* (2.466)	1.084** (2.127)	1.014* (2.736)
LCOMRE	1.049** (2.253)	0.997 (-0.611)	1.077*** (1.652)	0.999 (-0.666)
LRESI	1.221* (7.083)	0.992 (-1.411)	1.222* (3.527)	0.992 (-1.266)
Credit Risk				
LNYIELD	0.347* (-12.405)	0.873* (-5.769)	0.332* (-6.163)	0.795* (-9.395)
LAS	0.859* (-8.969)	1.034* (6.691)	0.863* (-5.001)	1.039* (7.292)
Liquidity Risk				
DEPIB	0.974* (-2.492)	1.026* (5.927)	0.934* (-2.630)	1.033* (7.015)
DEPLGE	0.907* (-8.002)	1.025* (6.313)	1.067* (-2.525)	1.017* (4.088)
SEC	0.972** (-2.249)	0.956* (-9.785)	0.947* (-2.555)	0.964* (-7.482)
Moral Hazard				
INSL	0.782* (-4.312)	0.982 (-0.886)	0.665* (-2.884)	0.988 (-0.592)
INTAS	2.573* (10.682)	1.084* (3.672)	3.477* (6.169)	1.097* (4.216)
Regional/Macroeconomic				
SPERYCH	--	--	1.065 (0.886)	0.759* (-6.869)
INTRS	--	--	0.447* (-4.037)	3.370* (18.111)
POIL	--	--	0.947* (-4.293)	1.044* (4.542)
Banking Sector Variable:				
STLNPI	--	--	0.001* (-9.835)	0.089* (5.364)
Model Statistics:				
Model χ^2	721.15*	867.18*	1317.10*	1200.95*
Pseudo R^2	0.459	--	0.838	--
Log likelihood	-425.301	-1495.680	-127.325	-1322.32
p (Weibull)	--	2.127* (22.831)	--	5.286* (30.638)

Notes: The dependent variable takes the value of one if a bank is intervened at time t+1 and the value zero otherwise. Probability of failure is estimated by fixed-effects logit. The odds ratio and hazard ratio depict exponentiated coefficients. The z statistics are given in parenthesis. P|z| is the test of the underlying coefficient being zero. One, two, and three asterisks indicate significance levels of 1, 5 and 10 percent, respectively.

Table 3.2: Estimation Results—U.S. Commercial Bank Distress in the Southwest

	(5)		(6)	
	(a) Probability of Distress Odds Ratio	(b) Weibull Hazard Hazard Ratio	(a) Probability of Distress Odds Ratio	(b) Weibull Hazard Hazard Ratio
Bank-Specific Variables:				
Market Risk				
LCI	0.977** (-2.114)	1.017* (4.233)	1.011 (0.933)	1.018* (4.659)
LCOMRE	1.034* (2.822)	1.021* (6.021)	1.040* (2.862)	1.026* (7.007)
LRESI	1.095* (7.048)	1.020* (4.667)	1.065* (4.345)	1.019* (4.362)
Credit Risk				
LNYIELD	0.442* (-17.073)	0.860* (-7.915)	0.493* (-13.068)	0.794* (-11.44)
LAS	0.909* (-9.637)	1.014* (4.061)	0.944* (-5.103)	1.016* (4.345)
Funding Sources				
DEPIB	0.976* (-3.002)	1.003 (1.361)	1.018*** (1.854)	1.009* (2.921)
DEPLGE	0.948* (-7.760)	1.004 (1.481)	1.008 (0.929)	0.995 -1.190)
SEC	0.923* (-10.089)	0.963* (-12.721)	0.915* (-9.725)	0.969* (-10.039)
Moral Hazard				
INSL	0.935* (-2.406)	0.979 -1.337)	0.961 -1.286)	0.990 -0.674)
INTAS	2.096* (14.037)	1.067* (3.028)	2.103* (11.745)	1.076* (3.459)
Regional/Macroeconomic:				
SPERYCH	--	--	0.938** (-2.303)	0.681* (-18.237)
INTRS	--	--	1.242* (3.312)	3.482* (35.332)
POIL	--	--	0.981* (-4.537)	1.058* (11.236)
Banking Sector Variable:				
STLNPI	--	--	0.001* (-14.973)	0.014* (10.099)
Model Statistics:				
Model χ^2	939.27*	1,167.49*	1,473.08*	3,074.60*
Pseudo R^2	0.253	--	0.397	--
Log likelihood	-1,383.971	-2,816.526	-1,117.065	-2,146.387
P (Weibull)	--	1.820* (26.383)	--	5.272* (58.707)

Number of banks (1985): 2,946
Number of records (1985–92): 17,528
Incidence of distress (COVR $\leq$ 0), 1985–92: 2,113

Notes: The dependent variable takes the value of one if a bank's coverage ratio is less than or equal to zero and the value zero otherwise.The z statistics are given in parenthesis and are based on robust (Huber and White) standard errors which account for correlated observations in grouped data. P|z| is the test of the underlying coefficient being zero. One, two, and three asterisks indicate significance levels of 1, 5 and 10 percent respectively.

Table 3.3. Estimation Results—U.S. Commercial Bank Failures in the Southwest (CAMEL)

	(1)		(2)	
	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio
CA (C)	0.281*	0.944*	--	--
	(-9.393)	(-4.683)		
NPLA *(A)*	1.945*	1.094*	--	--
	(8.315)	(11.507)		
LAS (M)	0.915*	1.001	0.933*	1.023*
	(-4.899)	(0.495)	(-8.522)	(6.188)
NI (E)	1.312*	0.998	0.775*	0.968*
	(3.123)	(-0.121)	(-13.506)	(-6.174)
SEC (L)	1.036**	0.948*	1.004	0.938*
	(2.196)	(-12.783)	(0.454)	(-15.134)
Model Statistics:				
Model χ^2	1307.95*	849.28*	360.44*	636.96*
Pseudo R^2	0.832	--	0.229	--
Log likelihood	-131.899	-1219.065	-605.656	-1541.409
p (Weibull)	--	1.670*	--	1.885*
		(15.647)		(23.810)

Notes: The dependent variable takes the value of one if a bank is intervened at time t+1 and the value zero otherwise. Probability of failure is estimated by fixed-effects logit. The odds ratio and hazard ratio depict exponentiated coefficients. The z statistics are given in parenthesis and are based on robust (Huber and White) standard errors which account for correlated observations in grouped data. P|z| is the test of the underlying coefficient being zero. One, two, and three asterisks indicate significance levels of 1, 5 and 10 percent, respectively.

Table 4.1. Estimation Results—U.S. Commercial Bank Failures in the Northeast

	(1)		(2)	
	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio
Proximate Indicators of Fragility:				
NPLA	3.559** (2.322)	1.221* (11.261)	--	--
EQ	--	--	0.243* (-3.331)	0.825* (-6.672)
Model Statistics:				
Model χ^2	128.43*	126.80*	121.87*	44.51*
Pseudo R^2	0.947	--	0.899	--
Log likelihood	-3.570	-28.610	-6.851	-43.077
p (Weibull)	--	4.569* (9.348)	--	5.073* (15.496)

Number of banks (1985): 261
Number of records (1985–92): 1,560
Number of failures (1986–93): 41

Notes: The dependent variable takes the value of one if a bank is intervened at time t+1 and the value zero otherwise. Probability of failure is estimated by fixed-effects logit. The odds ratio and hazard ratio depict exponentiated coefficients. The z statistics are given in parenthesis and are based on robust (Huber and White) standard errors which account for correlated observations in grouped data. P|z| is the test of the underlying coefficient being zero. One, two, and three asterisks indicate significance levels of 1, 5 and 10 percent, respectively.

Table 4.1. Estimation Results—U.S. Commercial Bank Failures in the Northeast (Concluded)

	(3)		(4)	
	(a)	(b)	(a)	(b)
	Proability of Failure Odds Ratio	Weibull Hazard Hazard Ratio	Probability of Failure Odds Ratio	Weibull Hazard HazardRatio
Bank-Specific Variables:				
Market Risk				
LCOMRE	1.124*** (1.606)	1.020 (1.280)	--	1.032** (2.320)
LRESI	1.222** (2.239)	0.992 (-0.578)	--	0.989 (-0.823)
Credit Risk				
LNYIELD	0.662*** (-1.742)	1.005 (0.058)	--	0.791** (-2.158)
Liquidity Risk				
DEPIB	0.640* (-2.538)	0.862** (-1.974)	--	0.908** (-1.967)
DEPLGE	0.759* (-3.124)	1.008 (0.524)	--	1.015 (0.839)
SEC	0.723* (-2.876)	0.882* (-4.847)	--	0.905* (-4.060)
Moral Hazard				
INSL	0.530 (-1.297)	0.939 (-0.751)	--	0.907 (-1.110)
Regional/Macroeconomic Variables:				
SPERYCH	--	--	0.299** (-1.902)	0.534* (-2.467)
INTRS	--	--	0.122** (-2.088)	0.857 (1.601)
Banking Sector Variable:				
STLNPI	--	--	0.001 (-0.930)	0.015*** (-1.847)
Model Statistics:				
Model χ^2	95.99*	45.05*	126.03*	98.74*
Pseudo R^2	0.708	--	0.930	--
Log likelihood	-19.788	-53.281	-4.772	15.346
p (Weibull)	--	5.818* (16.611)	--	80.041* (6.855)

Notes: The dependent variable takes the value of one if a bank is intervened at time t+1 and the value zero otherwise. Probability of failure is estimated by fixed-effects logit. The odds ratio and hazard ratio depict exponentiated coefficients. The z statistics are given in parenthesis and are based on robust (Huber and White) standard errors which account for correlated observations in grouped data. P|z| is the test of the underlying coefficient being zero. One, two, and three asterisks indicate significance levels of 1, 5 and 10 percent, respectively.
Model 4 (a) did not converge. Hence, the micro-macro components were separated.

Table 4.2. Estimation Results—U.S. Commercial Bank Distress in the Northeast

	(5)		(6)	
	(a)	(b)	(a)	(b)
	Probability of Distress Odds Ratio	Weibull Hazard Hazard Ratio	Probability of Distress Odds Ratio	Weibull Hazard Hazard Ratio
Bank-Specific Variables:				
Market Risk				
LCOMRE	1.129* (4.340)	1.041* (3.597)	1.236* (3.287)	1.048* (5.246)
LRESI	1.140* (4.296)	0.983** (-1.900)	1.001 (0.026)	0.983** (-2.041)
Credit Risk				
LNYIELD	0.818*** (-1.869)	1.039 (0.684)	0.710 (-1.538)	0.836* (-2.691)
Liquidity Risk				
DEPIB	0.922** (-2.213)	0.967 (-1.531)	0.995 (-0.101)	0.978 (-1.439)
DEPLGE	0.841* (-5.285)	1.002 (0.176)	0.914 (-1.397)	1.003 (0.338)
SEC	0.928** (-2.193)	0.936* (-3.846)	0.827* (-3.228)	0.952* (-3.299)
Moral Hazard				
INSL	0.960 (-0.311)	0.979 (-0.358)	1.276 (1.126)	0.945 (-0.961)
Regional/Macro. Variables:				
SPERYCH	--	--	0.389* (-5.450)	0.777*** (-1.849)
INTRS	--	--	0.886 (-0.305)	0.3009 (1.548)
Banking Sector Variable:				
STLNPI	--	--	0.001 (-1.241)	0.045** (-1.922)
Model Statistics:				
Model χ^2	157.70*	65.03*	317.00*	119.67*
Pseudo R^2	0.405	--	0.813	--
Log likelihood	-116.058	-54.238	-36.407	84.177
p (Weibull)	--	5.434* (18.044)	--	47.986* (5.949)

Number of Banks (1985): 261
Number of Records (1985–92): 1,560
Incidence of Distress (COVR $\leq$ 0), 1985–92: 134

Notes: The dependent variable takes the value of one if a bank's coverage ratio is less than or equal to zero and the value zero otherwise. Probability of distress is estimated by fixed-effects logit. The odds ratio and hazard ratio depict exponentiated coefficients. The z statistics are given in parenthesis and are based on robust (Huber and White) standard errors which account for correlated observations in grouped data. P|z| is the test of the underlying coefficient being zero. One, two, and three asterisks indicate significance levels of 1, 5 and 10 percent respectively.

Table 4.3. Estimation Results—U.S. Commercial Bank Failures in the Northeast (CAMEL)

	(1)		(2)	
	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio
CA (C)	--	0.898** (-2.000)	--	--
NPLA *(A)*	--	1.149* (4.497)	--	--
LAS (M)	--	1.044 (1.284)	1.107** (2.306)	1.012 (1.199)
NI (E)	--	0.968 (-0.655)	0.583* (-5.052)	0.829* (-7.693)
SEC (L)	--	0.977 (-0.554)	0.995 (-0.059)	0.898* (-4.498)
Model Statistics:				
Model χ^2	--	217.31*	69.35*	-97.52*
Pseudo R^2	--	--	0.511	--
Log likelihood	--	-16.240	-33.112	-35.547
p (Weibull)	--	5.642* (10.367)	--	6.306* (16.315)

Notes: The dependent variable takes the value of one if a bank is intervened at time t+1 and the value zero otherwise. Probability of failure is estimated by fixed-effects logit. The odds ratio and hazard ratio depict exponentiated coefficients. The z statistics are given in parenthesis and are based on robust (Huber and White) standard errors which account for correlated observations in grouped data. P|z| is the test of the underlying coefficient being zero. One, two, and three asterisks indicate significance levels of 1, 5 and 10 percent respectively.

Model 1(a) did not converge.

Table 5.1. Estimation Results—U.S. Commercial Bank Failures in California

	(1)		(2)	
	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio
Proximate Indicators of Fragility:				
NPLA	1.441* (5.622)	1.156* (9.600)	--	--
EQ	--	--	0.438* (-5.297)	0.634* (-14.093)
Model Statistics:				
Model χ^2	79.40	93.31*	86.08*	198.61*
Pseudo R^2	0.485	--	0.533	--
Log likelihood	-41.613	-144.808	-37.769	-100.082
p (Weibull)	--	1.381** (2.093)	--	1.537* (2.744)

Number of banks (1985) 562
Number of records (1985–92): 3,730
Number of failures (1986–93): 55

Notes: The dependent variable takes the value of one if a bank is intervened at time t+1 and the value zero otherwise. Probability of failure is estimated by fixed-effects logit. The odds ratio and hazard ratio depict exponentiated coefficients. The z statistics are given in parenthesis and are based on robust (Huber and White) standard errors which account for correlated observations in grouped data. P|z| is the test of the underlying coefficient being zero. One, two, and three asterisks indicate significance levels of 1, 5 and 10 percent, respectively.

Table 5.1. Estimation Results—U.S. Commercial Bank Failures in California (Concluded)

	(3)		(4)	
	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio
Bank-Specific Variables				
Market Risk				
LCOMRE	1.105* (2.779)	0.994 (-0.691)	0.952 (-0.535)	0.993 (-0.845)
LRESI	1.130* (3.147)	1.003 (0.448)	1.047 (0.514)	1.002 (0.291)
Credit Risk				
LNYIELD	0.855 (-1.305)	1.090*** (1.617)	1.362 (1.038)	1.122** (2.160)
Liquidity Risk				
DEPIB	0.935*** (-1.821)	1.009 (0.720)	0.823** (-2.069)	1.007 (0.517)
DEPLGE	0.746* (-4.851)	1.007 (0.497)	0.725** (-2.209)	1.011 (0.839)
SEC	0.978 (-0.325)	0.891* (-4.204)	0.596 (-1.500)	0.894* (-4.166)
Moral Hazard				
INSL	0.710 (-1.556)	1.114** (2.142)	0.395 (-1.522)	1.119** (2.307)
Regional/Macroeconomic				
SPERYCH	--	--	0.645 (-0.851)	0.834* (-2.428)
INTRS	--	--	0.067** (-1.898)	1.047 (0.171)
Banking Sector Variable:				
STLNPI	--	--	0.001** (-2.084)	0.001 (-0.794)
Model Statistics:				
Model χ^2	93.83*	39.63*	145.38*	57.70*
Pseudo R^2	0.581		0.900	--
Log likelihood	-33.897	-173.590	-8.120	-169.04
p (Weibull)	--	2.085* (4.272)	--	1.529** (2.178)

Notes: The dependent variable takes the value of one if a bank is intervened at time t+1 and the value zero otherwise. Probability of failure is estimated by fixed-effects logit. The odds ratio and hazard ratio depict exponentiated coefficients. The z statistics are given in parenthesis and are based on robust (Huber and White) standard errors which account for correlated observations in grouped data. P|z| is the test of the underlying coefficient being zero. One, two, and three asterisks indicate significance levels of 1, 5 and 10 percent, respectively.

Table 5.2. Estimation Results—U.S. Commercial Bank Distress in California

	(5)		(6)	
	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio
Bank-Specific Variables				
Market Risk				
LCOMRE	1.015*** (1.62)	1.010*** (1.573)	0.998 (-0.161)	1.009 (1.416)
LRESI	0.990 (-0.739)	0.996 (-0.621)	0.974*** (-1.767)	0.995 (-0.743)
Credit Risk				
LNYIELD	0.671* (-6.644)	0.934 (-0.553)	0.747* (-4.221)	0.986 (-0.442)
Liquidity Risk				
DEPIB	0.973 (-1.415)	0.994 (-0.742)	0.993 (-0.357)	0.997 (-0.464)
DEPLGE	0.976*** (-1.746)	1.005 (0.724)	0.992 (-0.527)	1.006 (0.773)
SEC	0.955** (-2.259)	0.953* (-5.809)	0.954** (-2.264)	0.927* (-5.733)
Moral Hazard				
INSL	0.952 (-0.529)	1.080* (2.436)	0.985 (-0.162)	1.083* (2.484)
Regional/Macroeconomic Variables:				
SPERYCH	--	--	0.810* (-3.800)	0.893* (-4.792)
INTRS	--	--	0.862 (-0.872)	1.059 (0.665)
Banking Sector Variable:				
STLNPI	--	--	2.255 (0.165)	24.977 (1.118)
Model Statistics:				
Model χ^2	81.97*	47.00*	109.28*	99.74*
Pseudo R^2	0.129	--	0.172	--
Log likelihood	-277.120	-469.341	-263.500	-490.231
p (Weibull)	--	1.543* (5.218)	--	1.539* (5.06)

Number of banks (1985): 562
Number of records (1985–92): 3,730
Incidence of distress (COVR $\leq$ 0), 1985–92: 244

Notes: The dependent variable takes the value of one if a bank's coverage ratio is less than or equal to zero and the value zero otherwise. Probability of distress is estimated by fixed-effects logit. The odds ratio and hazard ratio depict exponentiated coefficients. The z statistics are given in parenthesis and are based on robust (Huber and White) standard errors which account for correlated observations in grouped data. $P|z|$ is the test of the underlying coefficient being zero. One, two, and three asterisks indicate significance levels of 1, 5 and 10 percent, respectively.

Table 5.3. Estimation Results—U.S. CommercialBank Failures in California (CAMEL)

	(1)		(2)	
	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio
CA (C)	0.5838* (-3.138)	0.684* (-6.118)	--	--
NPLA *(A)*	1.425* (4.229)	1.043* (2.390)	--	--
LAS (M)	0.971 (-0.841)	0.994 (-0.310)	1.008 (0.368)	1.040** (2.176)
NI (E)	0.882 (-1.294)	0.876* (-3.686)	0.704* (-5.187)	0.800* (-6.424)
SEC (L)	1.057 (0.736)	0.915* (-2.708)	1.025 (0.491)	0.926** (-2.186)
Model Statistics:				
Model χ^2	103.17*	251.54*	40.02*	111.53*
Pseudo R^2	0.638	--	0.247	--
Log likelihood	-29.226	-84.318	-60.801	-141.238
p (Weibull)	--	1.632* (3.437)	--	1.706* (3.219)

Notes: The dependent variable takes the value of one if a bank is intervened at time t+1 and the value zero otherwise. Probability of failure is estimated by fixed-effects logit. The odds ratio and hazard ratio depict exponentiated coefficients. The z statistics are given in parenthesis and are based on robust (Huber and White) standard errors which account for correlated observations in grouped data. P|z| is the test of the underlying coefficient being zero. One, two, and three asterisks indicate significance levels of 1, 5 and 10 percent, respectively.

Table 6.1. Estimation Results—Bank Failures in Mexico

	(1)		(2)	
	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio
Proximate Indicators of Fragility:				
NPLA	1.916* (3.226)	1.174* (3.028)	--	--
EQ	--	--	0.307* (-2.992)	0.626* (-3.724)
Model Statistics:				
Model χ^2	14.95*	9.17*	11.96*	13.87*
Pseudo R^2	0.203	--	0.162	--
Log Likelihood	-29.366	-3.389	-30.862	4.745
p (Weibull)	--	6.686* (10.228)	--	7.911* (10.089)

Number of banks: 31
Number of records (1992Q1–1995Q3): 251
Number of failures (1994Q3–1995Q4): 16

Notes: The dependent variable takes the value of one if a bank is intervened at time t+1 and the value zero otherwise. Probability of failure is estimated by fixed-effects logit. The odds ratio and hazard ratio depict exponentiated coefficients. The z statistics are given in parenthesis and are based on robust (Huber and White) standard errors which account for correlated observations in grouped data. P|z| is the test of the underlying coefficient being zero. One, two, and three asterisks indicate significance levels of 1, 5 and 10 percent, respectively.

Table 6.1. Estimation Results—Bank Failures in Mexico (Concluded)

	(1)		(2)	
	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio
Bank-Specific				
Market Risk				
LRESI	1.763 (0.944)	1.064* (2.612)	1.498 (0.627)	1.061* (2.585)
LNONSEC	0.947 (-0.172)	0.990 (-0.729)	0.743 (-0.682)	0.985 (-1.155)
LAGR	1.199 (0.165)	1.104* (4.310)	0.289 (-0.490)	1.098* (3.975)
Credit Risk				
LAS	1.239** (2.195)	0.998 (-0.250)	1.323** (1.885)	0.999 (-0.116)
Funding Sources				
DEPPUB	1.078 (0.663)	0.987*** (-1.650)	1.284 (1.320)	0.993 (-0.929)
DEPIB	1.468** (2.069)	0.999 (-0.242)	1.560*** (1.737)	0.999 (-0.711)
SEC	0.303*** (-1.691)	1.067 (1.017)	0.195 (-1.372)	1.098 (1.157)
Moral Hazard				
INTAS	1.146 (1.162)	0.989 (-0.304)	1.223 (1.175)	0.968 (-0.716)
Macroeconomic Variables:				
DELEX	--	--	1.041 (0.951)	1.003***
INTRS	--	--	1.066 (0.656)	0.926 (1.376)
Banking Sector Variable:				
BSLNGDP	--	--	1.066 (0.247)	1.390***
Model Statistics:				
Model χ^2				
Pseudo R^2	0.689	--	0.763	--
Log likelihood	-11.465	-0.741	-8.719	4.929
P (Weibull)	--	8.268* (9.009)		11.980* (4.481)

Notes: The dependent variable takes the value of one if a bank is intervened at time t+1 and the value zero otherwise. Probability of failure is estimated by fixed-effects logit. The odds ratio and hazard ratio depict exponentiated coefficients. The z statistics are given in parenthesis and are based on robust (Huber and White) standard errors which account for correlated observations in grouped data. P|z| is the test of the underlying coefficient being zero. One, two, and three asterisks indicate significance levels of 1, 5 and 10 percent, respectively.

Table 6.2. Estimation Results—Bank Distress in Mexico

	(5)		(6)	
	(a)	(b)	(a)	(b)
	Probability of Failure Odds Ratio	Weibull Hazard Hazard Ratio	Probability of Failure Odds Ratio	Weibull Hazard Hazard Ratio
Bank-Specific Variables:				
Market Risk				
LRESI	1.940* (3.009)	1.012 (0.498)	1.643** (1.947)	1.012 (0.468)
LNONSEC	1.070 (0.836)	0.973* (-2.420)	0.988 (-0.120)	0.972** (-2.365)
LAGR	0.532 (-1.157)	1.075* (5.426)	0.455 (-1.114)	1.075* (5.449)
Credit Risk				
LAS	1.013 (0.456)	0.994 (-1.003)	1.046 (1.207)	0.994 (-1.013)
Funding Sources				
DEPPUB	0.960 (-0.806)	0.993 (-1.238)	1.056 (0.773)	0.993 (-1.210)
DEPIB	1.067 (1.416)	0.998 (-0.602)	1.131*** (1.718)	0.998 (-0.598)
SEC	1.345*** (-1.605)	1.162* (-2.476)	1.274 (1.164)	1.161* (-2.490)
Moral Hazard				
INTAS	1.028 (0.455)	1.003 (1.174)	1.022 (0.272)	1.005 (0.245)
Regional/Macroeconomic:				
DELEX	--	--	1.038 (0.846)	1.001 (0.282)
INTRS	--	--	1.091*** (1.618)	1.003 (0.316)
Banking Sector Variable:				
BSLNGDP	--	--	1.276** (1.943)	0.992 (-0.196)
Model Statistics:				
Model χ^2	38.97*	53.07*	60.73*	59.26*
Pseudo R^2	0.346	--	0.539	--
Log likelihood	-36.903	1.802	-26.024	1.832
P (Weibull)	--	1.751** (1.991)	--	1.737** (1.817)

Number of banks: 31
Number of records (1992Q1–1995Q3): 251
Incidence of Distress (COVR $\leq$ 1.5), 1992Q1–1995Q3: 57

Notes: The dependent variable takes the value of one if a bank's coverage ratio is less than or equal to 1.5 and the value zero otherwise. Probability of distress is estimated by fixed-effects logit. The odds ratio and hazard ratio depict exponentiated coefficients. The z statistics are given in parenthesis and are based on robust (Huber and White) standard errors which account for correlated observations in grouped data. P|z| is the test of the underlying coefficient being zero. One, two, and three asterisks indicate significance levels of 1, 5 and 10 percent, respectively.

Table 6.3. Estimation Results—Bank Failures in Mexico (CAMEL)

		(1)		(2)	
		(a)	(b)	(a)	(b)
		Probability of Failure Odds Ratio	Weibull Hazard Hazard Ratio	Probability of Failure Odds Ratio	Weibull Hazard Hazard Ratio
CA	(C)	0.908 (-0.228)	0.527* (-3.173)	--	--
NPLA	*(A)*	1.870*** (1.695)	1.196** (1.986)	--	--
LAS	(M)	1.006 (0.095)	1.032*** (1.669)	1.043 (1.006)	0.998 (-0.175)
PROFMARG	(E)	0.351* (-3.283)	1.076 (1.464)	0.333* (-3.574)	0.931* (-3.523)
SEC	(L)	0.683 (-1.323)	1.030 (0.332)	0.717 (-0.993)	1.074 (1.030)
Model Statistics:					
Model χ^2		43.76*	21.93*	40.41*	15.78*
Pseudo R^2		0.594	--	0.548	--
Log likelihood		-14.963	8.340	-16.634	-3.621
p (Weibull)		--	13.099* (9.712)	--	6.241* (8.315)

Notes: The dependent variable takes the value of one if a bank is intervened at time t+1 and the value zero otherwise. Probability of failure is estimated by fixed-effects logit. The odds ratio and hazard ratio depict exponentiated coefficients. The z statistics are given in parenthesis and are based on robust (Huber and White) standard errors which account for correlated observations in grouped data. P|z| is the test of the underlying coefficient being zero. One, two, and three asterisks indicate significance levels of 1, 5 and 10 percent, respectively.

Table 7.1. Estimation Results—Bank Failures in Colombia

	(1)		(2)	
	(a)	(b)	(a)	(b)
	Probability of Failure Odds Ratio	Exponential Hazard Hazard Ratio	Probability of Failure Odds Ratio	Exponential Hazard Hazard Ratio
Proximate Indicators of Fragility:				
NPLA	1.341 (1.183)	1.132* (5.711)	--	--
CA	--	--	1.563 (1.178)	1.168* (-5.424)
Model Statistics:				
Model χ^2	7.66*	32.62*	7.59*	29.42*
Pseudo R^2	0.554	--	0.548	--
Log likelihood	-3.084	-16.720	-3.120	-17.516

Number of banks: 18
Number of records (1980–88): 132
Number of failures (1980–89): 5

Notes: The dependent variable takes the value of one if a bank is intervened at time t+1 and the value zero otherwise. Probability of failure is estimated by fixed-effects logit. The odds ratio and hazard ratio depict exponentiated coefficients. The z statistics are given in parenthesis and are based on robust (Huber and White) standard errors which account for correlated observations in grouped data. P|z| is the test of the underlying coefficient being zero. One, two, and three asterisks indicate significance levels of 1, 5 and 10 percent, respectively.

Models 1 (b) and 2 (b), using a Weibull parametric distribution, produced a p value of 1 and, hence, an exponential distribution was estimated.

Table 7.1. Estimation Results—Bank Failures in Colombia (Concluded)

	(3)		(4)	
	(a) Proability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio
Bank-Specific Variables:				
Credit Risk				
LNYIELD	1.506	1.255	--	1.225**
Liquidity Risk				
DEPPUB	--	1.049***	--	1.063*
DEPIB	0.894	1.036	--	1.100
INTDEP	1.596	1.235*	--	1.304*
Moral Hazard				
INTAS	0.370	0.555***	--	0.565*
Regional/Macroeconomic				
PEXP	--	--	0.816	1.107
Banking Sector Variable:				
BSLNGDP	--	--	1.183	0.572
Model Statistics:				
Model χ^2	6.24	15.06*	5.23***	24.13*
Pseudo R^2	0.451	--	0.378	--
Log likelihood	-3.796	-11.200	-4.302	9.723
p (Weibull)	--	1.281	--	3.353***

Notes: The dependent variable takes the value of one if a bank is intervened at time t+1 and the value zero otherwise. Probability of failure is estimated by fixed-effects logit. The odds ratio and hazard ratio depict exponentiated coefficients. The z statistics are given in parenthesis and are based on robust (Huber and White) standard errors which account for correlated observations in grouped data. P|z| is the test of the underlying coefficient being zero. One, two, and three asterisks indicate significance levels of 1, 5 and 10 percent, respectively.

Model 4 (a) did not converge. Hence, the micro-macro components were separated.

Table 7.2. Estimation Results—Bank Distress in Colombia

	(5)		(6)	
	(a)	(b)	(a)	(b)
	Probability of Distress Odds Ratio	Weibull Hazard Hazard Ratio	Probability of Distress Odds Ratio	Weibull Hazard Hazard Ratio
Bank-Specific Variables:				
Credit Risk				
LNYIELD	0.556* (-2.337)	0.911 (-1.114)	0.403** (-2.050)	0.932 (-0.916)
Liquidity Risk				
DEPPUB	1.093 (0.772)	1.012 (0.599)	1.309*** (1.710)	1.005 (0.252)
DEPIB	1.362*** (1.873)	1.089** (2.291)	1.648 (1.528)	1.094** (2.326)
INTDEP	1.559 (2.677)	1.080 (0.430)	1.495*** (1.579)	0.993 (-0.040)
Moral Hazard				
INTAS	2.257*** (1.797)	1.105 (0.366)	4.900** (1.967)	1.772 (0.639)
Regional/Macro. Variables:				
PEXP	--	--	1.236** (-1.948)	1.166* (3.033)
Banking Sector Variable:				
BSLNGDP	--	--	2.275* (2.472)	1.247** (1.922)
Model Statistics:	--	--		
Model χ^2	15.21*	11.07**	26.16*	31.65*
Pseudo R^2	0.340	--	0.585	--
Log likelihood	-14.738	-19.037	-9.263	-15.872
p (Weibull)	--	1.910* (2.380)	--	2.388* (5.196)

Number of banks: 18
Number of records (1980–88): 132
Incidence of distress (COVR ≤ 1.5), 1980–89: 16

Notes: The dependent variable takes the value of one if a bank's coverage ratio is less than or equal to 1.5 and the value zero otherwise. Probability of distress is estimated by fixed-effects logit. The odds ratio and hazard ratio depict exponentiated coefficients. The z statistics are given in parenthesis and are based on robust (Huber and White) standard errors which account for correlated observations in grouped data. P|z| is the test of the underlying coefficient being zero. One, two, and three asterisks indicate significance levels of 1, 5 and 10 percent, respectively.

Table 7.3. Estimation Results—Bank Failures in Colombia (CAMEL)

	(1)		(2)	
	(a) Probability of Failure Odds Ratio	(b) Exponential Hazard Hazard Ratio	(a) Probability of Failure Odds Ratio	(b) Weibull Hazard Hazard Ratio
CA (C)	--	1.018 (0.203)	--	--
NPLA *(A)*	--	1.106*** (1.557)	--	--
LAS (M)	--	0.939 (-0.678)	--	0.850 (-1.366)
NI (E)	--	1.071** (1.994)	--	1.057** (1.993)
SEC (L)	--	1.000 (0.011)	--	0.922 (-0.833)
Model Statistics:				
Model χ^2	--	37.21*	--	6.44***
Pseudo R^2	--	--	--	--
Log likelihood	--	-15.666	--	-11.679
p (Weibull)	--	--	--	1.327 (0.761)

Notes: The dependent variable takes the value of one if a bank is intervened at time t+1 and the value zero otherwise. Probability of failure is estimated by fixed-effects logit. The odds ratio and hazard ratio depict exponentiated coefficients. The z statistics are given in parenthesis and are based on robust (Huber and White) standard errors which account for correlated observations in grouped data. P|z| is the test of the underlying coefficient being zero. One, two, and three asterisks indicate significance levels of 1, 5 and 10 percent, respectively.

Models 1(a) and 2(a) did not converge. Model 1(b), using a Weibull parametric distribution, produced a p value of 1 and, hence, an exponential distribution was estimated.

Table 8. Summary of Empirical Results

	Increased Probability of Failure/Distress	Reduced Survival Time
A. Proximate indicators of fragility:		
High ratio of nonperforming loans to total assets		
Southwest	Yes	Yes
Northeast	Yes	Yes
California	Yes	Yes
Mexico	Yes	Yes
Colombia	n.s.	Yes
Low ratio of capital to total assets		
Southwest	Yes	Yes
Northeast	Yes	Yes
California	Yes	Yes
Mexico	Yes	Yes
Colombia	n.s.	Yes
B. Market risk: 1/		
Southwest	Yes	Yes
Northeast	Yes	Yes
California	Yes	Yes
Mexico	Yes	Yes
Colombia	n.a.	n.a.
C. Credit risk: 1/		
Southwest	ind.	Yes
Northeast	ind.	ind.
California	ind.	ind.
Mexico	Yes	n.s.
Colombia	ind.	ind.

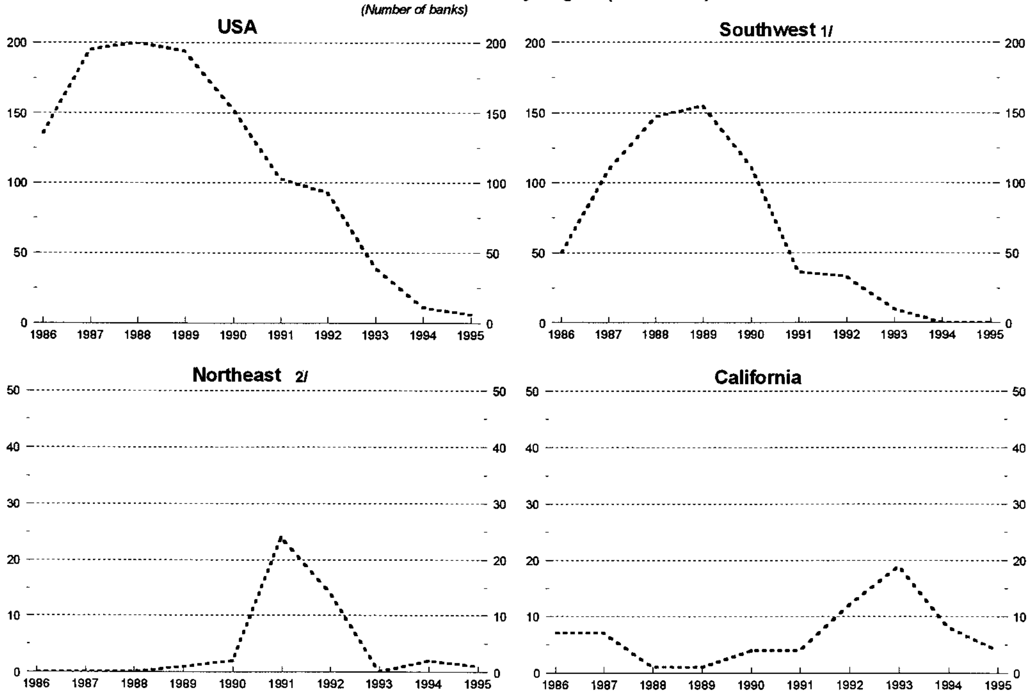
Table 8. Summary of Empirical Results (Concluded)

	Increased Probability of Failure/Distress	Reduced Survival Time
D. Liquidity risk: 1/		
Southwest	Yes	Yes
Northeast	Yes	Yes
California	Yes	Yes
Mexico	Yes	Yes
Colombia	Yes	Yes
E. Moral hazard: 1/		
Southwest	Yes	Yes
Northeast	n.s.	n.s.
California	n.s.	Yes
Mexico	n.s.	n.s.
Colombia	Yes	No
F. Contagion: 1/		
Southwest	No	Yes
Northeast	n.s.	No
California	No	n.s.
Mexico	Yes	Yes
Colombia	Yes	Yes

1/ "Yes" indicates that one or more variables in the failure or distress equations suggest the presence of this type of risk. If so, the probability of failure/distress would increase and/or the expected survival time would diminish. "No" indicates that the results do not suggest that this type of risk factor was present.

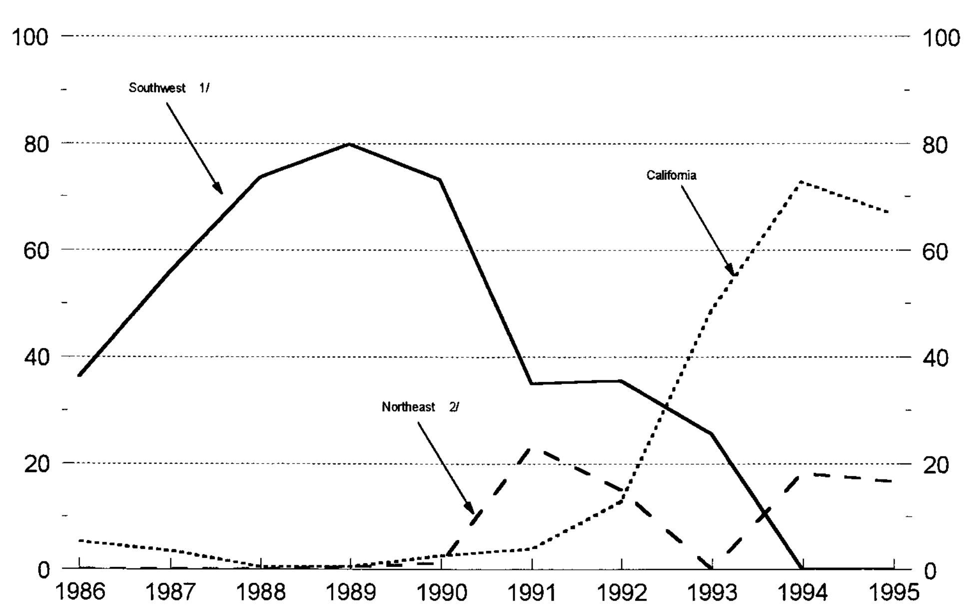
Notes:
n.s. = not statistically significant.
n.a. = variables not available.
ind. = indeterminate; the variable used can take either sign and still be consistent with the presence of certain type of risks (e.g. high yield on loans may be consistent with high default risk, but a low yield can also indicate that risk is not priced properly).

Figure 1. U.S. Commercial Bank Failures by Region (1986-1995)
(Number of banks)



Source: National Authorities.
1/ Texas, Oklahoma and Louisiana.
2/ New Hampshire, Connecticut and Massachusetts.

Figure 2. U.S. Commercial Bank Failures by Region (1986-1995)
(Share of total U.S. failures)

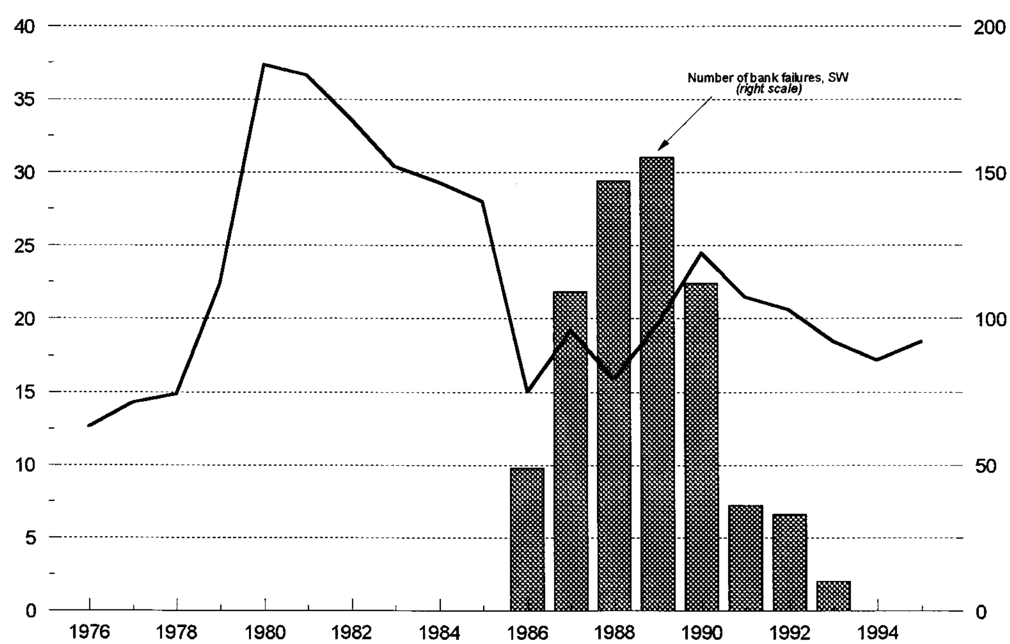


Source:National Authorities
1/ Texas, Oklahoma and Louisiana.
2/ New Hampshire, Connecticut and Massachusetts.

Figure 3. U.S. State Personal Income - Southwest
(Annual percent change)

Source: U.S. Bureau of Economic Analysis; National Authorities.

Figure 4. Oil Prices - West Texas Intermediate
(Dollars per barrel)



Source: International Monetary Fund, International Financial Statistics database; National Authorities.

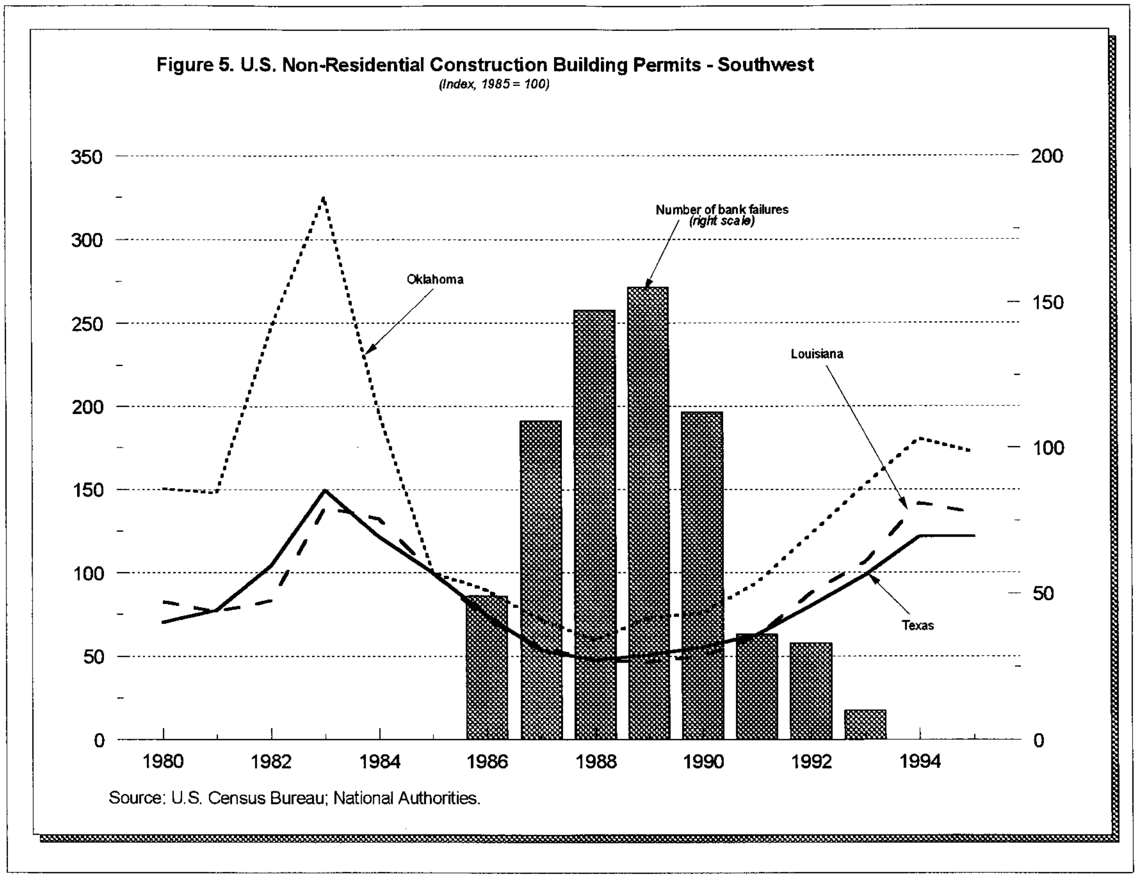


Figure 5. U.S. Non-Residential Construction Building Permits - Southwest
(Index, 1985 = 100)
Number of bank failures (right scale)
Oklahoma
Louisiana
Texas
350
300
250
200
150
100
50
0
200
150
100
50
0
1980
1982
1984
1986
1988
1990
1992
1994
Source: U.S. Census Bureau; National Authorities.

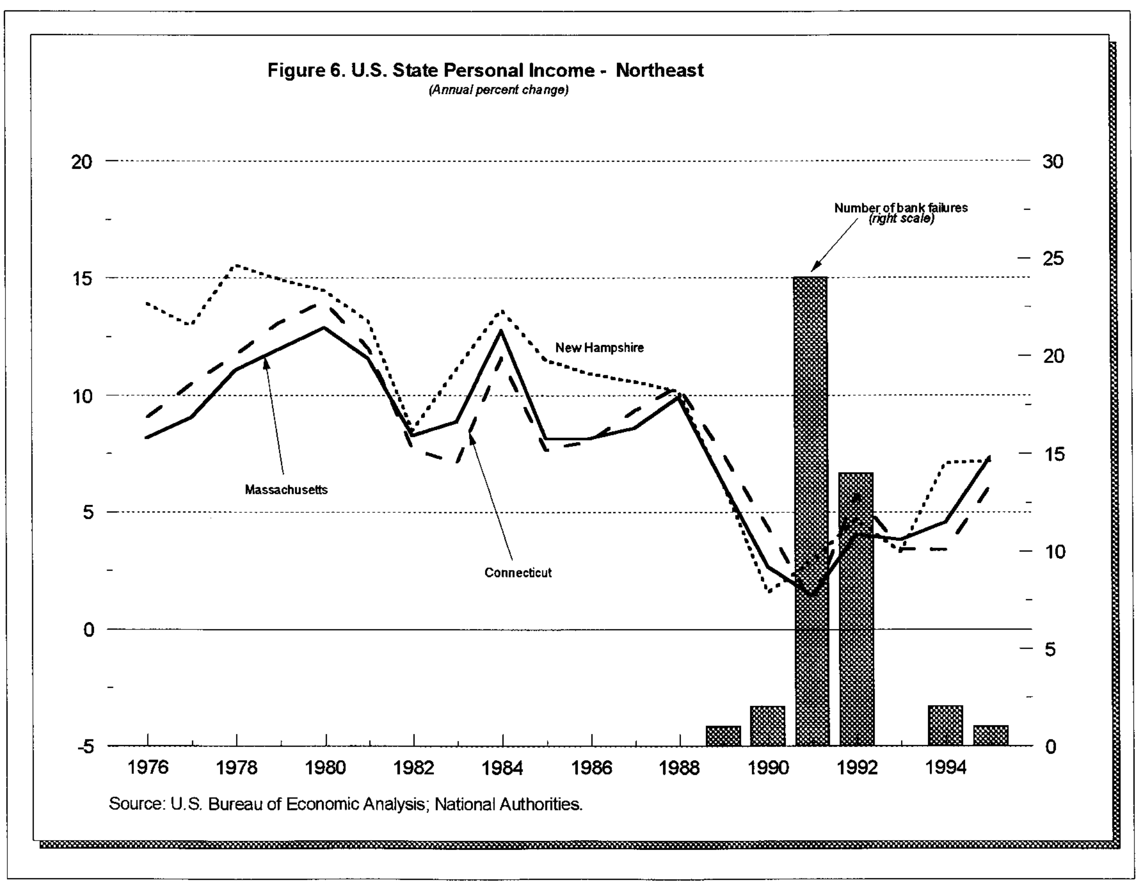
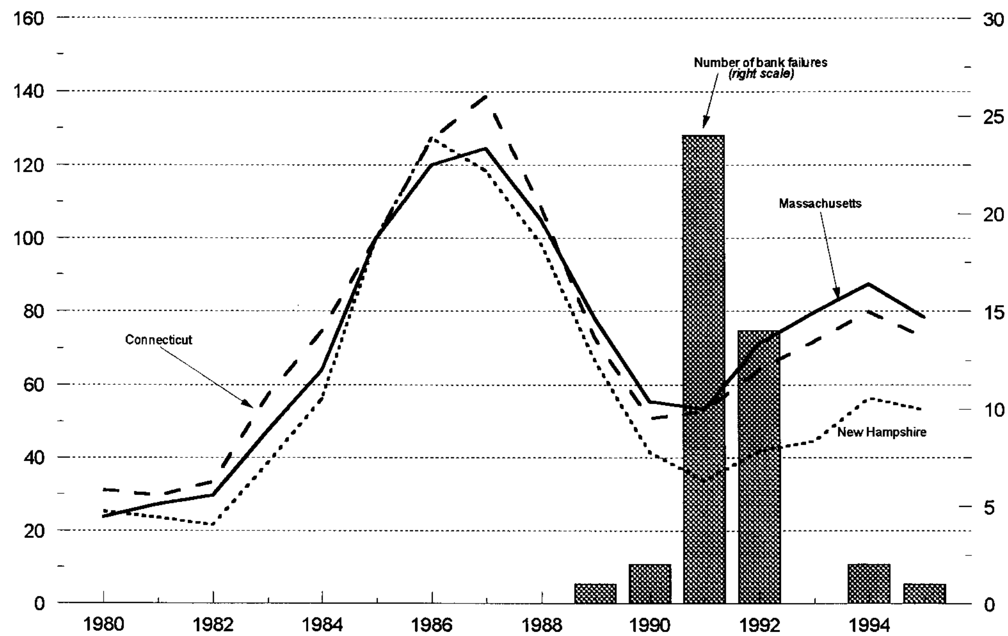


Figure 6. U.S. State Personal Income - Northeast
(Annual percent change)
Number of bank failures (right scale)
New Hampshire
Massachusetts
Connecticut
20
15
10
5
0
-5
30
25
20
15
10
5
0
1976
1978
1980
1982
1984
1986
1988
1990
1992
1994
Source: U.S. Bureau of Economic Analysis; National Authorities.

Figure 7. U.S. Non-Residential Construction Building Permits - Northeast

(Index, 1985 = 100)



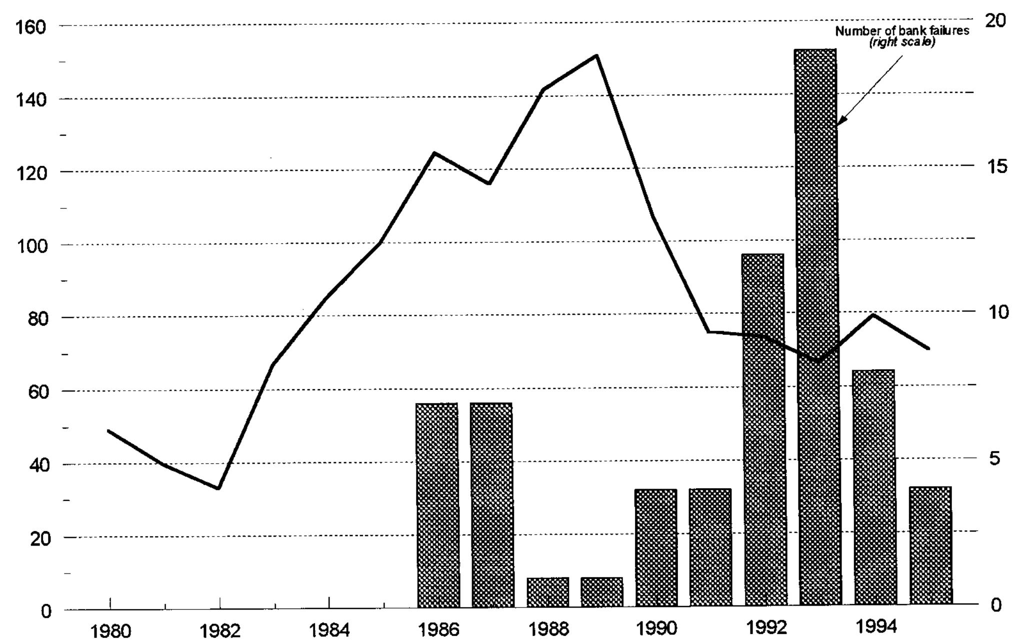
Source: U.S. Census Bureau; National Authorities.

Figure 8. U.S. State Personal Income - California

(Annual percent change)

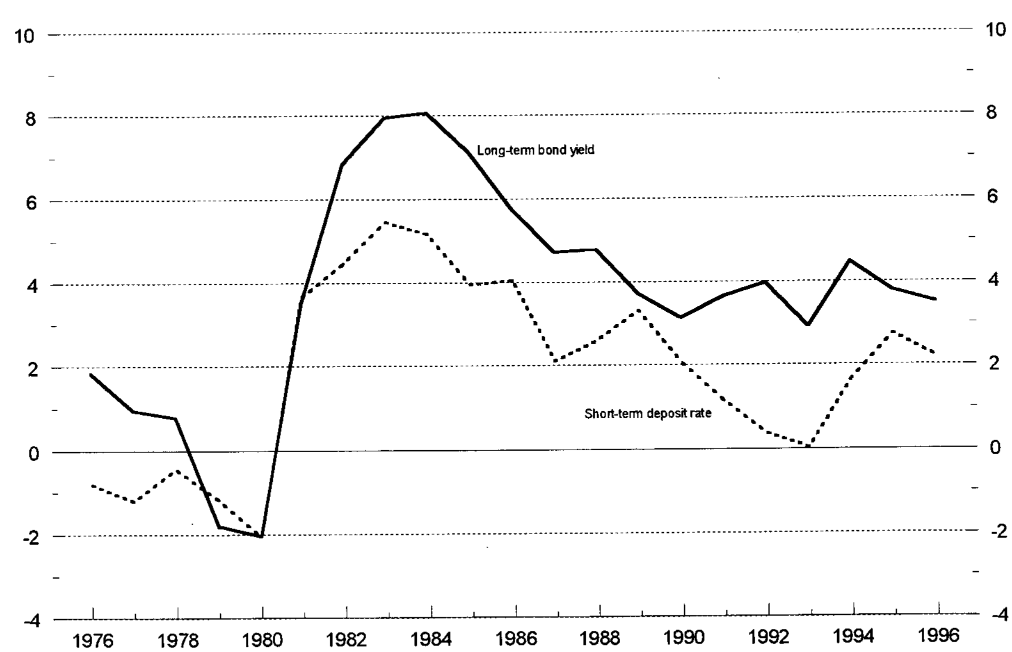
Source: U.S. Bureau of Economic Analysis; National Authorities.

Figure 9. U.S. Non-Residential Construction Building Permits - California
(Index, 1985 = 100)



Source: U.S. Census Bureau; National Authorities.

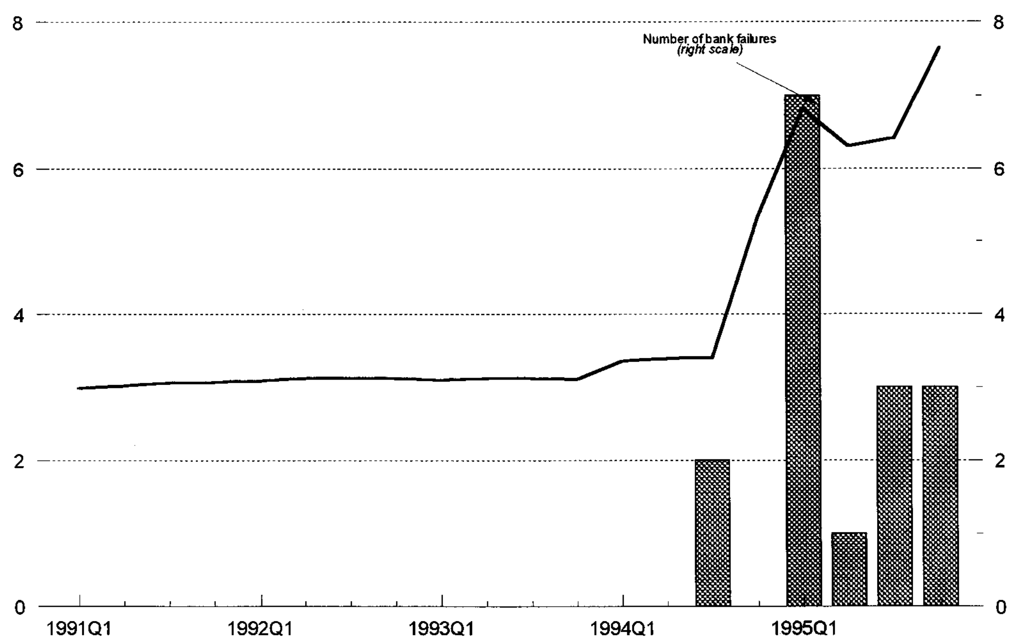
Figure 10. U.S. Real Interest Rates
(Percent per anum)



Source: International Monetary Fund, International Financial Statistics database.

Figure 11. Mexico: Nominal Exchange Rate

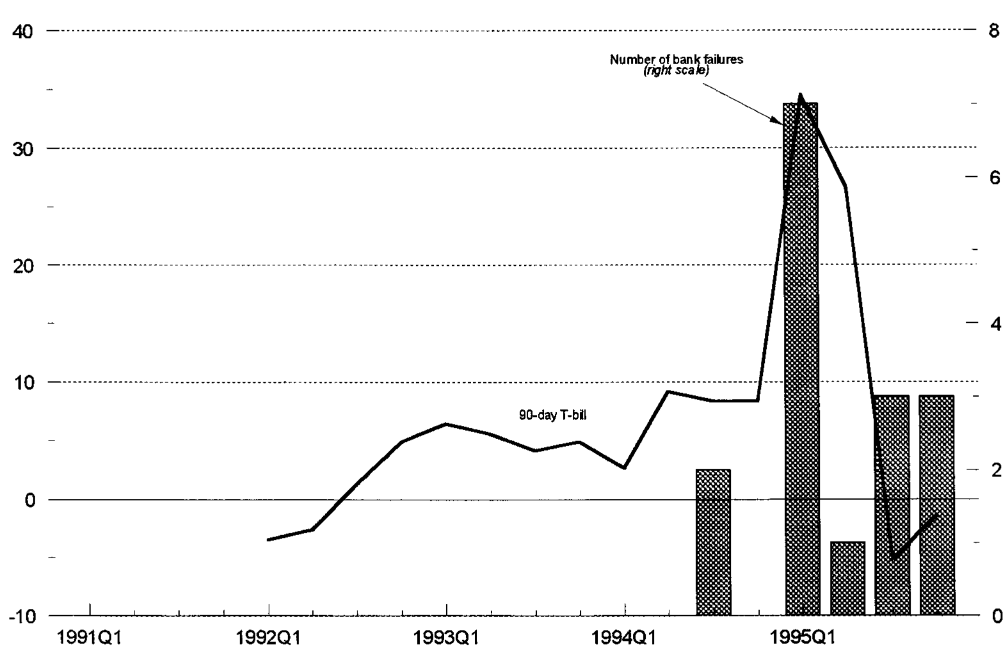
(Pesos per US dollar)



Source: International Monetary Fund, International Financial Statistics database; Press Releases.

Figure 12. Mexico: Short-term Real Interest Rates

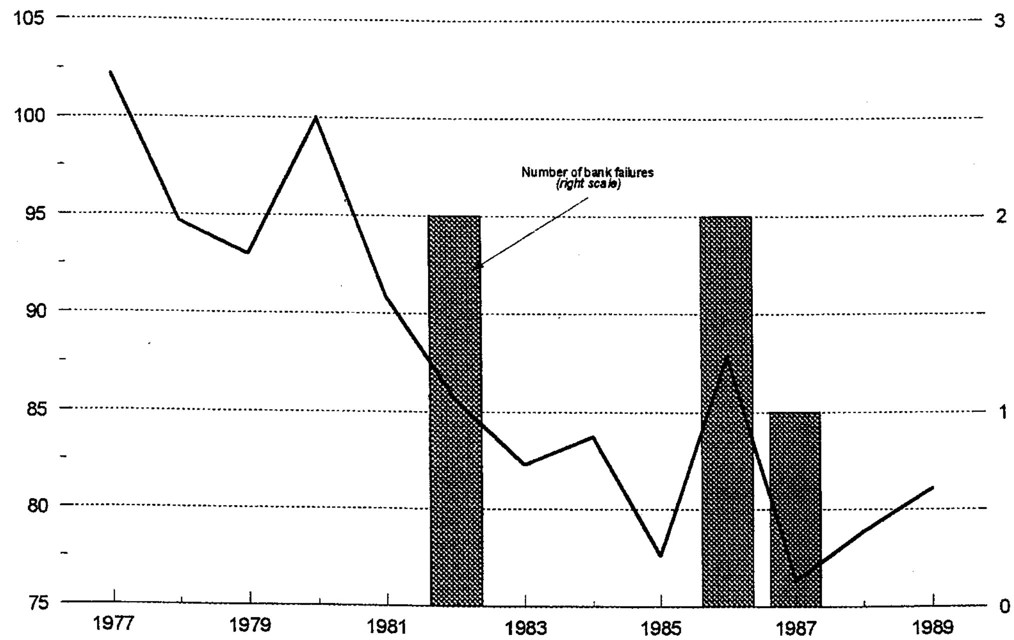
(Percent per anum)



Source: International Monetary Fund, International Financial Statistics database.

Figure 13. Colombia: Price of Exports

(Index, 1980=100)



Source: International Monetary Fund, International Financial Statistics database; National Authorities.

Figure 14.1. U.S. Banking System Failures - Southwest

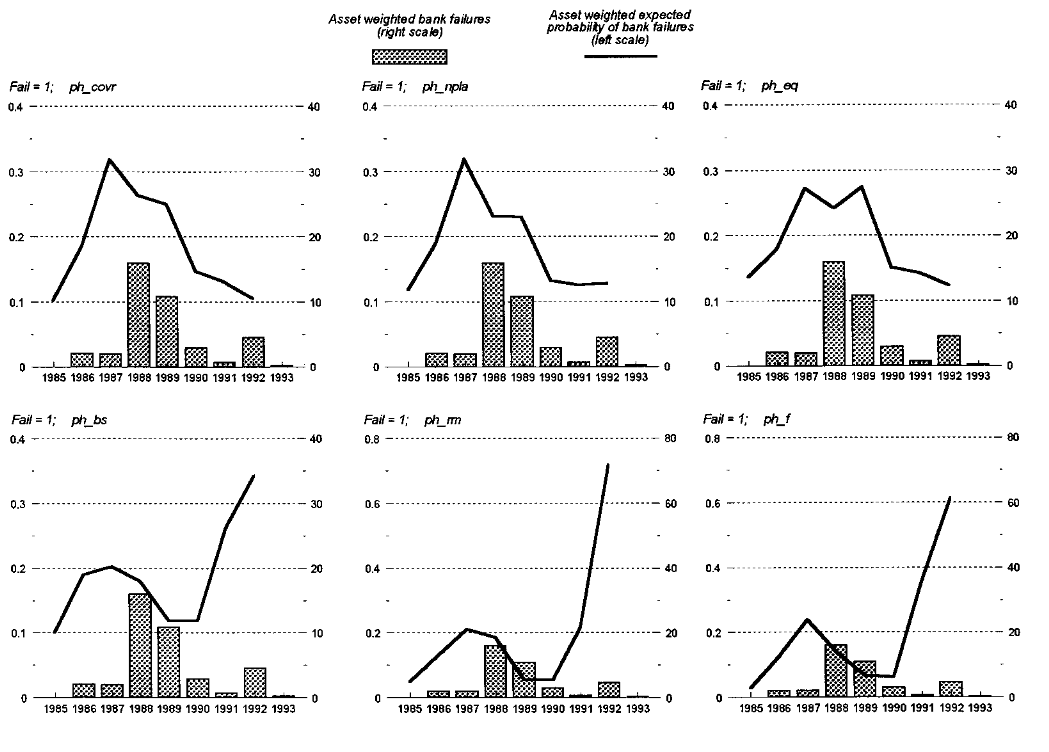


Figure 14.1 (concluded). U.S. Banking System Failures - Southwest

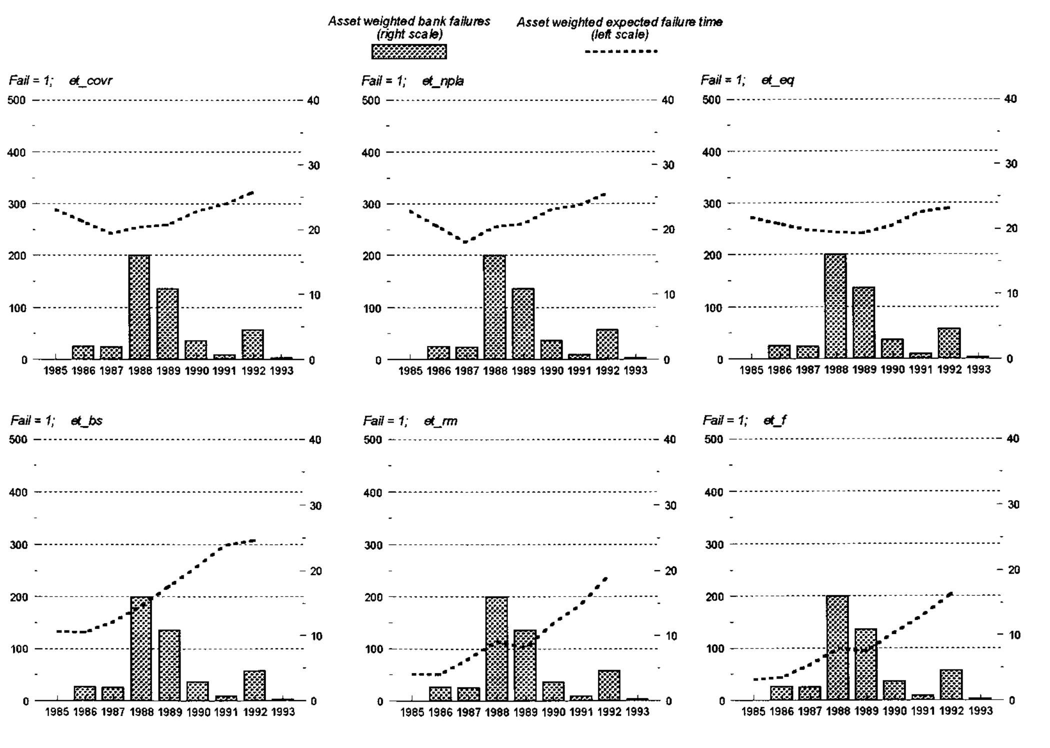


Figure 14.2. U.S. Banking System Distress - Southwest

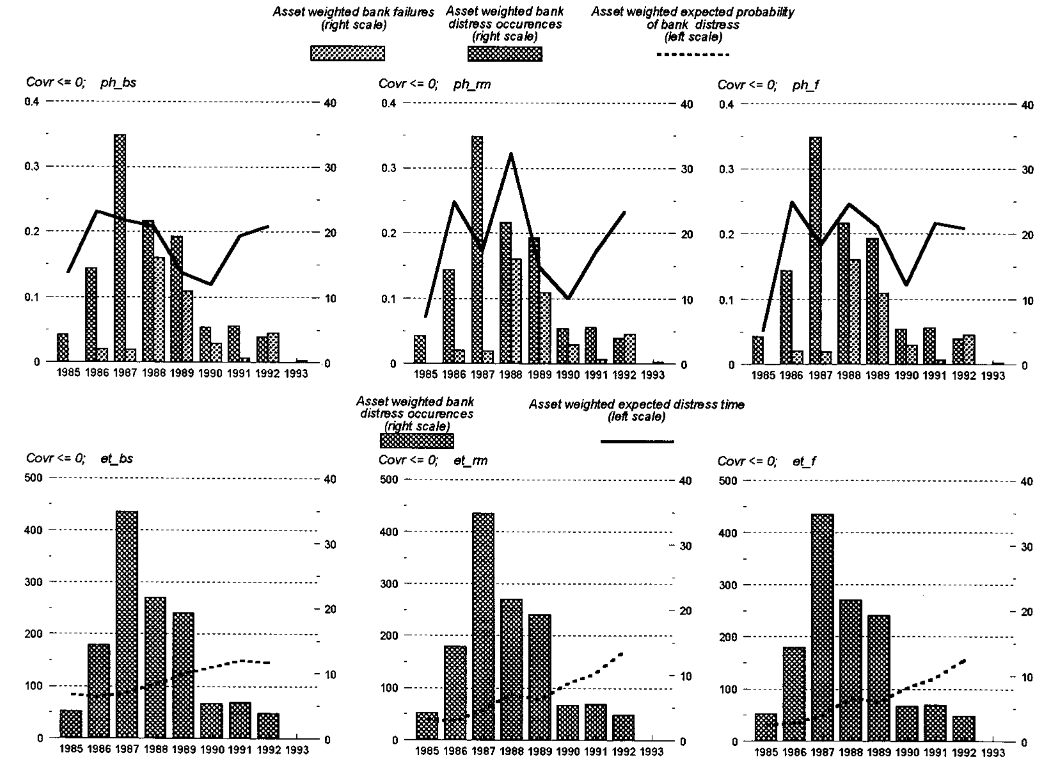


Figure 14.3. U.S. Banking System Failures - Southwest (CAMEL)

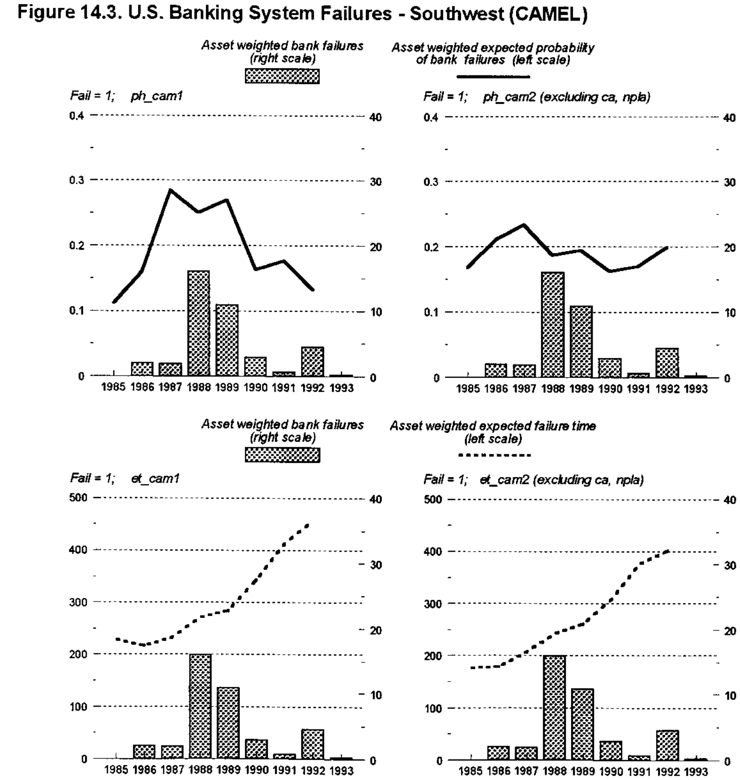


Figure 15.1. U.S. Banking System Failures - Northeast

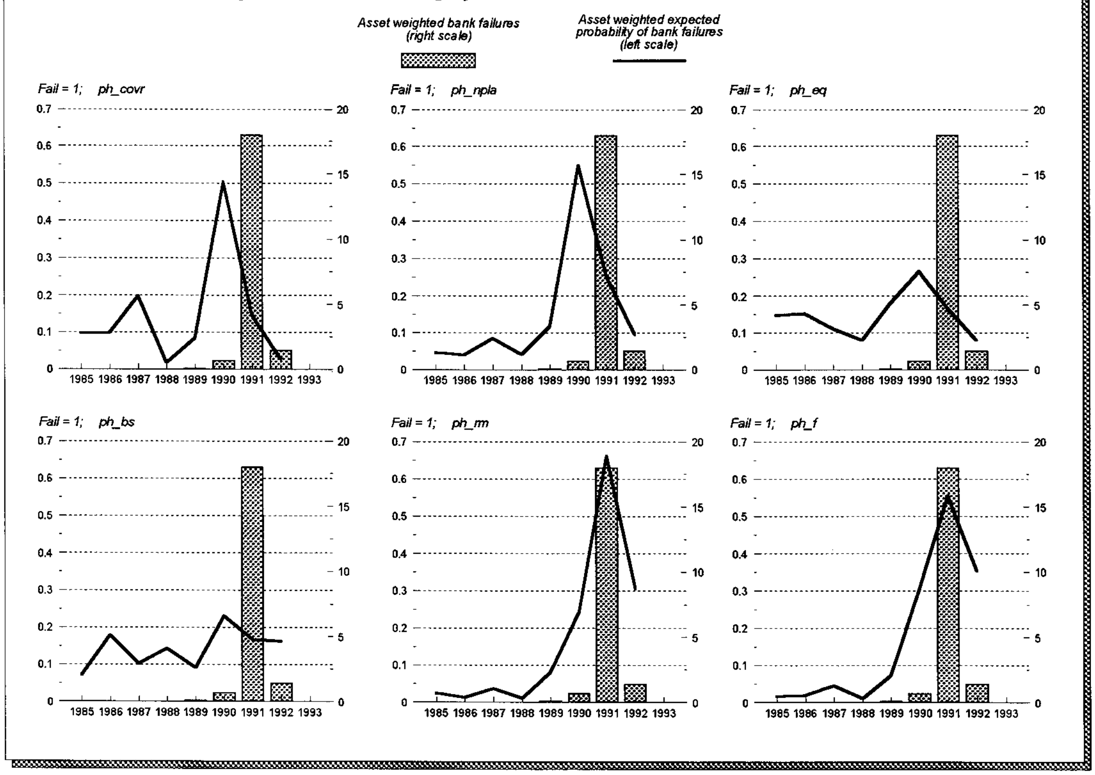


Figure 15.1 (concluded). U.S. Banking System Failures - Northeast

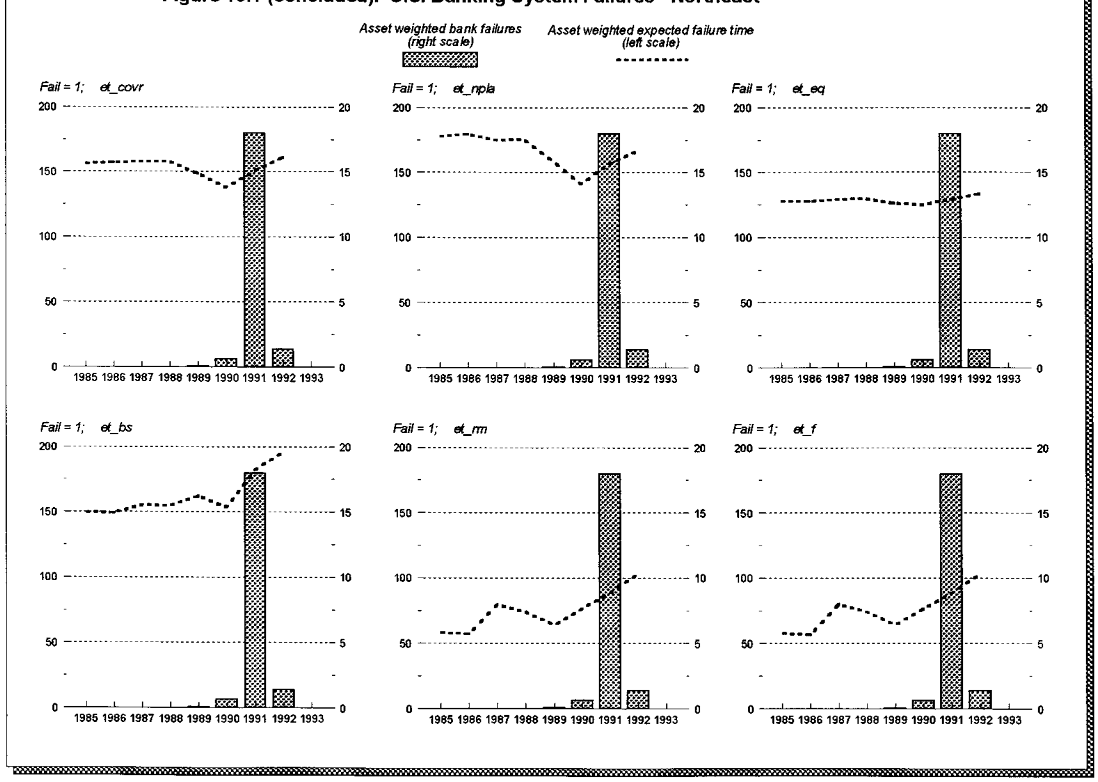


Figure 15.2. U.S. Banking System Distress - Northeast

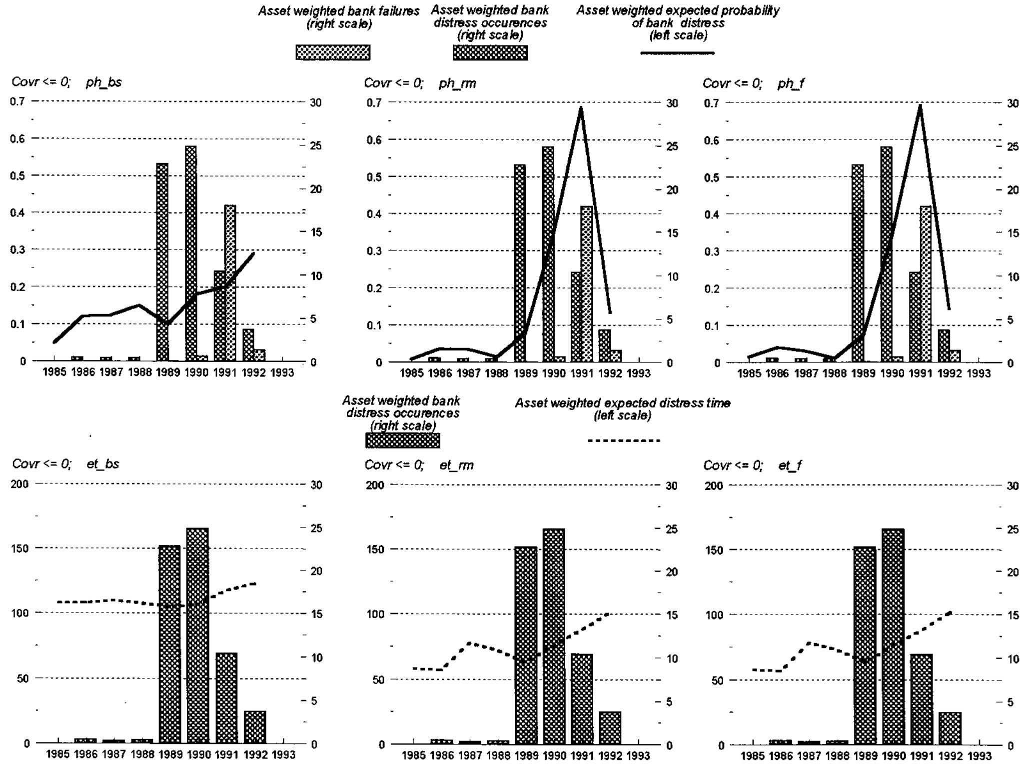


Figure 15.3. U.S. Banking System Failures - Northeast (CAMEL)

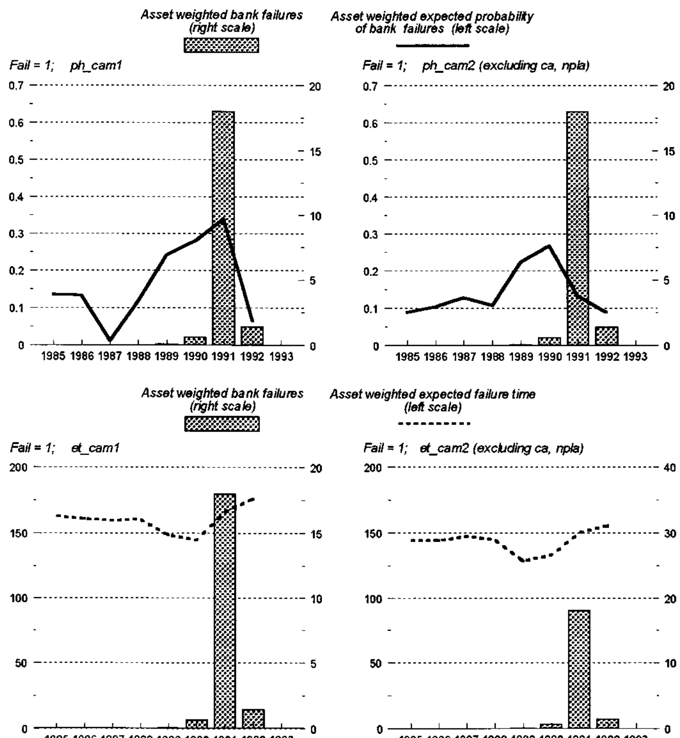


Figure 16.1. U.S. Banking System Failures - California

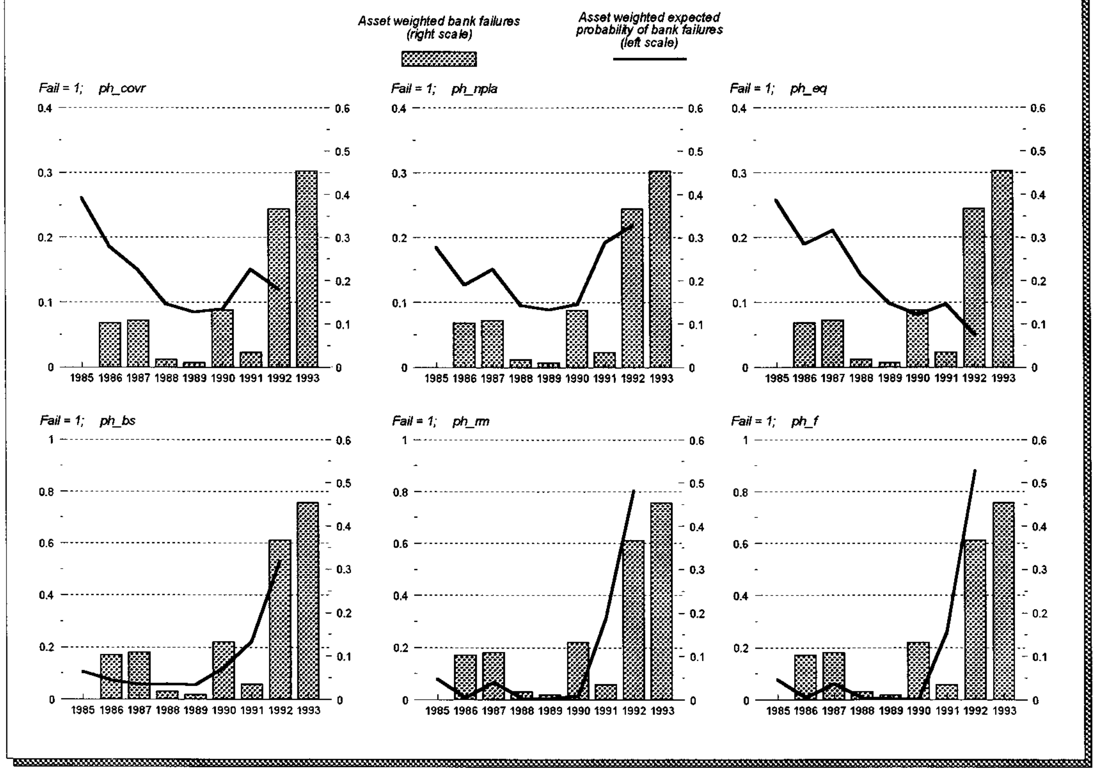


Figure 16.1 (concluded). U.S. Banking System Failures - California

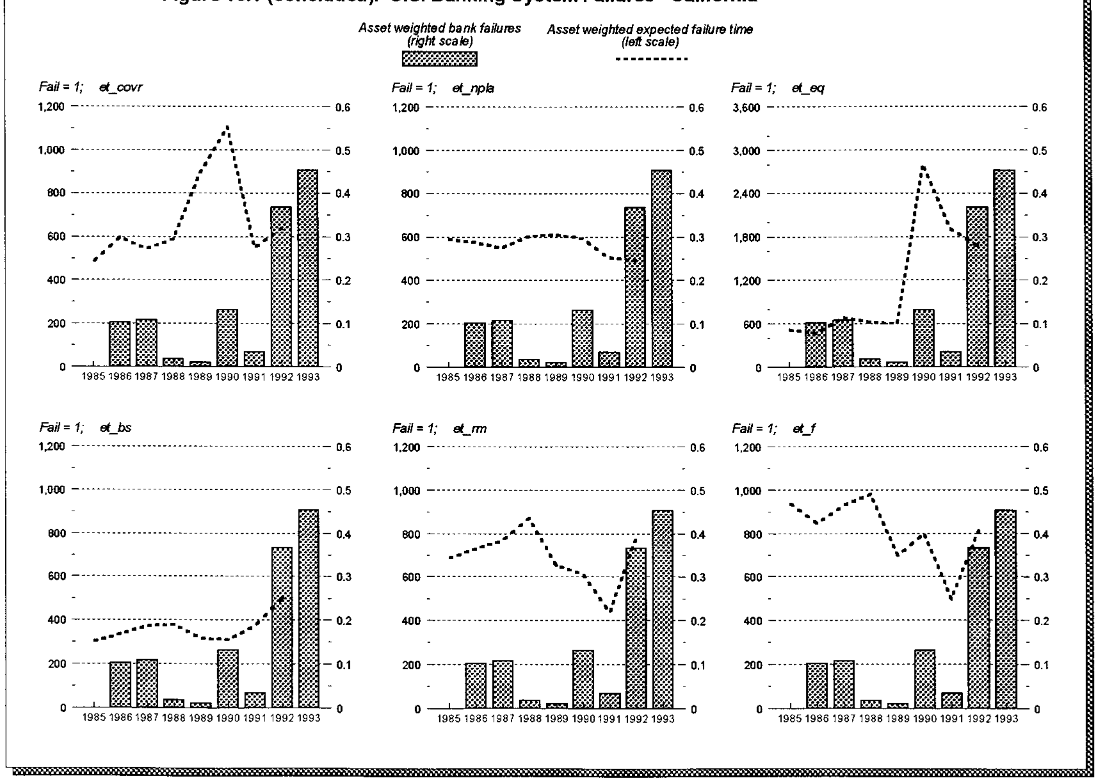


Figure 16.2. U.S. Banking System Distress - California

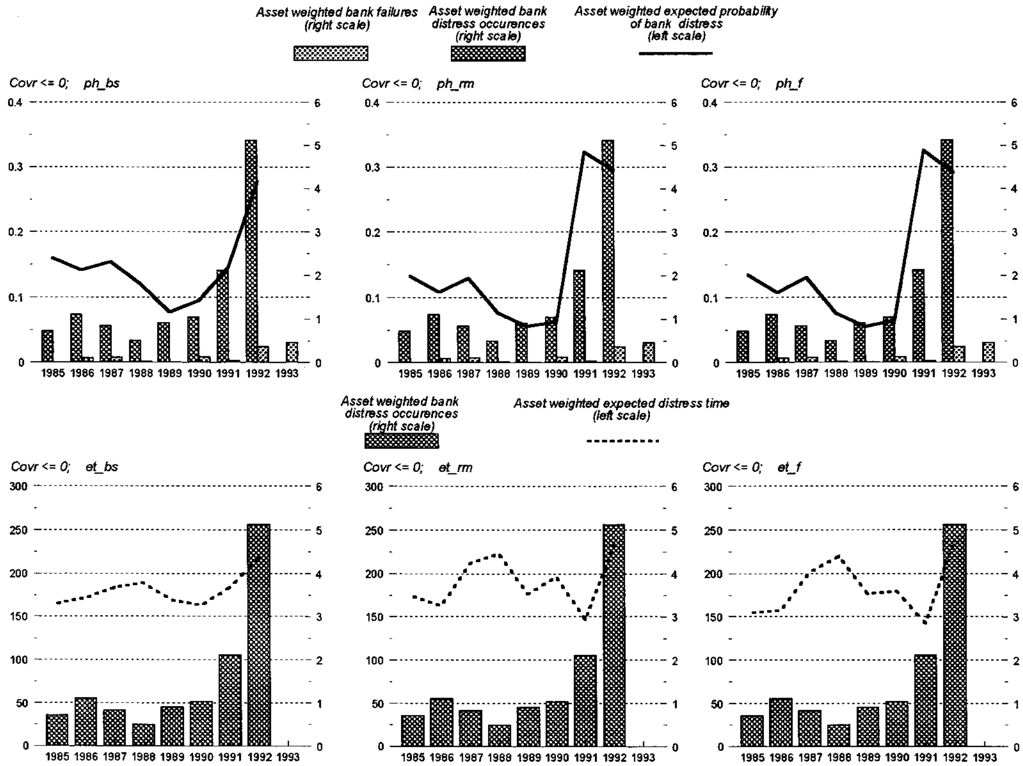
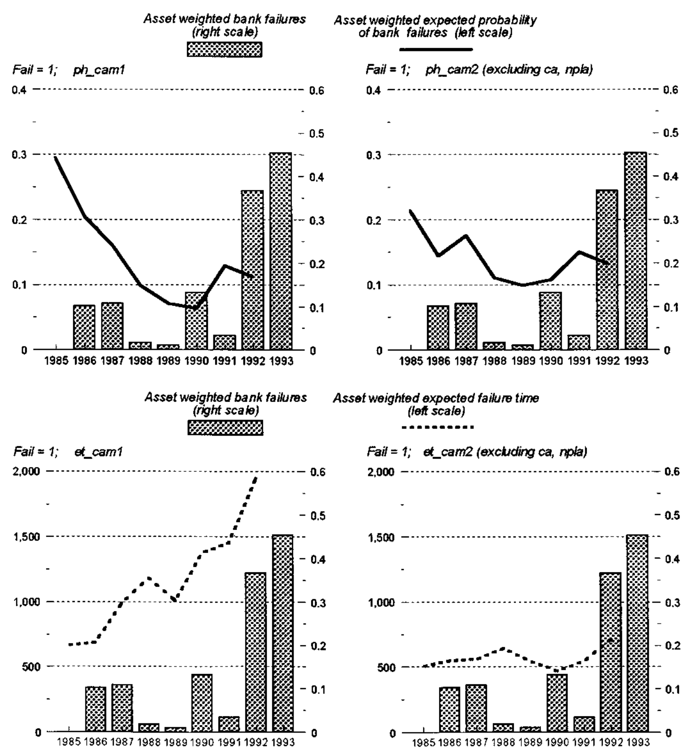


Figure 16.3. U.S. Banking System Failures - California (CAMEL)



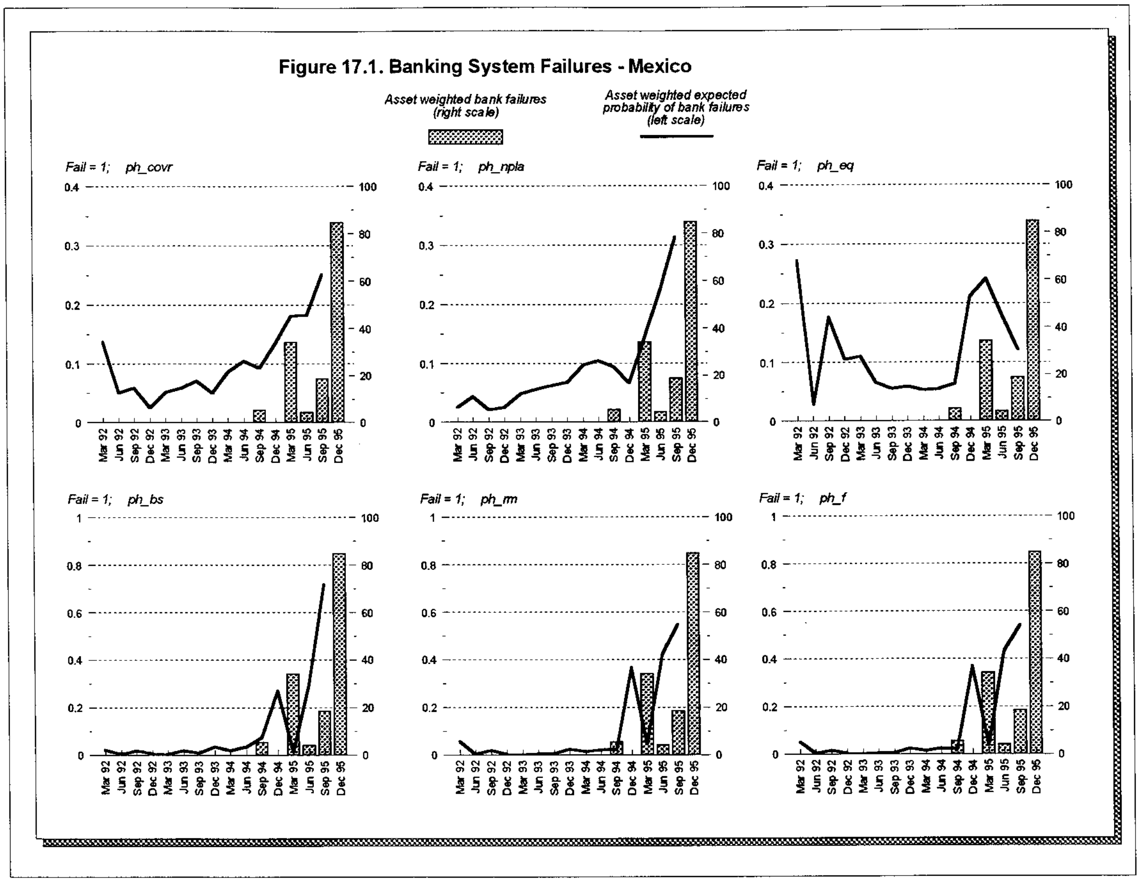


Figure 17.1. Banking System Failures - Mexico
Asset weighted bank failures (right scale)
Asset weighted expected probability of bank failures (left scale)
Fail = 1; ph_covr
Fail = 1; ph_npla
Fail = 1; ph_eq
Fail = 1; ph_bs
Fail = 1; ph_rm
Fail = 1; ph_f
Mar 92 Jun 92 Sep 92 Dec 92 Mar 93 Jun 93 Sep 93 Dec 93 Mar 94 Jun 94 Sep 94 Dec 94 Mar 95 Jun 95 Sep 95 Dec 95

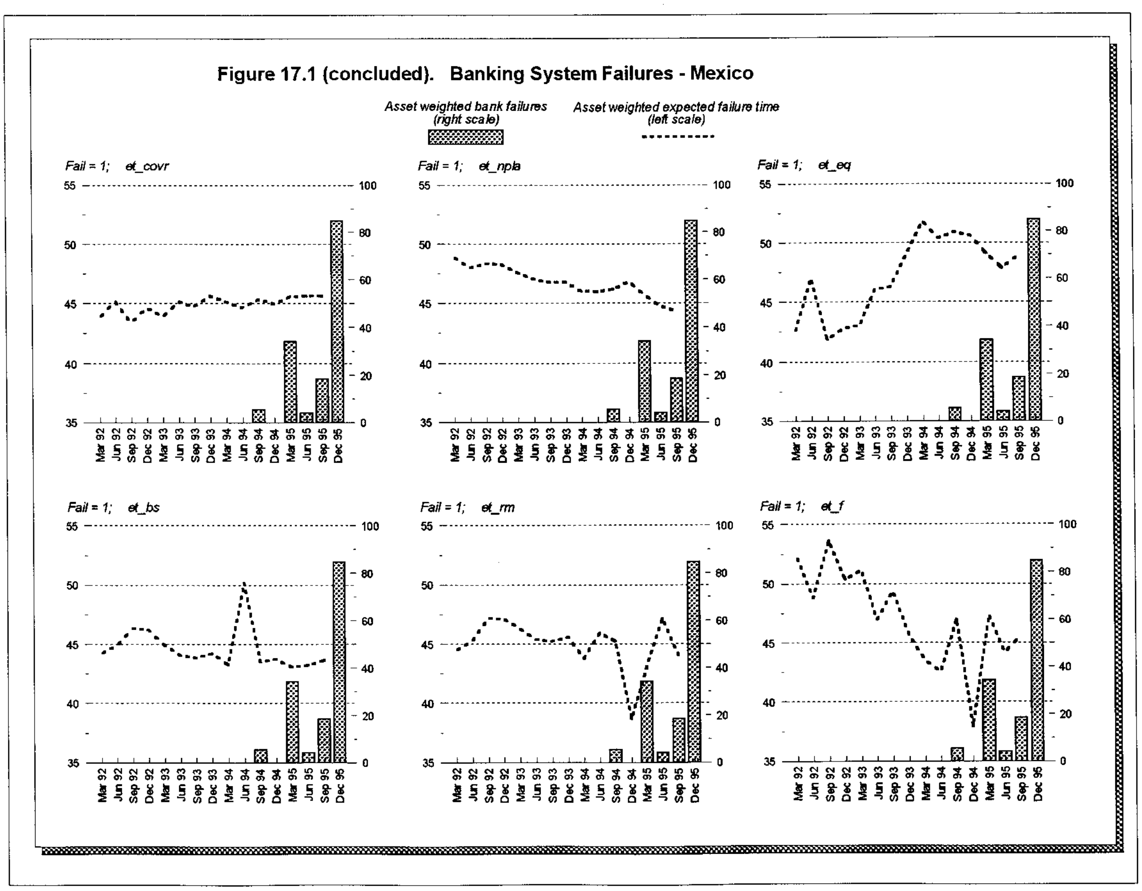


Figure 17.1 (concluded). Banking System Failures - Mexico
Asset weighted bank failures (right scale)
Asset weighted expected failure time (left scale)
Fail = 1; et_covr
Fail = 1; et_npla
Fail = 1; et_eq
Fail = 1; et_bs
Fail = 1; et_rm
Fail = 1; et_f
Mar 92 Jun 92 Sep 92 Dec 92 Mar 93 Jun 93 Sep 93 Dec 93 Mar 94 Jun 94 Sep 94 Dec 94 Mar 95 Jun 95 Sep 95 Dec 95

Figure 17.2. Banking System Distress - Mexico

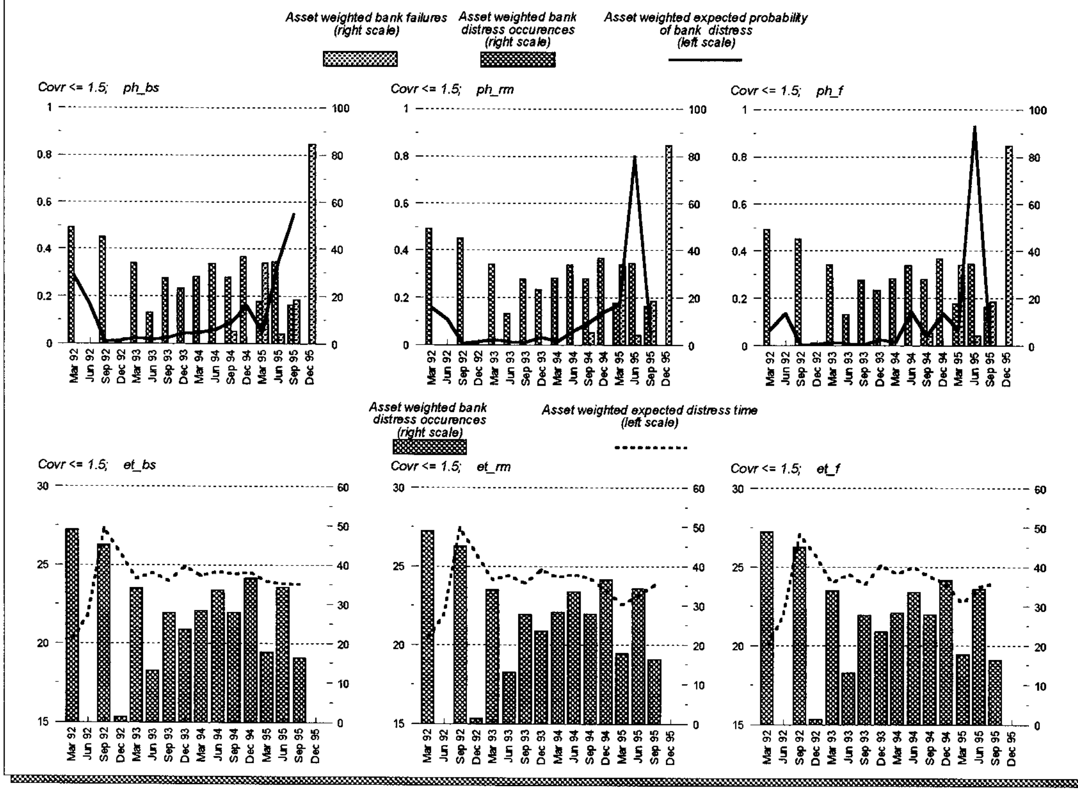
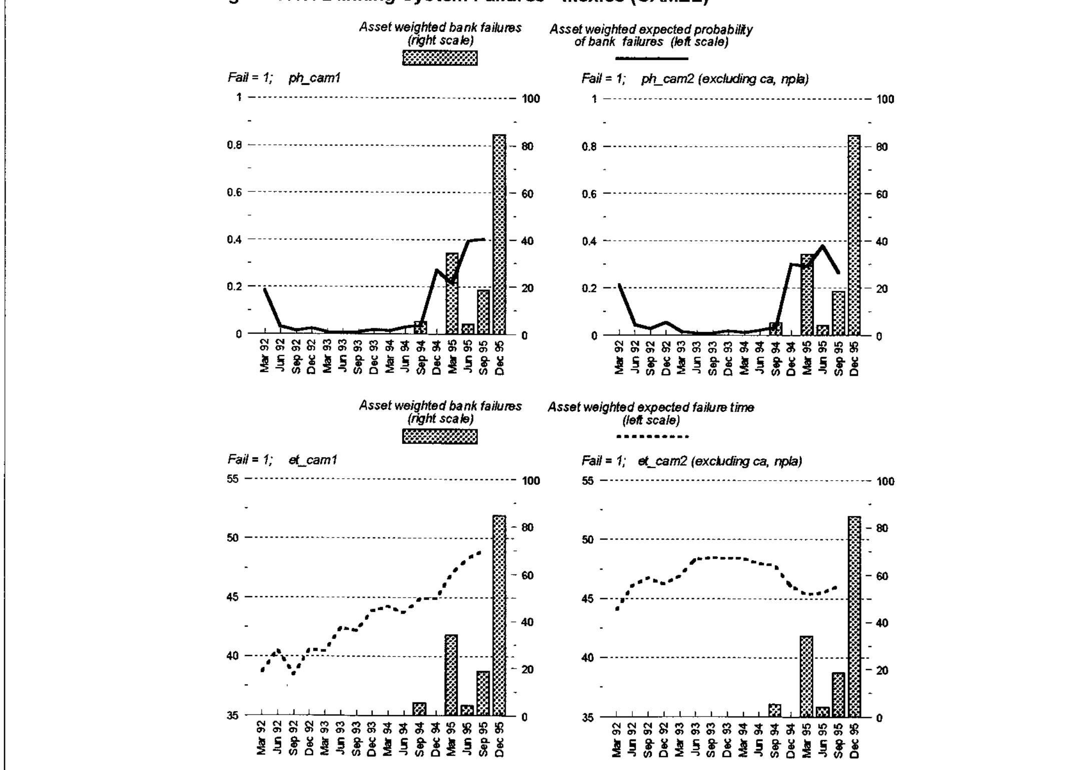


Figure 17.3. Banking System Failures - Mexico (CAMEL)



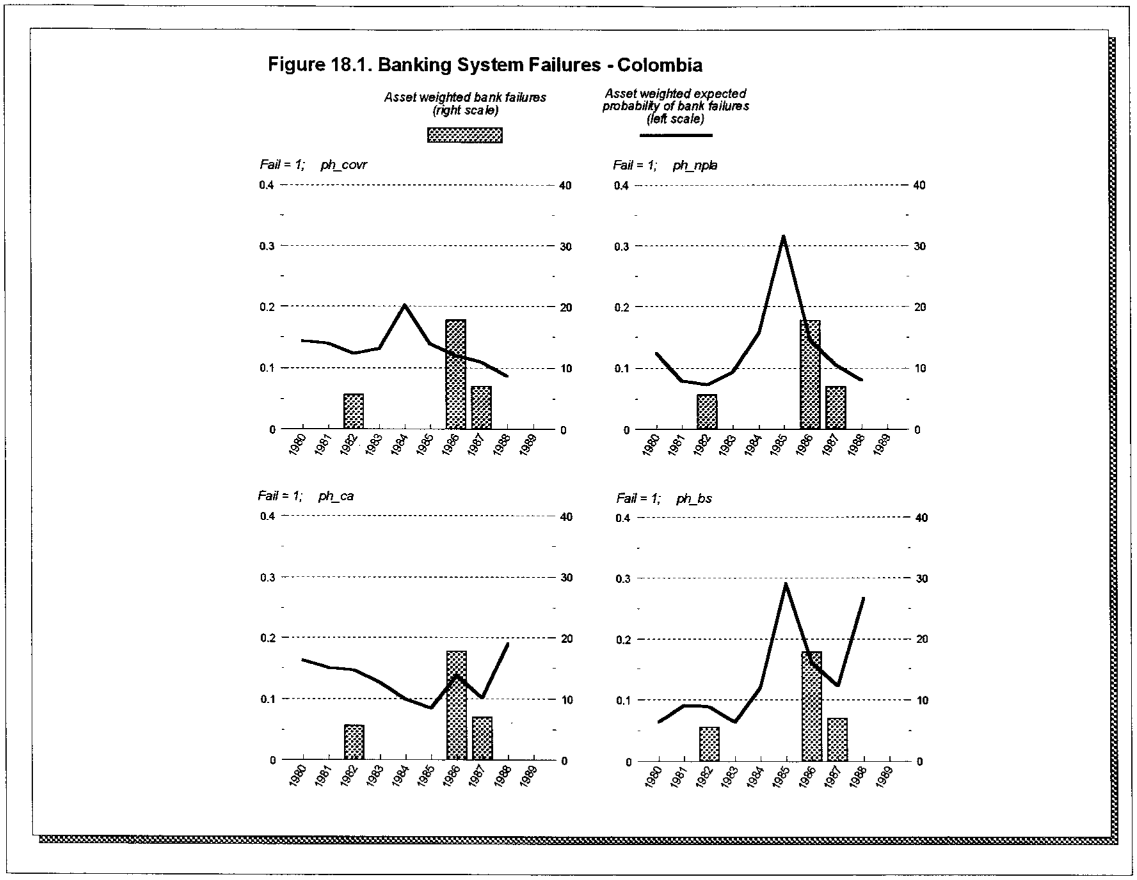


Figure 18.1. Banking System Failures - Colombia

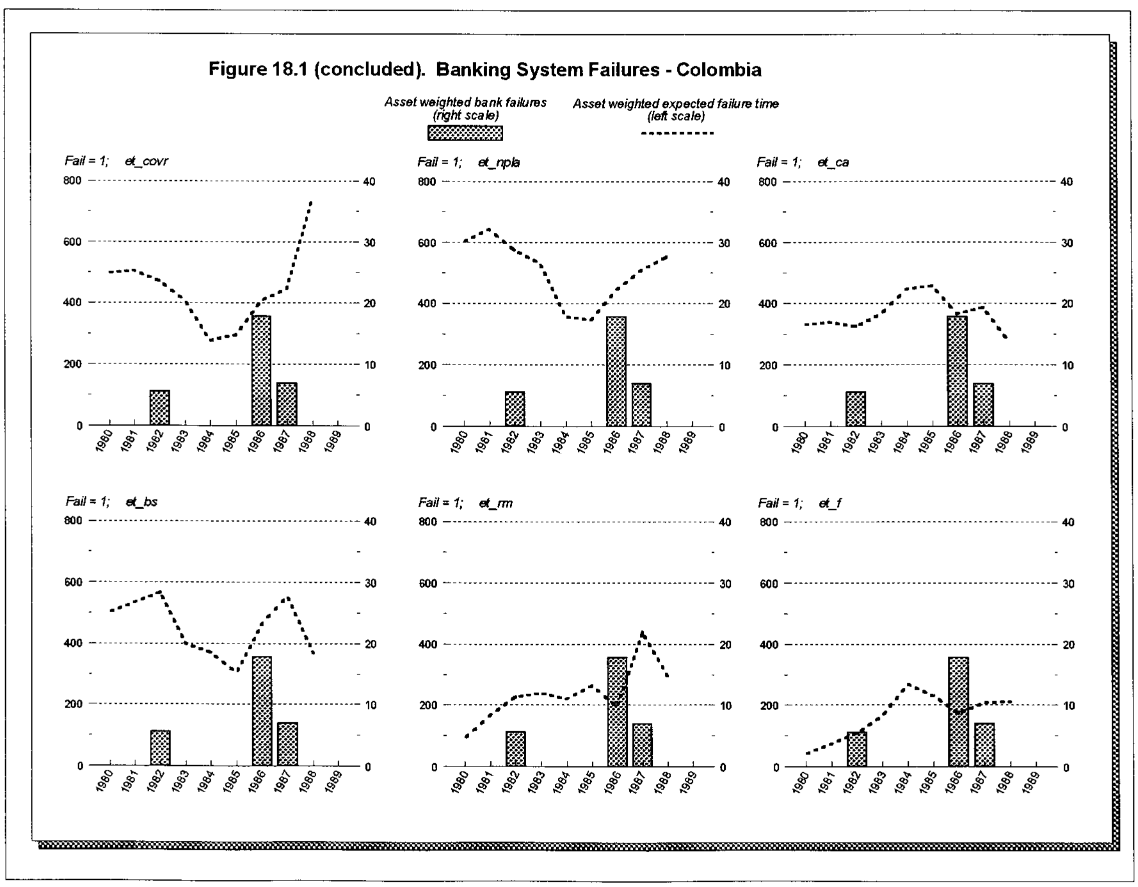


Figure 18.1 (concluded). Banking System Failures - Colombia

Figure 18.2. Banking System Distress - Colombia

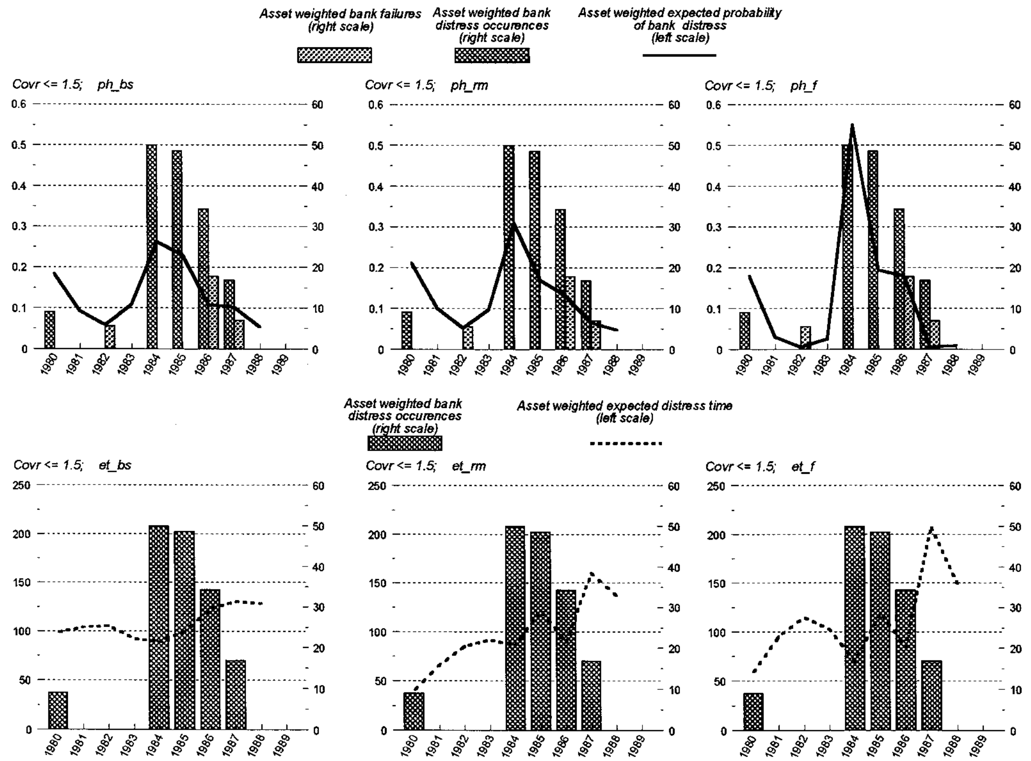
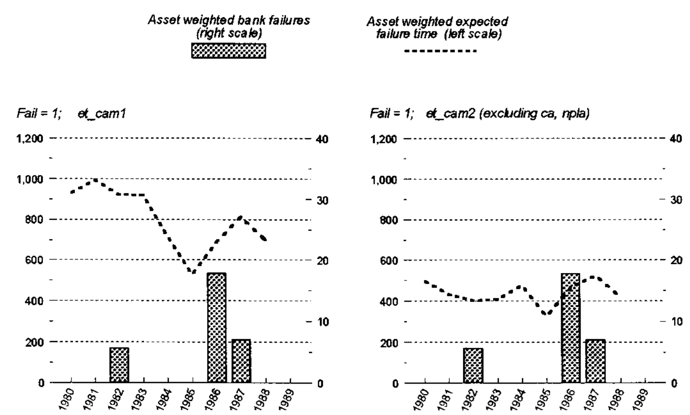


Figure 18.3. Banking System Failures - Colombia (CAMEL)



Selected Empirical Studies of U.S. Bank Failures

Authors	Variables	CAMEL Category 1/	Authors	Variables	CAMEL Category
Sinkey (1975)	• Loan Revenue/Total Revenue • Other Expenses/Total Revenue • Operating Expense/Operating Income • Loans/(Capital + Reserves) • Revenue from State and Local Obligations/Total Revenue • Loans/Assets	A M M C E A	Barth *et al.* (1985)	• Total Net Worth/total Assets • Not Income/Total Assets • Interest Sensitive Funds/Total Funds • Liquid Assets/Total Assets • Log of Total Assets	C E E L L
Altman (1977)	• Net Worth/Total Assets • Net Operating Income/Gross Operating Income • Real Estate Owned/Total Assets • Earned Surplus/Total Assets • Total Loans/Total Savings • FHLB Advances/Net Worth	C E A C A C	Benston (1985)	• Net Worth/Total Assets • Net Income/Total Assets • Change in Interest and Fee Income/Earning Assets • Change in Interest and Depositors' Dividends/Earning Assets	C E E E
Martin (1997)	• Gross Capital/Adjusted Risk Assets • Net Income/ (Total Assets-Cash Items in Process) • (Commercial and Industrial Loans + Loans to REIT's and Mortgage Bankers + Construction Loans + Commercial Real Estate Loans)/Total Assets • Gross Charge-offs/(Net Operating Income + Loss Provision)	C E A A	Gajewsky (1988)	• Regulator-Recognized Capital/Assets • Nonaccrual Loans/Total Assets • Loans Past-Due 90 days or more (still accruing interest)/Total Assets • Net Loans/Total Assets • Sensitive Deposits/Total Deposits • Agricultural Loans/Total Loans • Commercial and Industrial Loans/Total Loans • Net Income/Total Assets • Corporate Structure • County-Level Oil and Gas Earnings/Total County Earnings (1982)	C A A M M M M E M Regional/ Macro.
Avery and Hanweek (1984)	• Log of Total Bank Assets Less Loan Reserves (TA) • Net Loans /Total Assets • (Equity Capital + Loan Loss Reserve Allowances)/TA • Commercial and Industrial Loans/Net Loans • Net After-Tax Income/TA • Herfindahl Index for Bank's Local Banking Marker • Semiannual Percentage Change in Total Deposits within each Bank's Local Banking Market	C A C A E E E			

Selected Empirical Studies of U.S. Bank Failures (Concluded)

Authors	Variables	CAMEL Category 1/	Authors	Variables	CAMEL Category
Thomson (1991)	• Book equity capital plus the reserve for loan and lease losses minus the sum of loans 90 days past due but still accruing and nonaccruing loans/total assets • Net chargeoffs/total loans • Loan portfolio Herfindahl index constructed from: real estate loans, loans to depository institutions, loans to individuals, commercial and industrial loans, foreign loans and agricultural loans • Net loans and leases/total assets • Nondeposit liabilities/cash and investment securities • Overhead/total assets • Net income after taxes/total assets • Loans to insiders/total assets • Log of average deposits per banking office • Output Herfindahl Index constructed using state-level gross domestic output • Unemployment rate in the county where the bank is headquartered • Percent change in state-level personal income • State-level small-business failure rate	C A A M L M E A L Regional/ Macro	Cole and Gunther (1997)	• Equity capital • Past due loans • Nonaccrual loans • Other real estate owned • Net income • Investment securities • Large certificates of deposit	C A A A E L L
Lane *et al* (1986)	• Log capital/total assets • Log total loans/total capital • Log fed. funds sold + securities purchased/total assets • Net loan recoveries/total loans • Log provision for loan losses/total operating expense • Log gross loan charge-offs/net income + provision of loan losses • Log commercial and industrial loans/total loans • Real estate loans/total loans • Loan revenue/net loans • Total operating income/total assets • Interest on deposit/total time and savings deposits • Income taxes/earnings before taxes and security transactions • Log total operating expense/total operating income • Net income/total assets • Net income/total capital • Net income/gross operating income • Total loans/total deposits • Total loans/total assets • Log cash and U.S. securities/total assets • Log municipal securities/total assets • Log fed. funds purchased + securities sold/total assets	C C C A A A A A M M M E E E E E L L L L L	Whalen (1991)	• Total loans/total assets • Commercial and industrial loans/total assets • Commercial real estate loans/total assets • Large domestic time deposits/total assets • Net income/average total assets • Operating expenses/average total assets • Primary capital/average total assets (PCR) • PCR less total nonperforming loans/average total assets • Total net chargeoffs/average net loans plus leases • Total nonperforming loans/total loans plus leases • Percent change in state's resident housing permits	M A A L E M C C A A Regional/ Macro.

Sources: Demirgüç-Kunt's (1989) survey; and Thomson (1991), Cole and Gunther (1997), Lane *et al* (1986), Whalen (1991).
1/ CAMEL: C = Capital A =Asset quality: M = Management: E = Earnings; L = Liquidity

Summary Statistics of Failed Banks vs. Non-Failed Banks

Table 9. U.S. Commercial Banks—Southwest (December 1985–December 1992)

Censored Banks			Uncensored Banks (Failed)		
Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.
NPLA	2.731	2.736	NPLA	6.925	6.241
NPLLRA	1.744	2.412	NPLLRA	5.026	5.382
NPLL	5.723	5.476	NPLL	11.390	10.550
CA	9.485	4.036	CA	6.694	4.811
EQ	8.497	4.156	EQ	4.795	5.713
COVR	6.753	5.317	COVR	-0.230	9.340
LCI	11.202	8.001	LCI	18.886	10.074
LCOMRE	10.116	7.164	LCOMRE	14.749	8.612
LRESI	9.221	6.763	LRESI	10.312	6.663
LAGR	4.471	7.531	LAGR	2.581	6.161
LCON	11.154	7.701	LCON	13.679	9.069
LAS	46.884	15.159	LAS	61.836	13.094
LNYIELD	11.285	1.639	LNYIELD	11.190	1.533
INTDEP	5.457	24.212	INTDEP	6.078	1.170
INTSPR	5.826	24.204	INTSPR	5.111	1.661
DEPLGE	15.749	9.751	DEPLGE	23.454	12.091
DEPIB	4.961	8.879	DEPIB	7.370	10.311
SEC	29.911	17.520	SEC	13.098	9.833
INTAS	8.626	1.463	INTAS	9.208	1.519
INSL	0.855	1.570	INSL	1.468	2.451
NI	0.424	2.549	NI	-2.272	5.273
ROE	3.827	41.505	ROE	49.831	4,803.979
EXPW	1.713	0.640	EXPW	1.893	1.250
EXPP	0.559	0.363	EXPP	0.772	0.505
SIZE	10.658	1.008	SIZE	10.728	1.193

Notes: The variables are defined in Table 2.

Summary Statistics of Failed Banks vs. Non-Failed Banks

Table 10. U.S. Commercial Banks—Northeast (December 1985–December 1992)

Censored Banks			Uncensored Banks (Failed)		
Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.
NPLA	2.075	2.699	NPLA	4.635	6.137
NPLLRA	1.088	2.209	NPLLRA	3.096	5.040
NPLL	3.063	4.092	NPLL	6.128	8.012
CA	9.865	11.011	CA	10.511	12.477
EQ	8.877	11.162	EQ	8.972	13.064
COVR	7.789	11.615	COVR	5.876	15.415
LCI	14.739	10.015	LCI	21.814	13.489
LCOMRE	16.420	10.191	LCOMRE	22.988	14.119
LRESI	22.040	13.220	LRESI	17.703	12.385
LAGR	0.048	0.366	LAGR	0.006	0.037
LCON	10.579	10.827	LCON	8.106	6.901
LAS	65.855	15.895	LAS	72.755	15.729
LNYIELD	10.809	1.863	LNYIELD	10.818	2.529
INTDEP	13.414	270.558	INTDEP	6.480	9.343
INTSPR	-2.590	270.646	INTSPR	4.352	9.633
DEPLGE	9.081	8.853	DEPLGE	15.374	9.836
DEPIB	5.362	10.711	DEPIB	5.117	10.021
SEC	16.684	10.877	SEC	10.446	12.050
INTAS	10.037	53.253	INTAS	8.800	2.284
INSL	0.617	1.453	INSL	1.098	2.170
NI	0.409	1.777	NI	-1.086	3.950
ROE	5.647	25.839	ROE	-38.118	175.127
EXPW	2.116	3.494	EXPW	1.934	2.008
EXPP	0.659	0.742	EXPP	0.670	0.436
SIZE	11.890	1.464	SIZE	11.620	1.553

Notes: The variables are defined in Table 2.

Summary Statistics of Failed Banks vs. Non-Failed Banks

Table 11. U.S. Commercial Banks—California (December 1985–December 1992)

Censored Banks			Uncensored Banks (Failed)		
Variable	**Mean**	**Std. Dev.**	**Variable**	**Means**	**Std. Dev.**
NPLA	2.186	2.775	NPLA	5.559	6.187
NPLLRA	1.159	2.522	NPLLRA	4.126	5.892
NPLL	3.323	4.743	NPLL	7.980	8.508
CA	10.160	6.367	CA	7.782	5.327
EQ	9.134	6.407	EQ	6.349	5.481
COVR	7.974	7.113	COVR	2.222	8.931
LCI	18.628	11.952	LCI	20.631	13.169
LCOMRE	20.437	13.101	LCOMRE	21.449	15.153
LRESI	12.272	11.517	LRESI	11.998	11.517
LAGR	0.601	2.343	LAGR	0.107	0.712
LCON	11.446	14.791	LCON	13.463	16.810
LAS	65.515	14.058	LAS	69.050	13.454
LNYIELD	12.112	2.211	LNYIELD	13.058	2.581
INTDEP	51.320	1748.899	INTDEP	5.448	1.914
INTSPR	-39.207	1748.977	INTSPR	7.610	2.661
DEPLGE	15.602	9.853	DEPLGE	19.466	11.381
DEPIB	4.945	8.608	DEPIB	4.804	7.343
SEC	11.670	10.819	SEC	6.246	6.583
INTAS	9.307	2.739	INTAS	10.551	2.728
INSL	0.521	1.272	INSL	0.721	1.319
NI	0.383	1.813	NI	-1.113	3.105
ROE	5.590	21.295	ROE	-36.469	178.551
EXPW	2.551	1.267	EXPW	3.059	1.324
EXPP		0.476	EXPP	1.103	0.549
SIZE		1.345	SIZE	10.995	0.994

Notes: The variables are defined in Table 2.

Summary Statistics of Failed Banks vs. Non-Failed Banks

Table 12. Mexican Banks (March 1992–September 1995)

Censored Banks			Uncensored Banks (Failed)		
Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.
NPLA	2.837	4.144	NPLA	5.435	2.150
NPLLRA	1.412	2.857	NPLLRA	3.346	1.917
NPLL	2.572	3.212	NPLL	7.601	2.757
CA	31.005	26.554	CA	7.335	1.857
EQ	29.580	27.402	EQ	5.246	1.302
RISKCA	39.094	45.381	RISKCA	8.847	1.524
COVR	28.168	28.210	COVR	1.900	2.066
LRESI	1.669	2.441	LRESI	12.322	7.744
LNONSEC	71.875	24.623	LNONSEC	53.216	9.904
LAGR	0.953	1.832	LAGR	3.507	7.827
LAS	77.376	54.457	LAS	71.712	11.148
DEPPUB	45.831	23.284	DEPPUB	56.300	8.521
DEPIB	7.982	12.908	DEPIB	8.723	5.096
SEC	1.467	2.153	SEC	2.797	1.986
INTAS	8.980	7.694	INTAS	8.898	4.505
PROFMARG	15.575	18.914	PROFMARG	4.771	2.853
SIZE	0.542	0.760	SIZE	5.967	5.960

Notes: RISCKA represents the risk-weighted capital-to-assets ratio reported by the Comisión Nacional Bancaria y de Valores. The other variables are defined in Table 2.

Summary Statistics of Failed Banks vs. Non-Failed Banks

Table 13. Colombian Banks (December 1980–December 1988)

Censored Banks			Uncensored Banks (Failed)		
Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.
NPLA	3.116	2.776	NPLA	7.299	8.374
NPLLRA	2.406	2.341	NPLLRA	4.843	4.343
NPLL	6.724	5.641	NPLL	18.128	21.978
EQ	9.266	2.377	EQ	8.898	2.944
CA	9.977	2.487	CA	11.496	6.371
COVR	6.860	3.726	COVR	4.197	5.623
LAS	45.489	6.645	LAS	41.040	3.477
LNYIELD	25.870	8.905	LNYIELD	25.277	9.918
INTSPR	15.176	5.884	INTSPR	15.165	5.816
DEPPUB	35.690	15.472	DEPPUB	37.126	7.030
DEPIB	11.054	5.479	DEPIB	14.051	8.494
SEC	18.759	7.135	SEC	21.523	6.190
INTDEP	10.693	5.142	INTDEP	10.112	5.106
INTAS	13.554	4.699	INTAS	12.319	4.537
NI	19.341	8.540	NI	21.591	10.615
ROE	225.166	118.957	ROE	214.514	98.296
EXPW	2.922	1.124	EXPW	3.063	1.986
SIZE	17.457	1.109	SIZE	17.138	1.316

Notes: The variables are defined in Table 2.

Figure 19. U.S. Failed Banks vs. Non-Failed Banks - Southwest

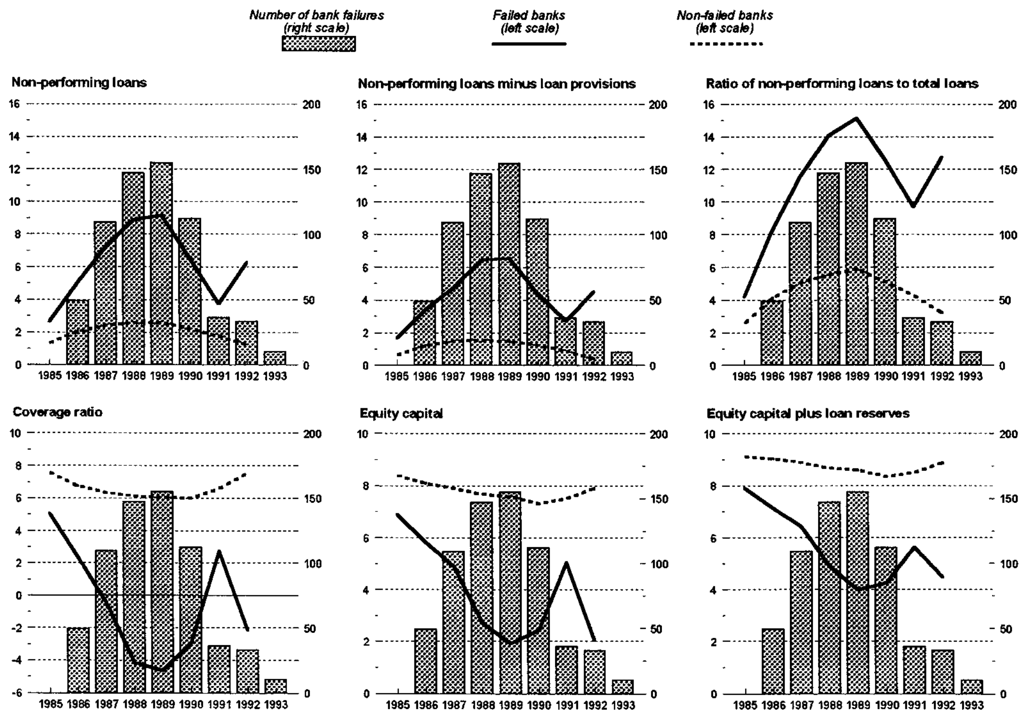


Figure 19 (continued). U.S. Failed Banks vs. Non-Failed Banks - Southwest

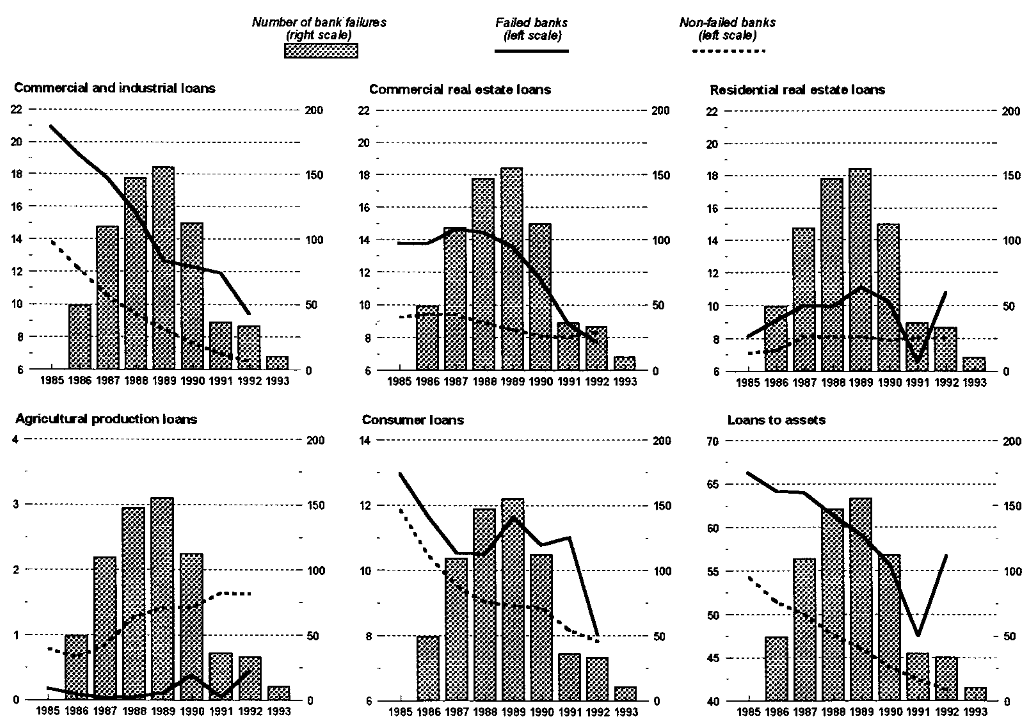


Figure 19 (continued). U.S. Failed Banks vs. Non-Failed Banks - Southwest

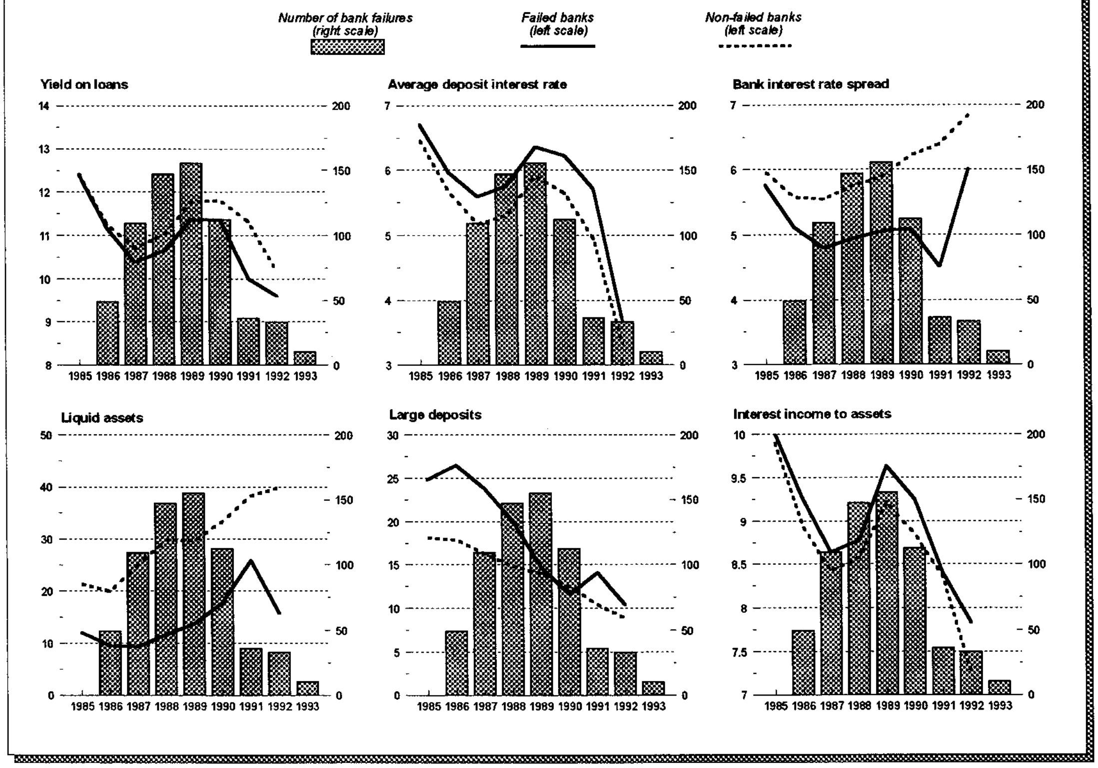


Figure 19 (concluded). U.S. Failed Banks vs. Non-Failed Banks - Southwest

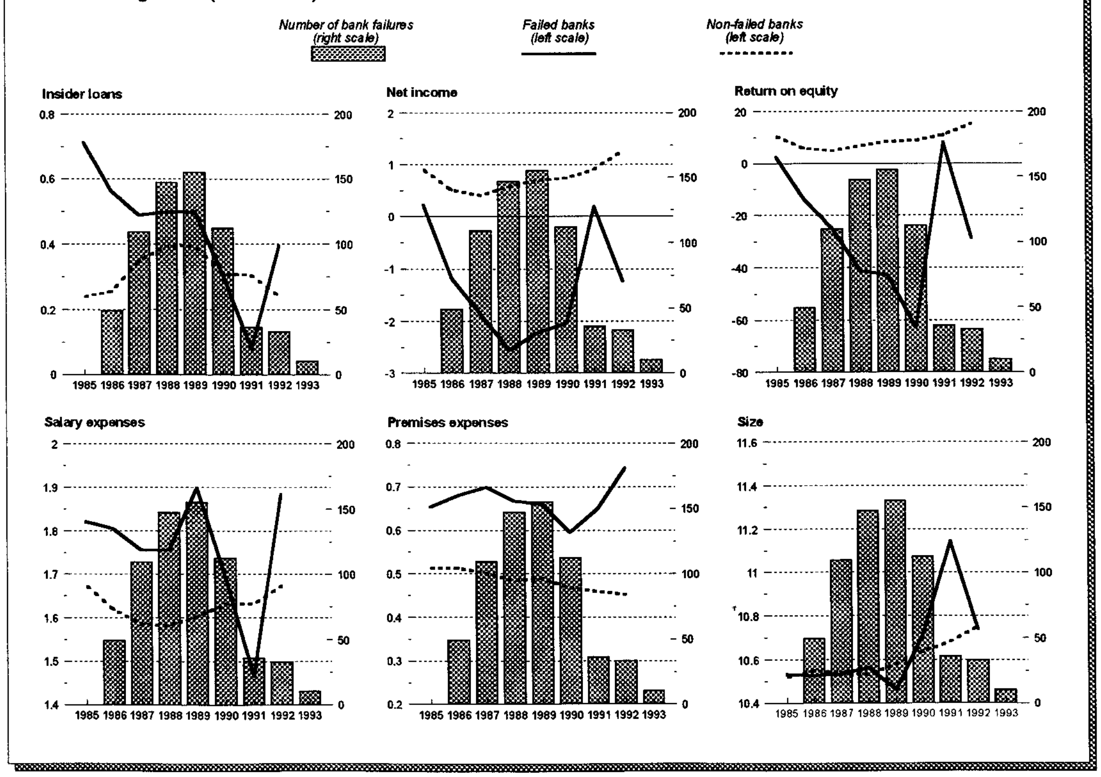


Figure 20. U.S. Distressed Banks vs. Non-Distressed Banks - Southwest

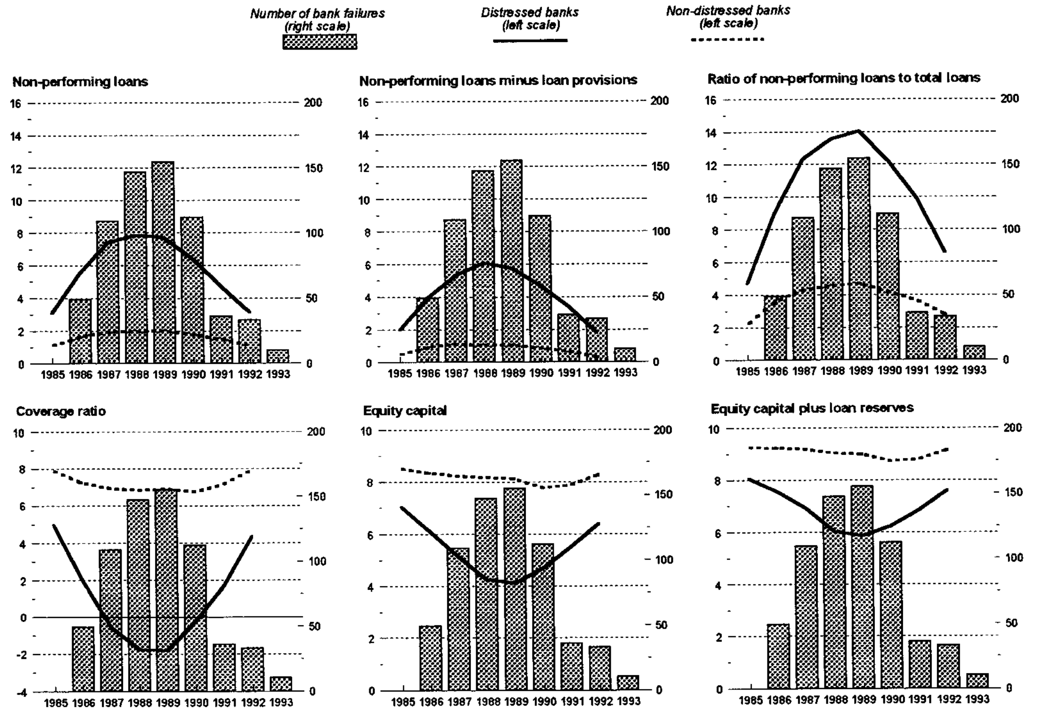


Figure 20 (continued). U.S. Distressed Banks vs. Non-Distressed Banks - Southwest

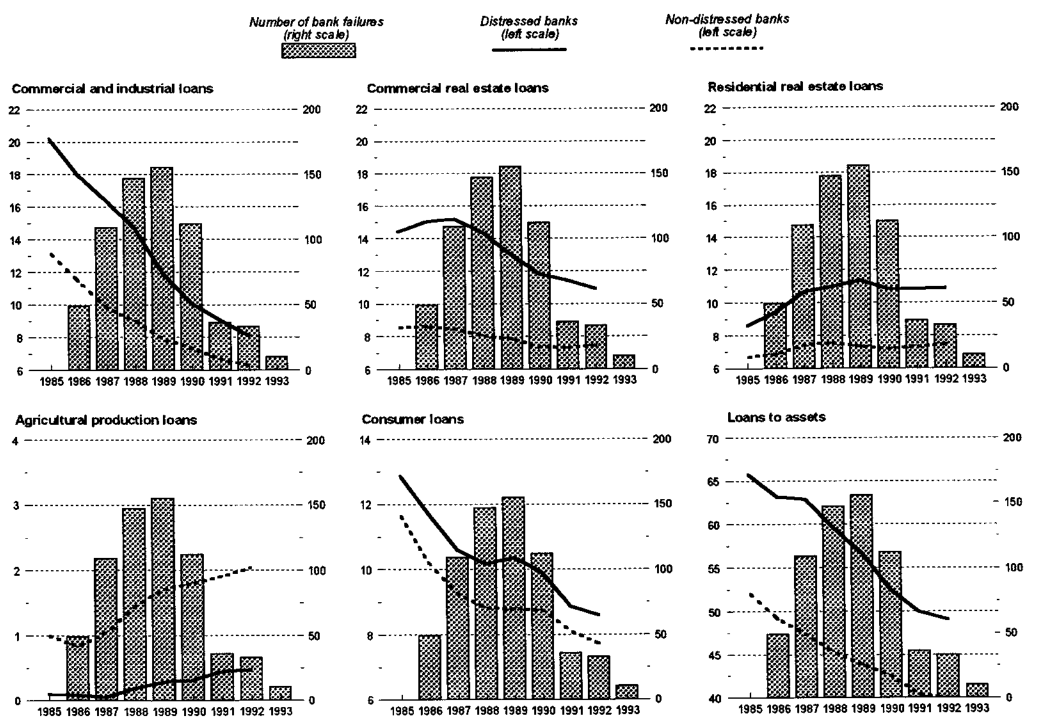


Figure 20 (continued). U.S. Distressed Banks vs. Non-Distressed Banks - Southwest

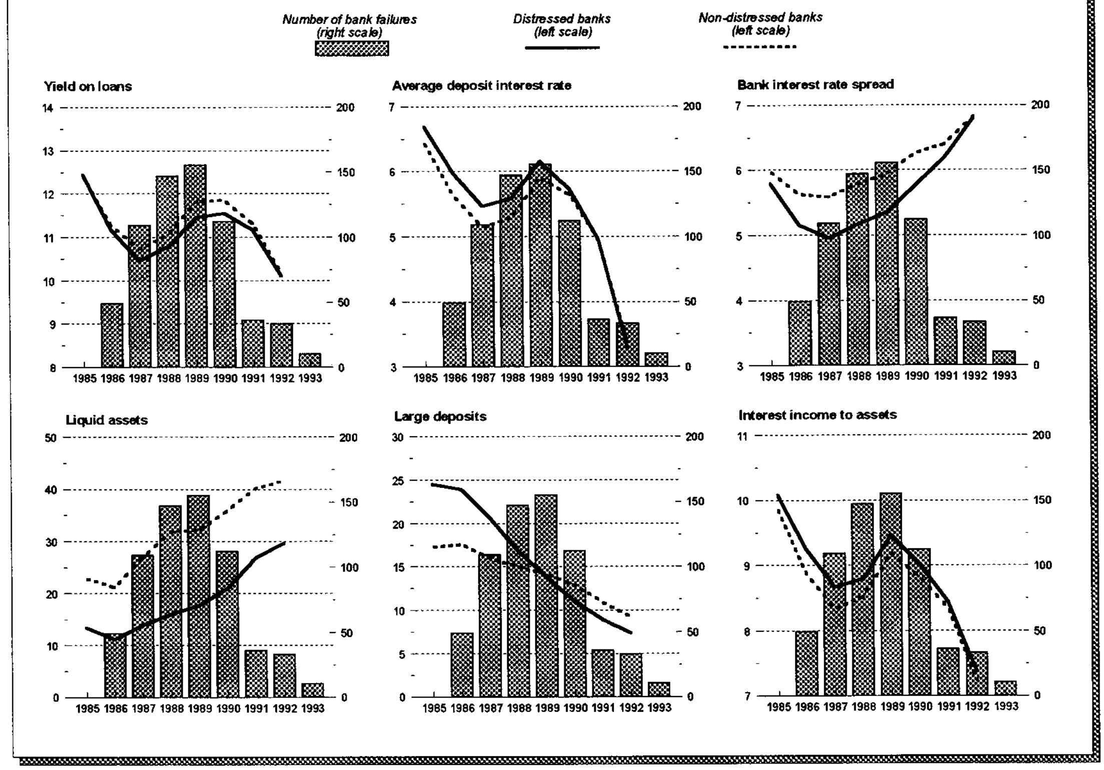


Figure 20 (concluded). U.S. Distressed Banks vs. Non-Distressed Banks - Southwest

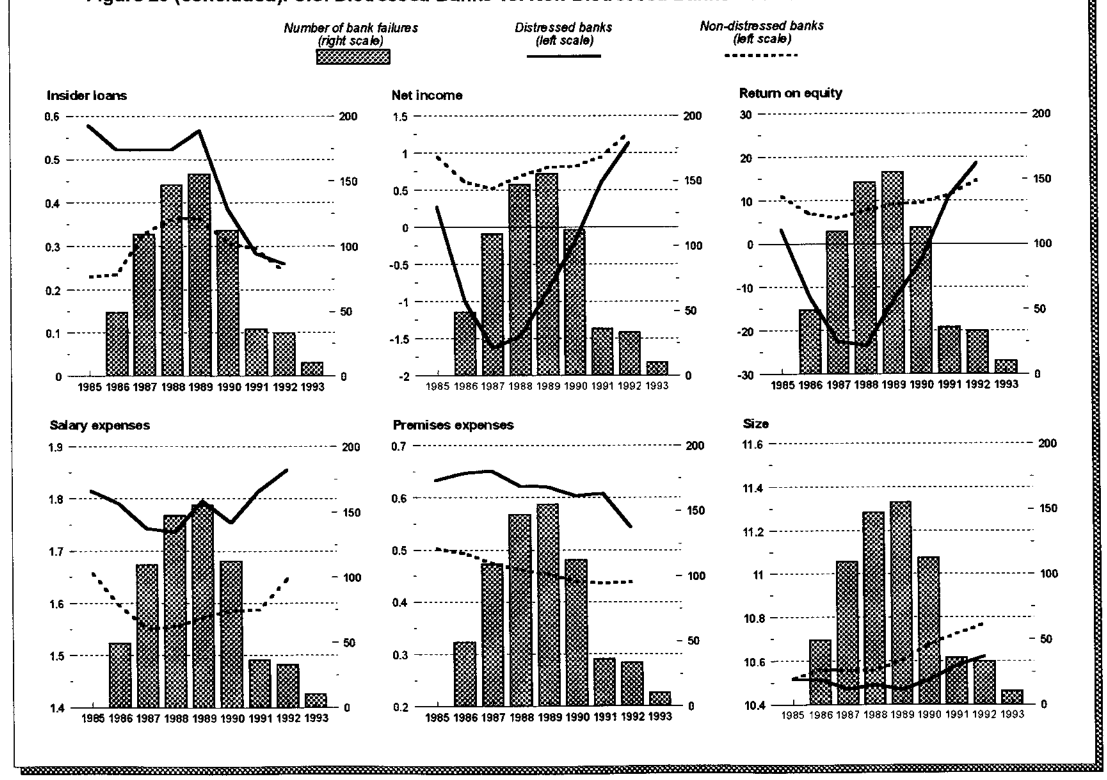


Figure 21. U.S. Failed Banks vs. Non-Failed Banks - Northeast

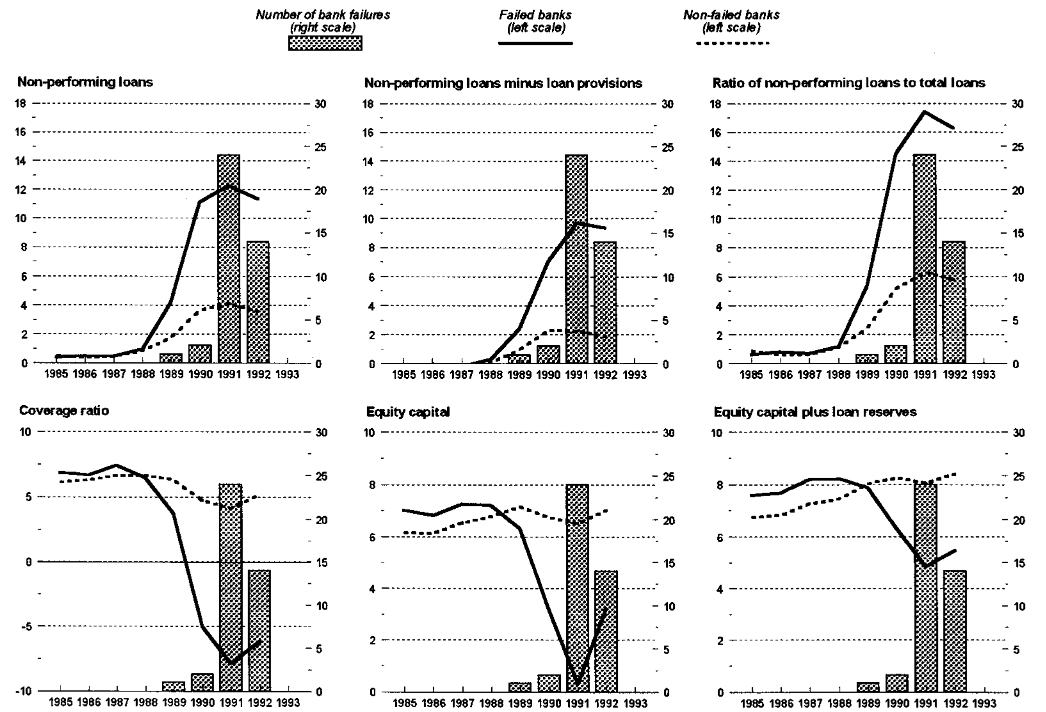
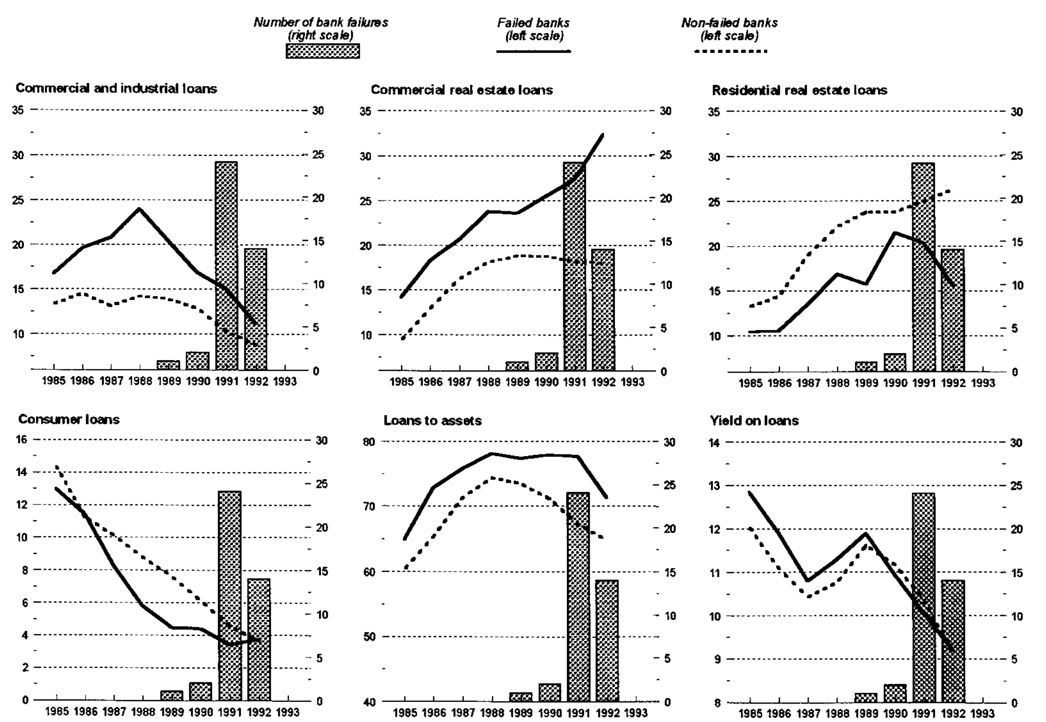


Figure 21 (continued). U.S. Failed Banks vs. Non-Failed Banks - Northeast



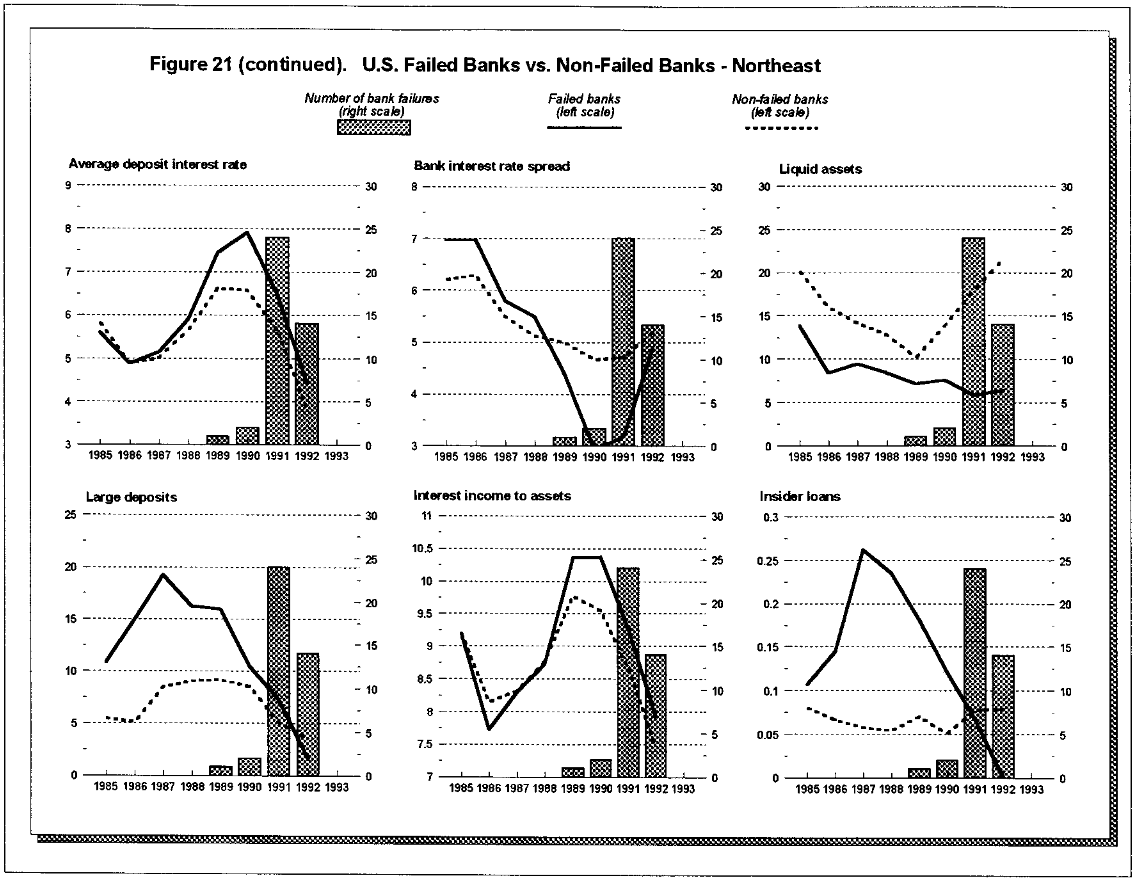


Figure 21 (continued). U.S. Failed Banks vs. Non-Failed Banks - Northeast
Number of bank failures (right scale)
Failed banks (left scale)
Non-failed banks (left scale)
Average deposit interest rate
Bank interest rate spread
Liquid assets
Large deposits
Interest income to assets
Insider loans
1985 1986 1987 1988 1989 1990 1991 1992 1993

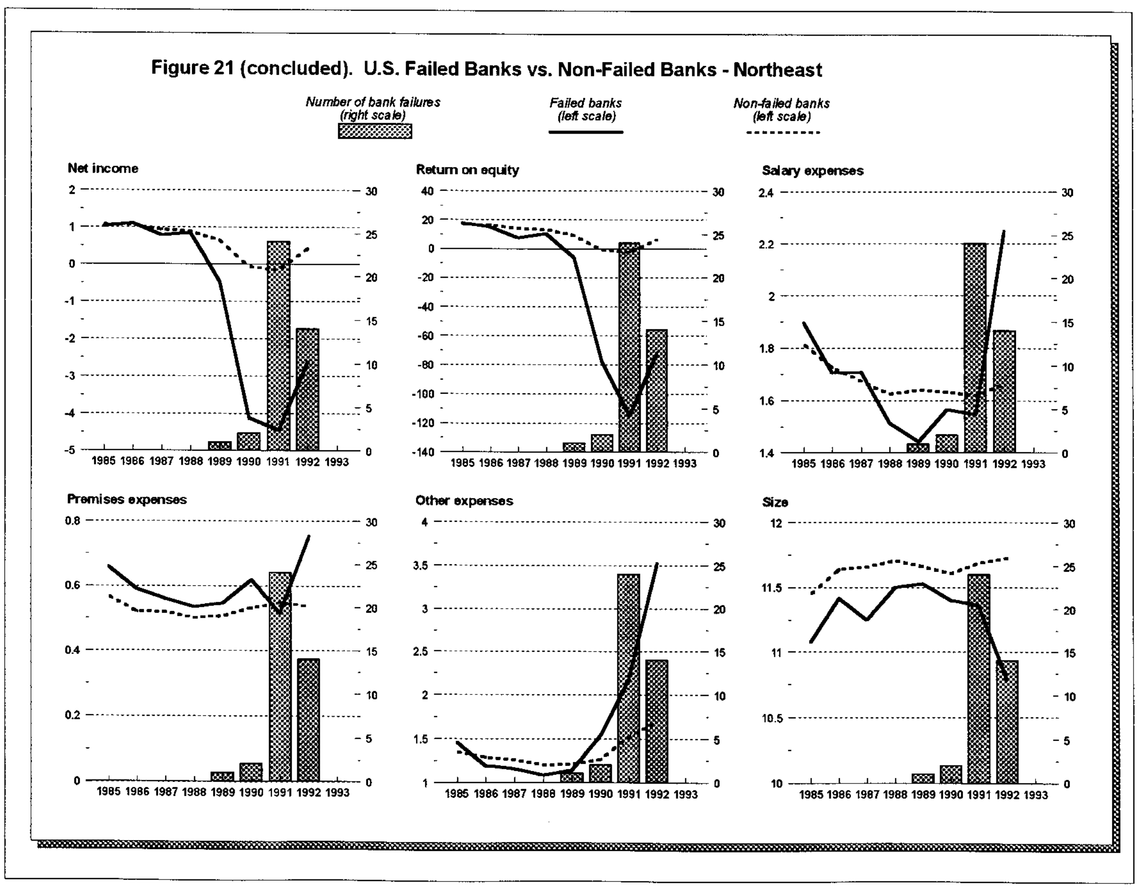


Figure 21 (concluded). U.S. Failed Banks vs. Non-Failed Banks - Northeast
Number of bank failures (right scale)
Failed banks (left scale)
Non-failed banks (left scale)
Net income
Return on equity
Salary expenses
Premises expenses
Other expenses
Size
1985 1986 1987 1988 1989 1990 1991 1992 1993

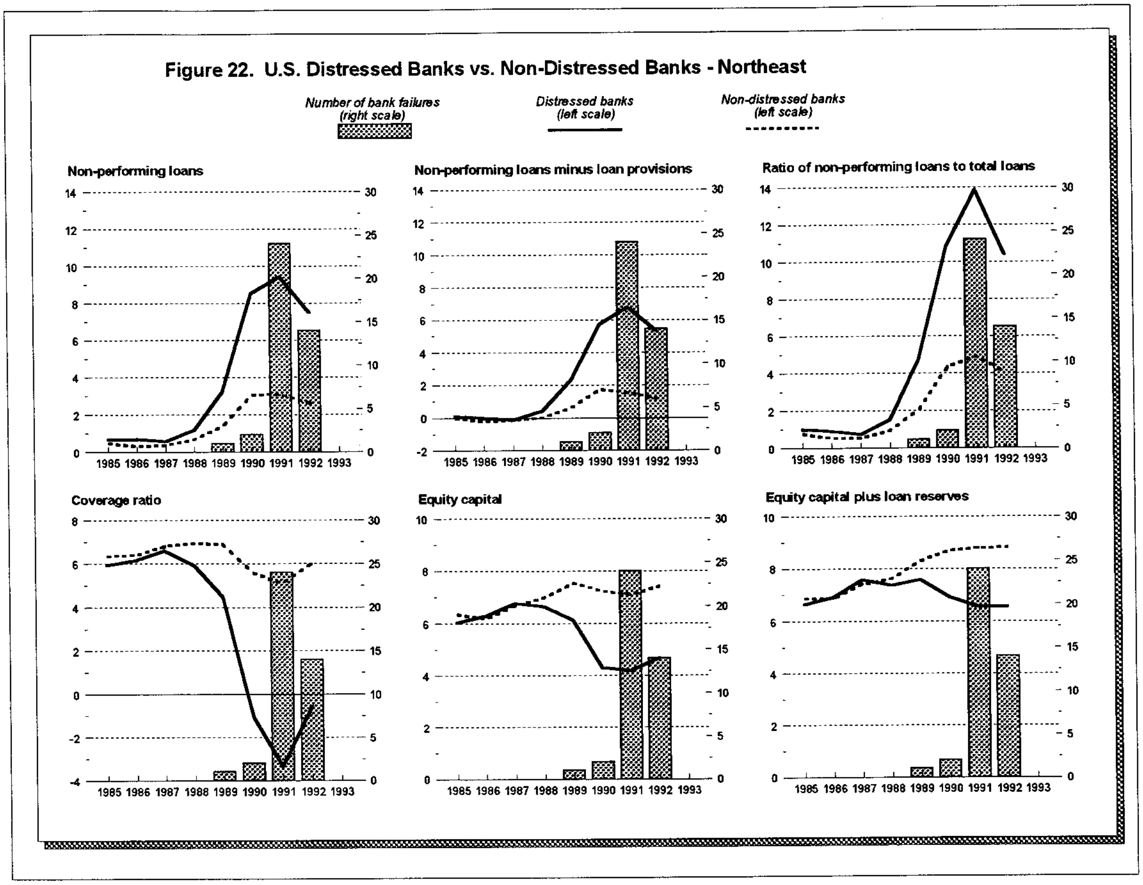


Figure 22. U.S. Distressed Banks vs. Non-Distressed Banks - Northeast
Number of bank failures (right scale)
Distressed banks (left scale)
Non-distressed banks (left scale)
Non-performing loans
Non-performing loans minus loan provisions
Ratio of non-performing loans to total loans
Coverage ratio
Equity capital
Equity capital plus loan reserves
1985 1986 1987 1988 1989 1990 1991 1992 1993

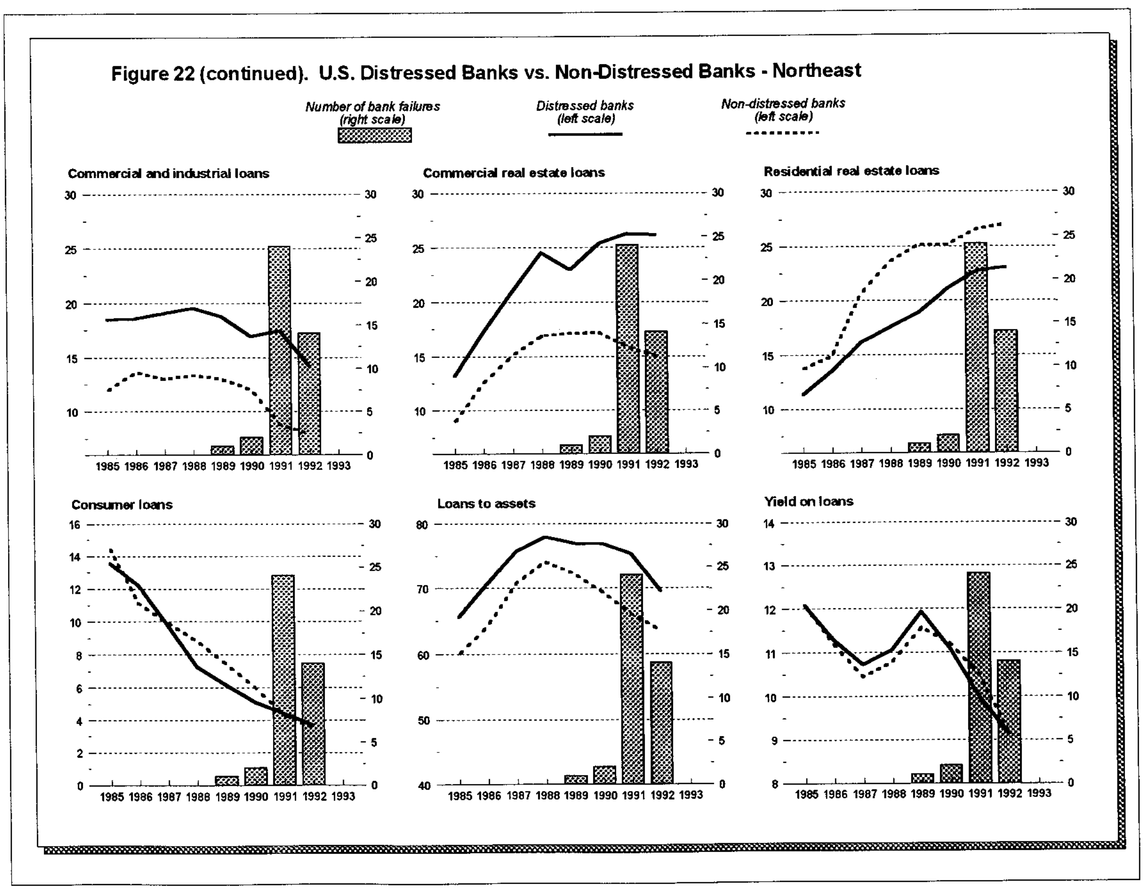


Figure 22 (continued). U.S. Distressed Banks vs. Non-Distressed Banks - Northeast
Number of bank failures (right scale)
Distressed banks (left scale)
Non-distressed banks (left scale)
Commercial and industrial loans
Commercial real estate loans
Residential real estate loans
Consumer loans
Loans to assets
Yield on loans
1985 1986 1987 1988 1989 1990 1991 1992 1993

Figure 22 (continued). U.S. Distressed Banks vs. Non-Distressed Banks - Northeast

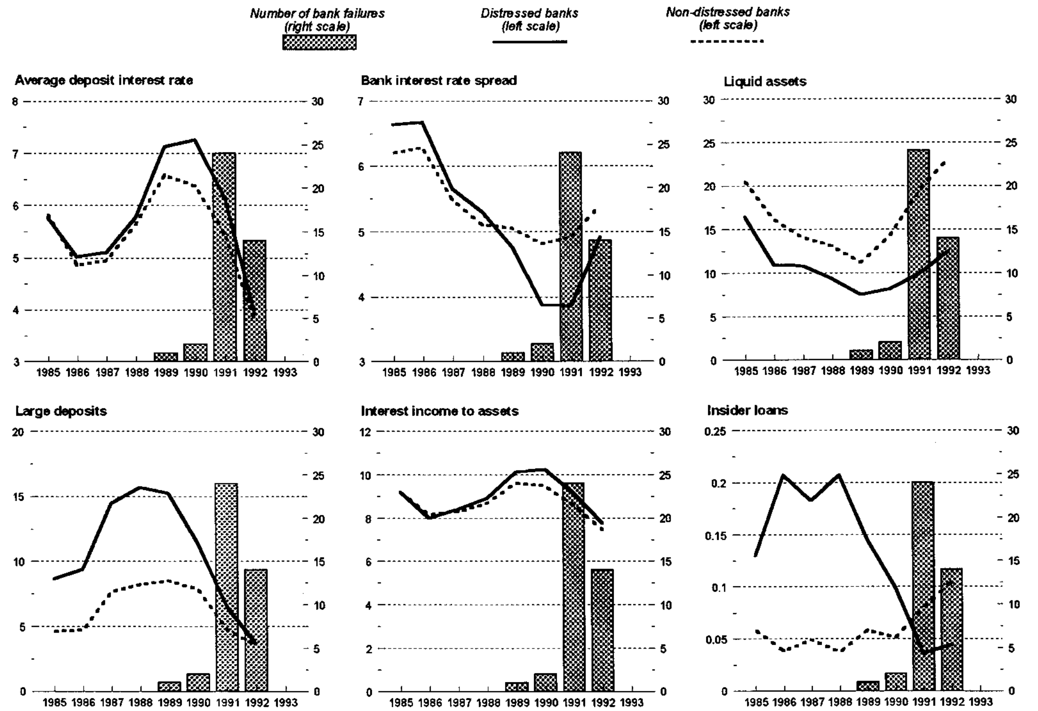


Figure 22 (concluded). U.S. Distressed Banks vs. Non-Distressed Banks - Northeast

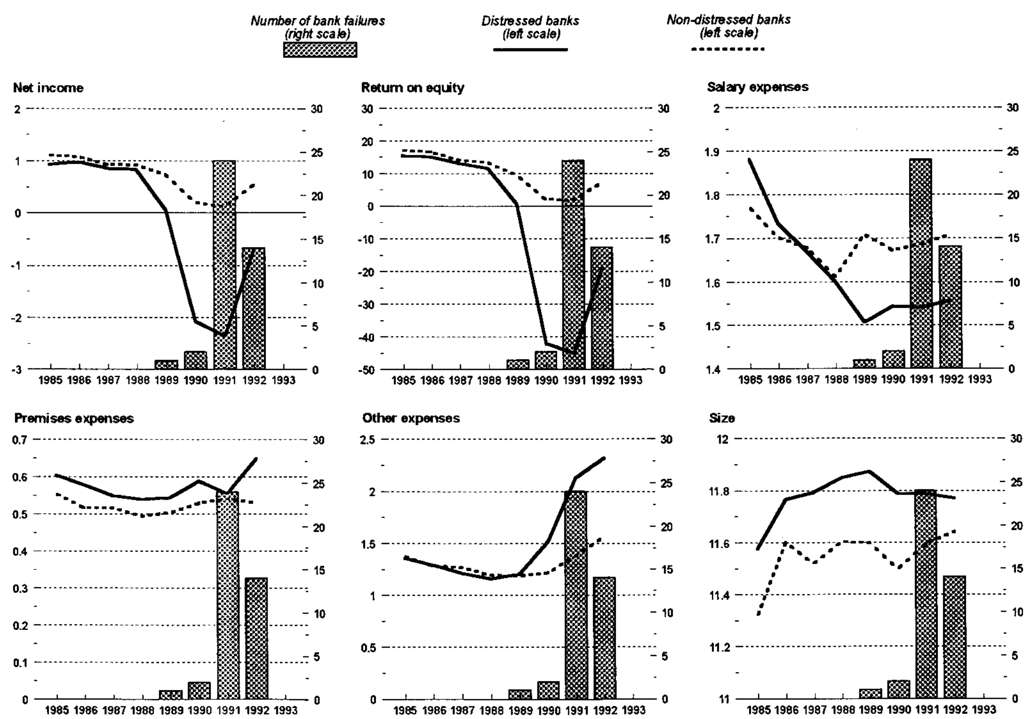


Figure 23. U.S. Failed Banks vs. Non-Failed Banks - California

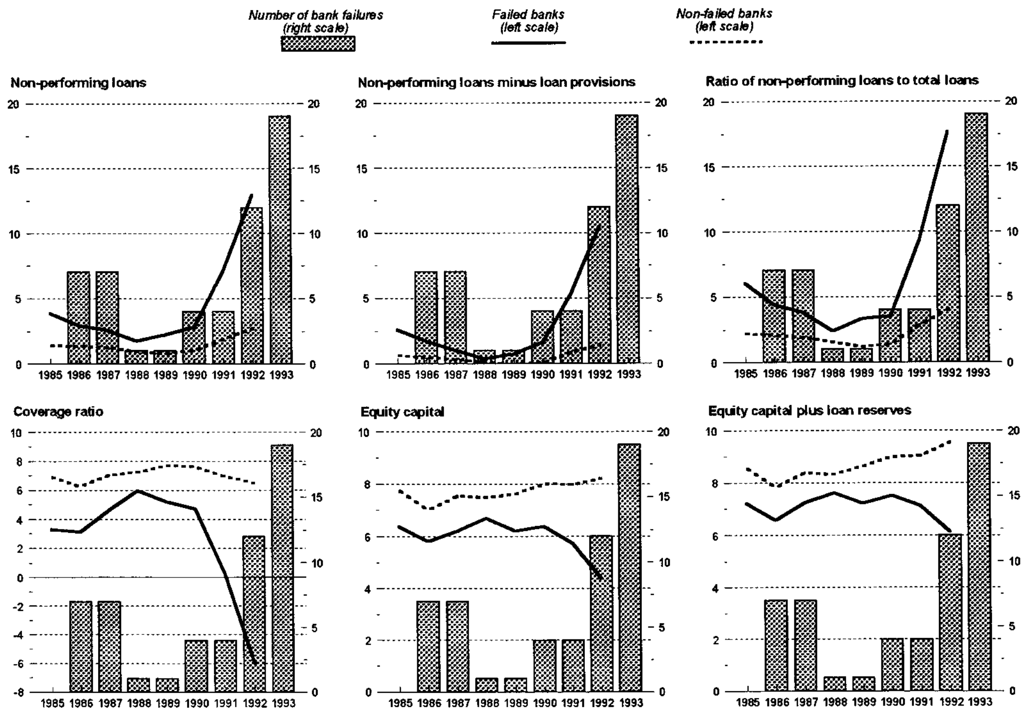


Figure 23 (continued). U.S. Failed Banks vs. Non-Failed Banks - California

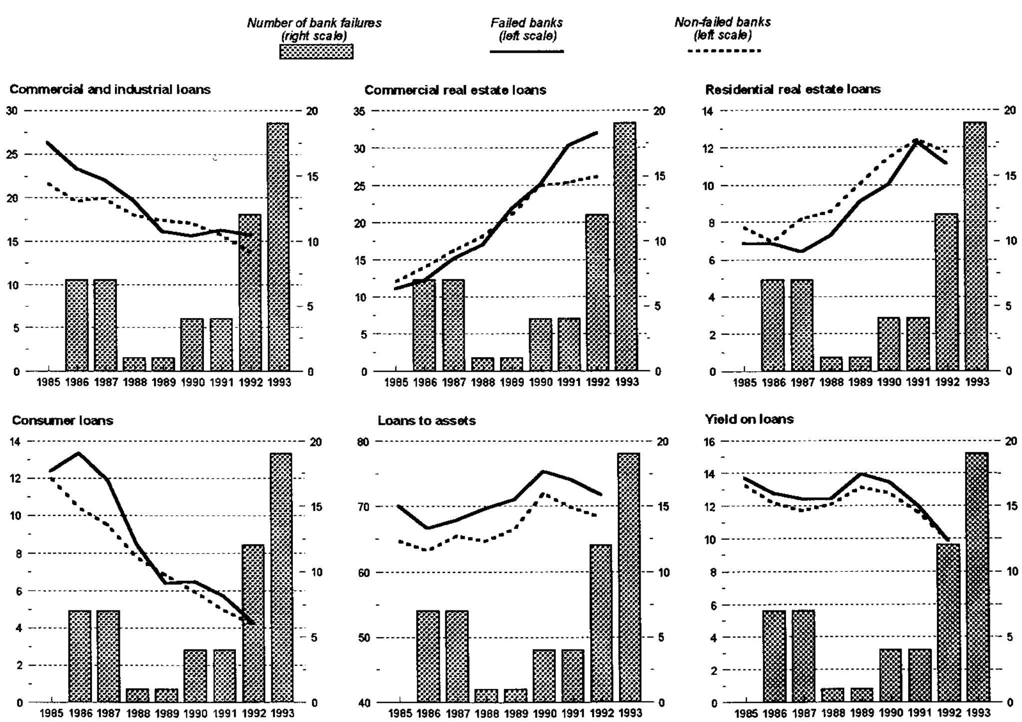


Figure 23 (continued). U.S. Failed Banks vs. Non-Failed Banks - California

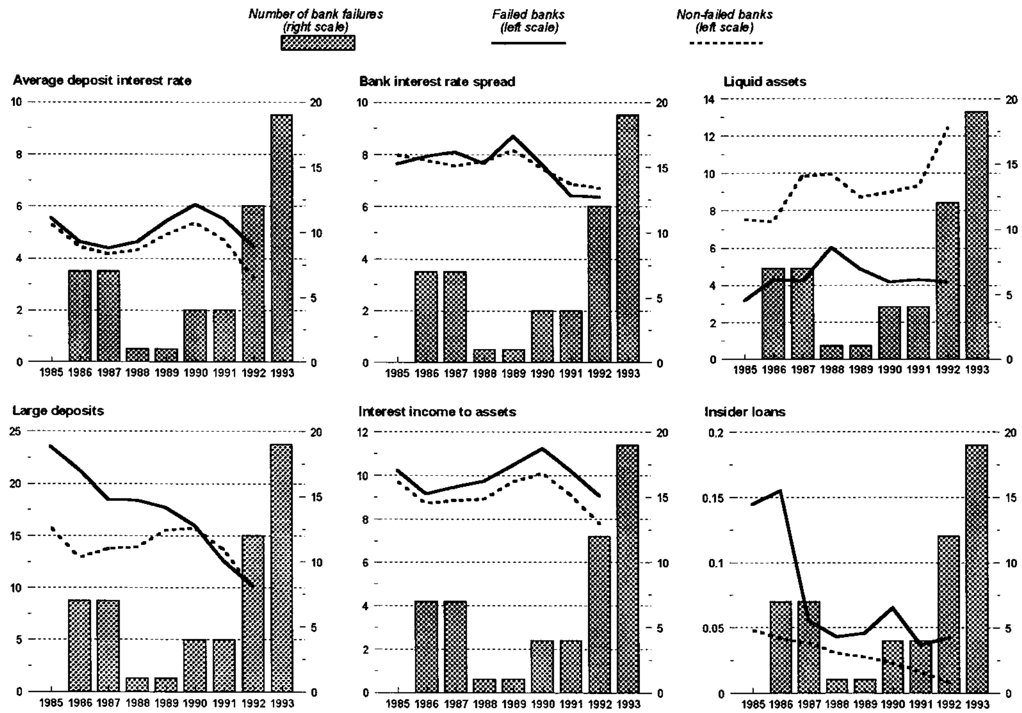


Figure 23 (concluded). U.S. Failed Banks vs. Non-Failed Banks - California

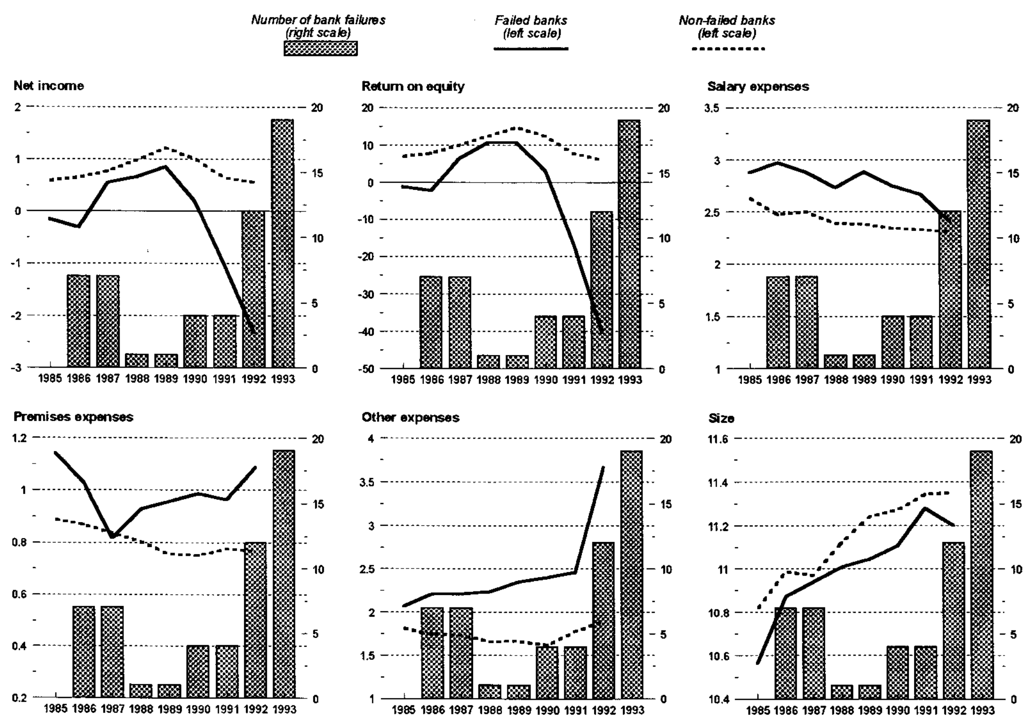


Figure 24. U.S. Distressed Banks vs. Non-Distressed Banks - California

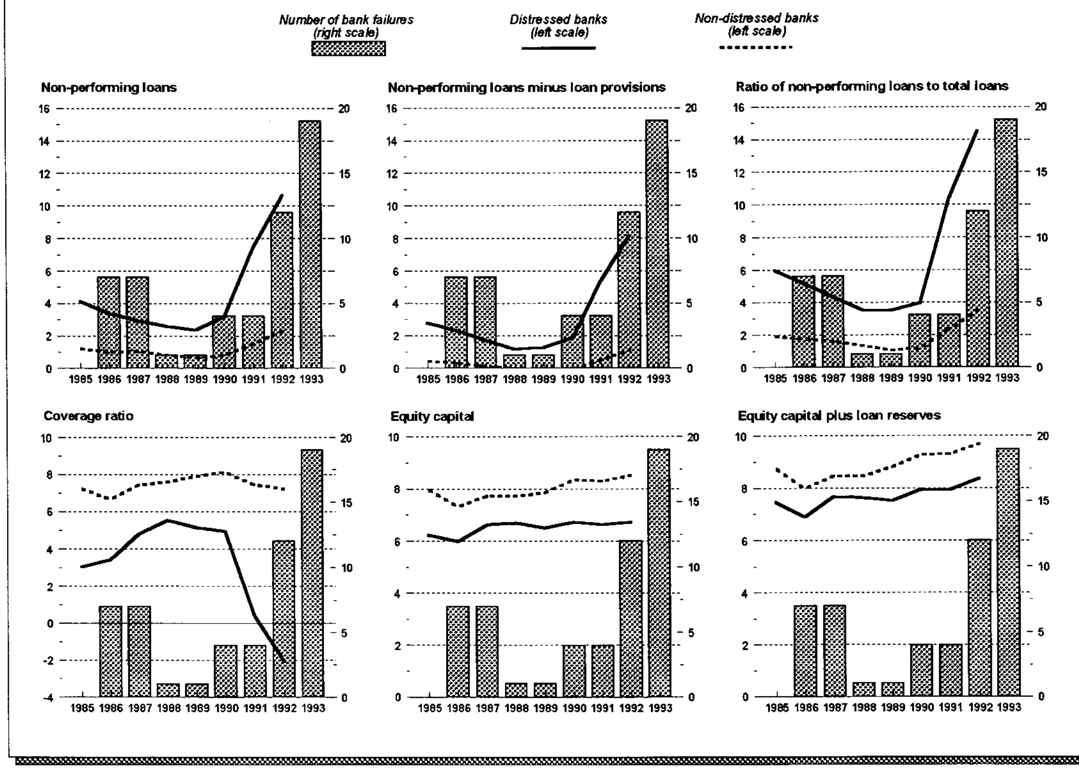


Figure 24 (continued). U.S. Distressed Banks vs. Non-Distressed Banks - California

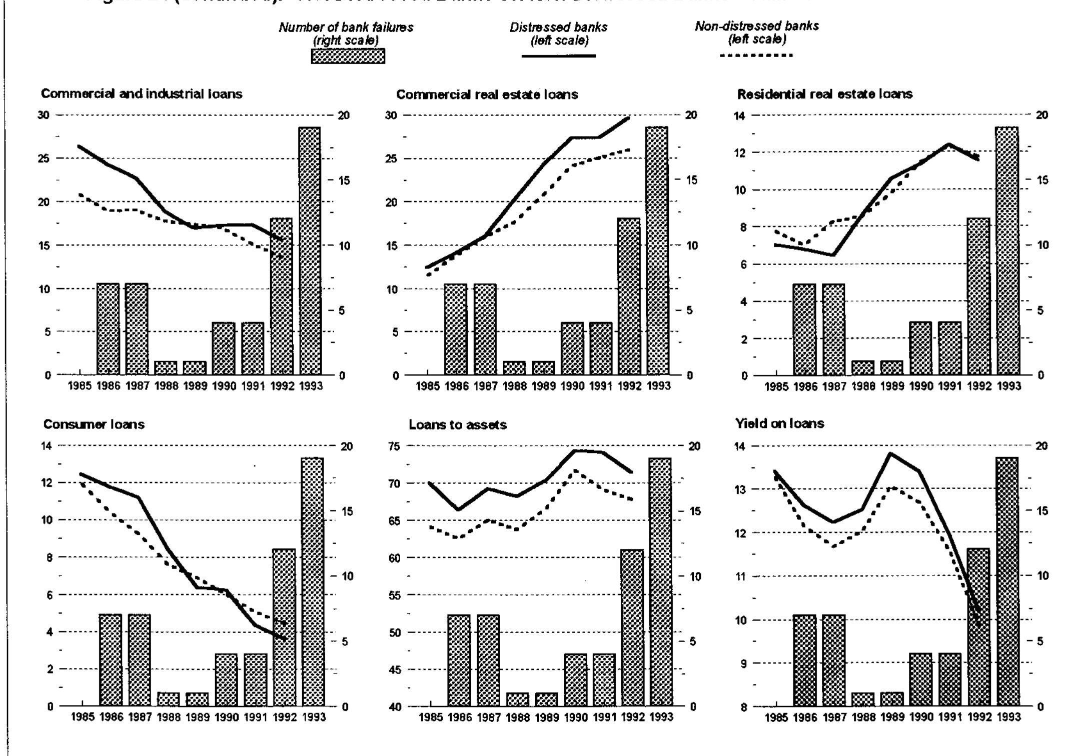


Figure 24 (continued). U.S. Distressed Banks vs. Non-Distressed Banks - California

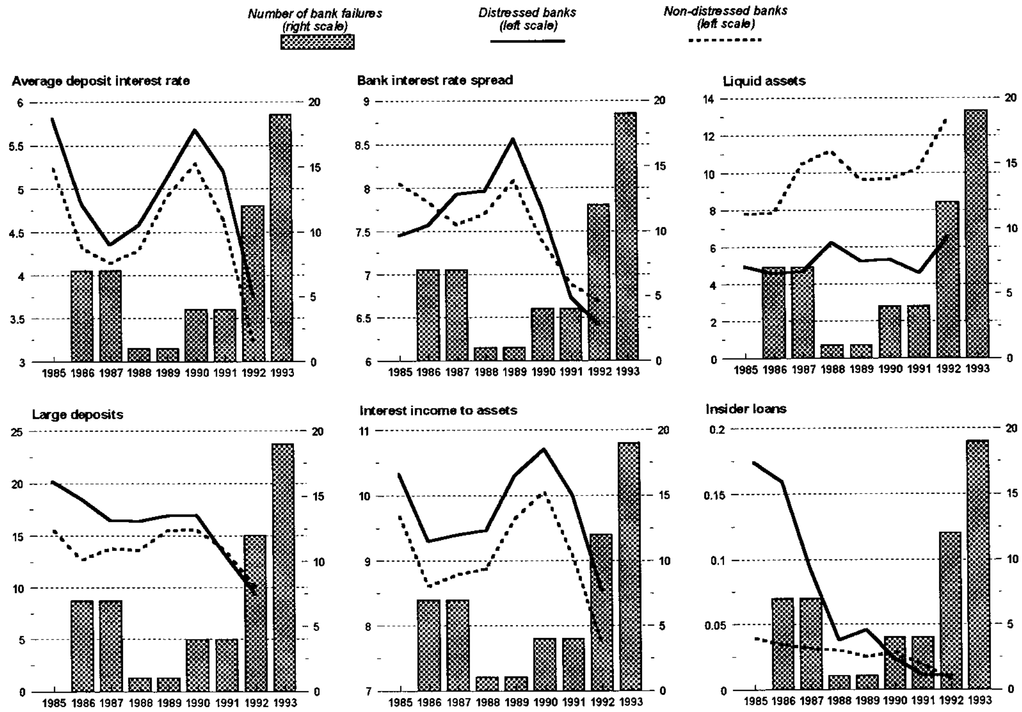
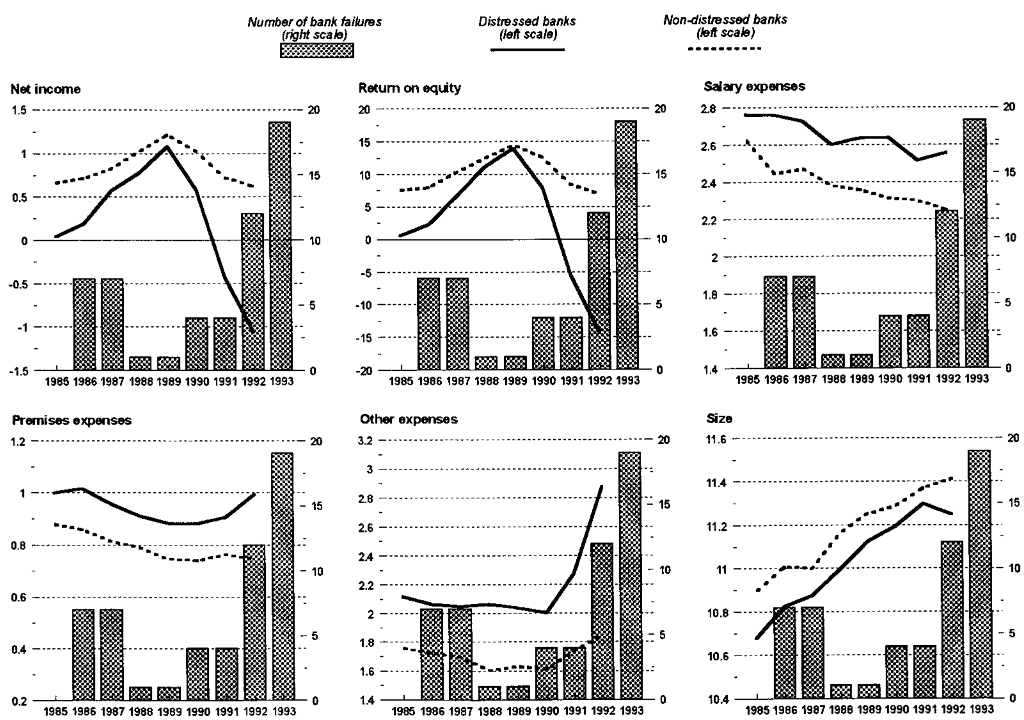


Figure 24 (concluded). U.S. Distressed Banks vs. Non-Distressed Banks - California



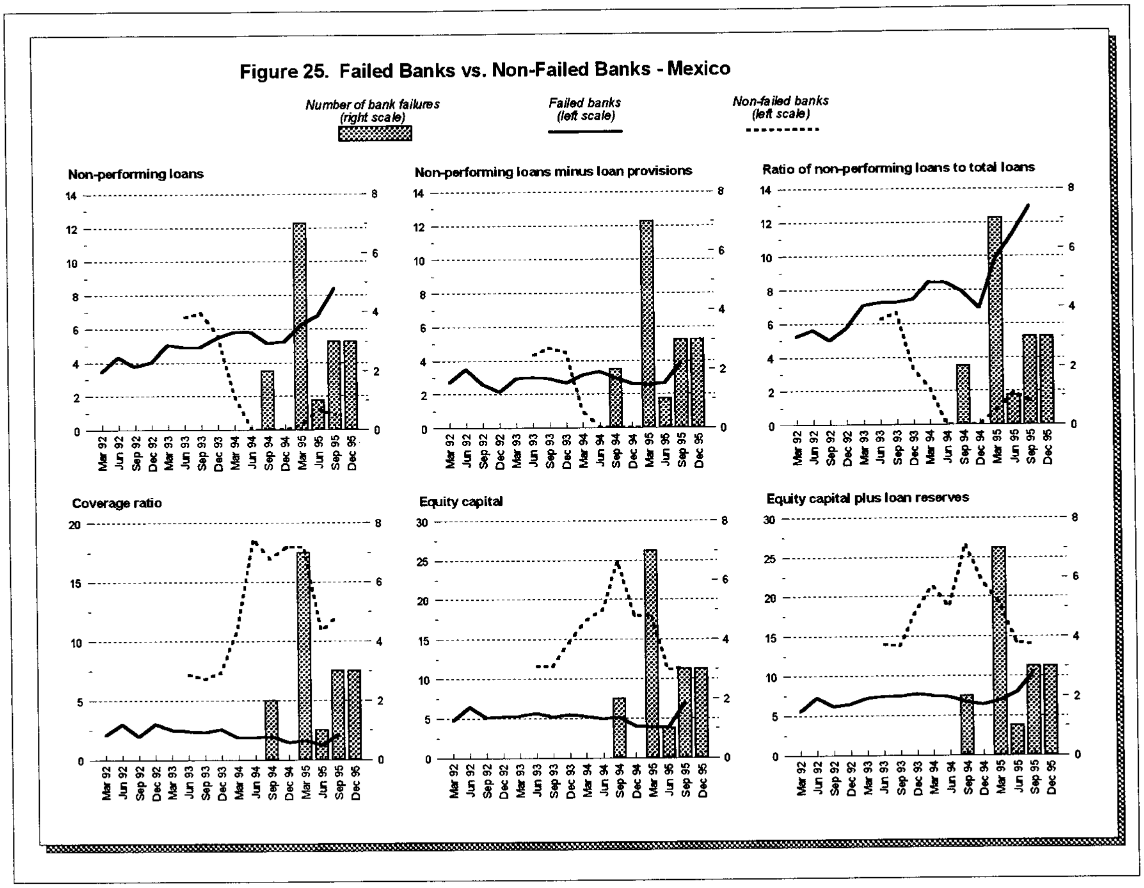


Figure 25. Failed Banks vs. Non-Failed Banks - Mexico
Number of bank failures (right scale)
Failed banks (left scale)
Non-failed banks (left scale)
Non-performing loans
Non-performing loans minus loan provisions
Ratio of non-performing loans to total loans
Coverage ratio
Equity capital
Equity capital plus loan reserves
Mar 92 Jun 92 Sep 92 Dec 92 Mar 93 Jun 93 Sep 93 Dec 93 Mar 94 Jun 94 Sep 94 Dec 94 Mar 95 Jun 95 Sep 95 Dec 95

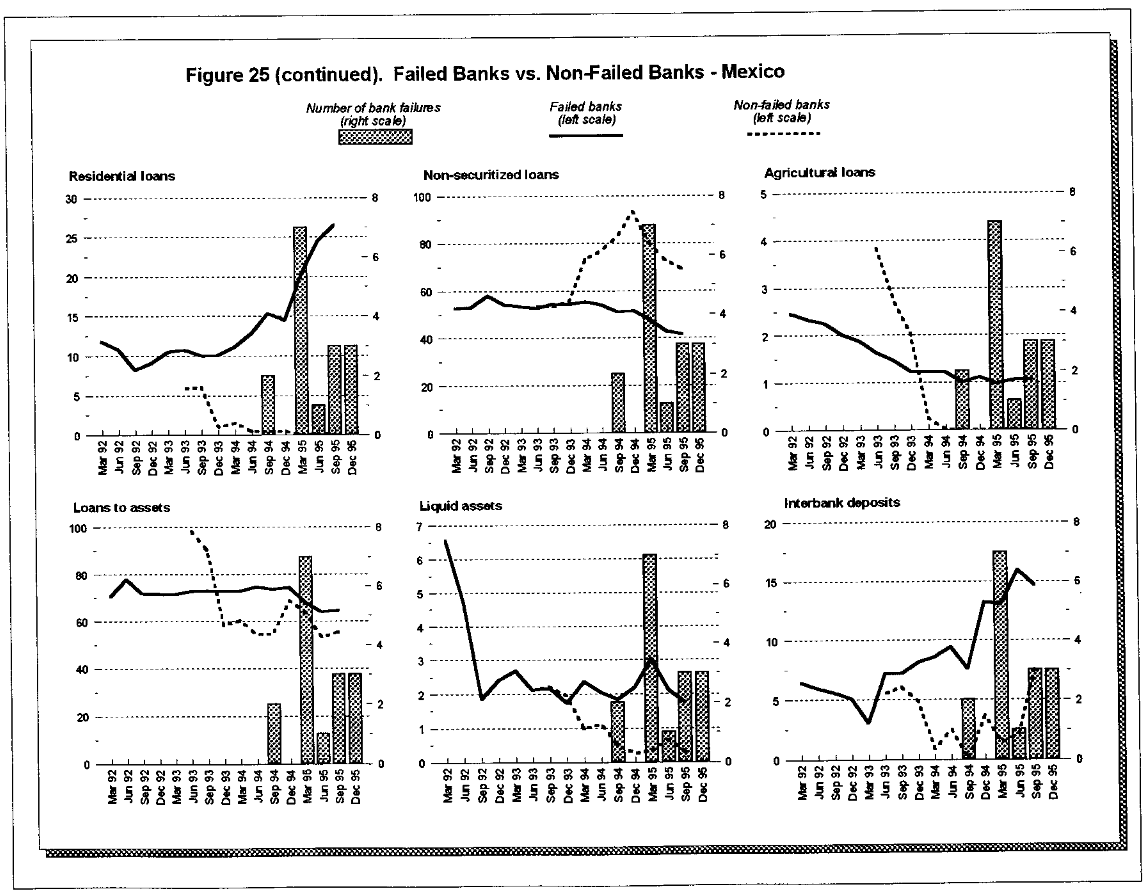


Figure 25 (continued). Failed Banks vs. Non-Failed Banks - Mexico
Number of bank failures (right scale)
Failed banks (left scale)
Non-failed banks (left scale)
Residential loans
Non-securitized loans
Agricultural loans
Loans to assets
Liquid assets
Interbank deposits
Mar 92 Jun 92 Sep 92 Dec 92 Mar 93 Jun 93 Sep 93 Dec 93 Mar 94 Jun 94 Sep 94 Dec 94 Mar 95 Jun 95 Sep 95 Dec 95

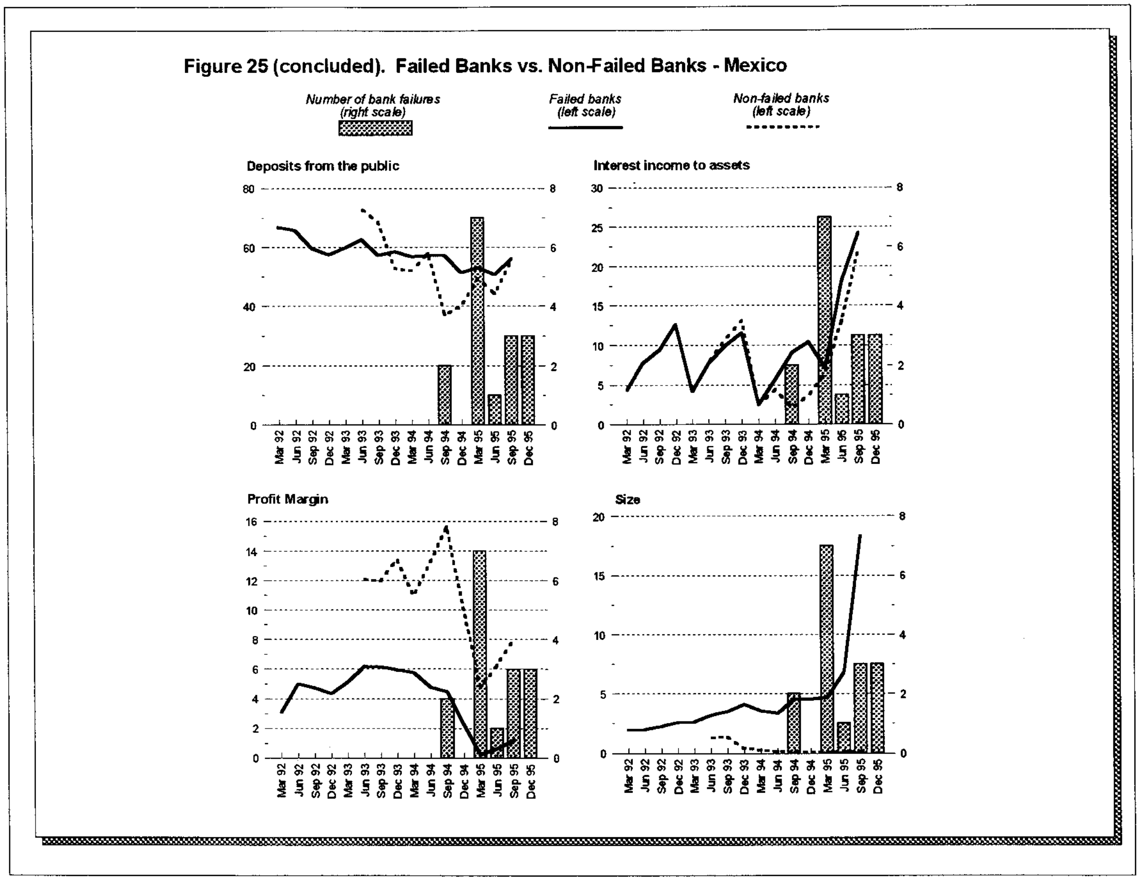


Figure 25 (concluded). Failed Banks vs. Non-Failed Banks - Mexico
Number of bank failures (right scale)
Failed banks (left scale)
Non-failed banks (left scale)
Deposits from the public
Interest income to assets
Profit Margin
Size
Mar 92
Jun 92
Sep 92
Dec 92
Mar 93
Jun 93
Sep 93
Dec 93
Mar 94
Jun 94
Sep 94
Dec 94
Mar 95
Jun 95
Sep 95
Dec 95

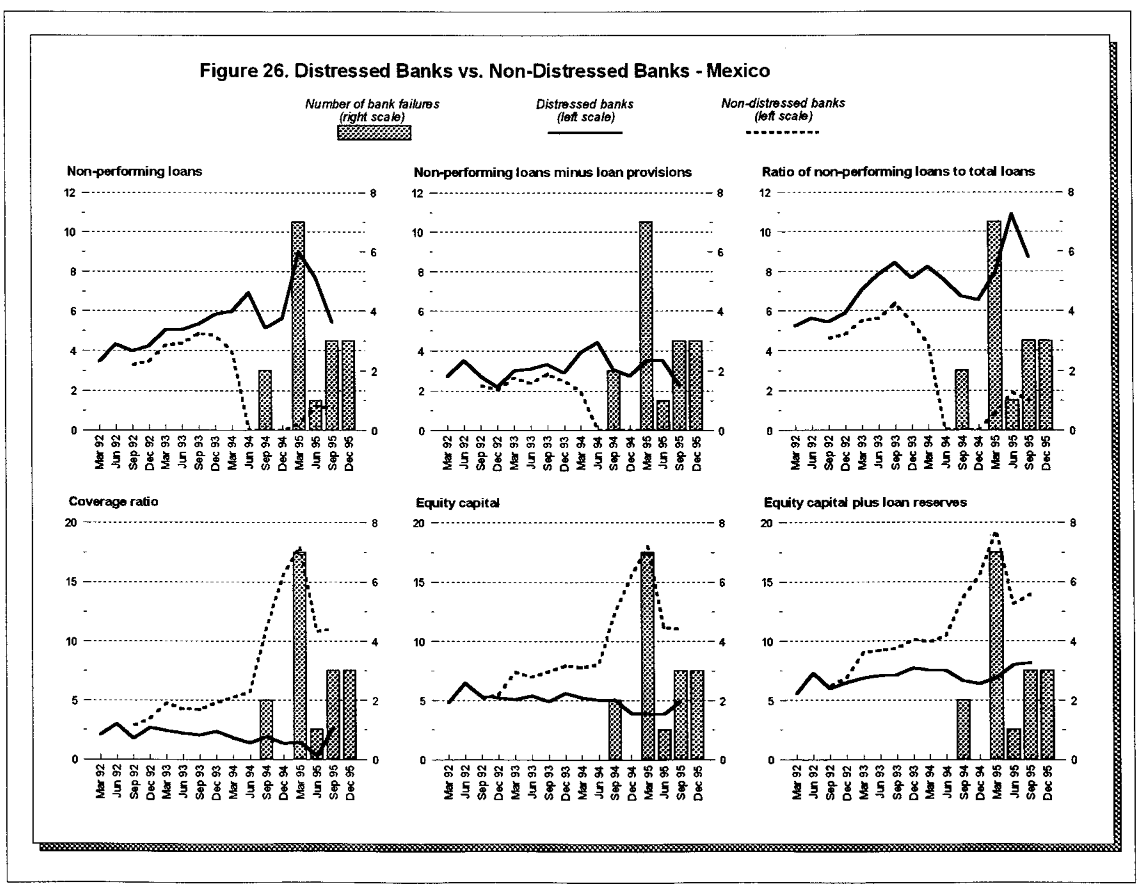


Figure 26. Distressed Banks vs. Non-Distressed Banks - Mexico
Number of bank failures (right scale)
Distressed banks (left scale)
Non-distressed banks (left scale)
Non-performing loans
Non-performing loans minus loan provisions
Ratio of non-performing loans to total loans
Coverage ratio
Equity capital
Equity capital plus loan reserves
Mar 92
Jun 92
Sep 92
Dec 92
Mar 93
Jun 93
Sep 93
Dec 93
Mar 94
Jun 94
Sep 94
Dec 94
Mar 95
Jun 95
Sep 95
Dec 95

Figure 26 (continued). Distressed Banks vs. Non-Distressed Banks - Mexico

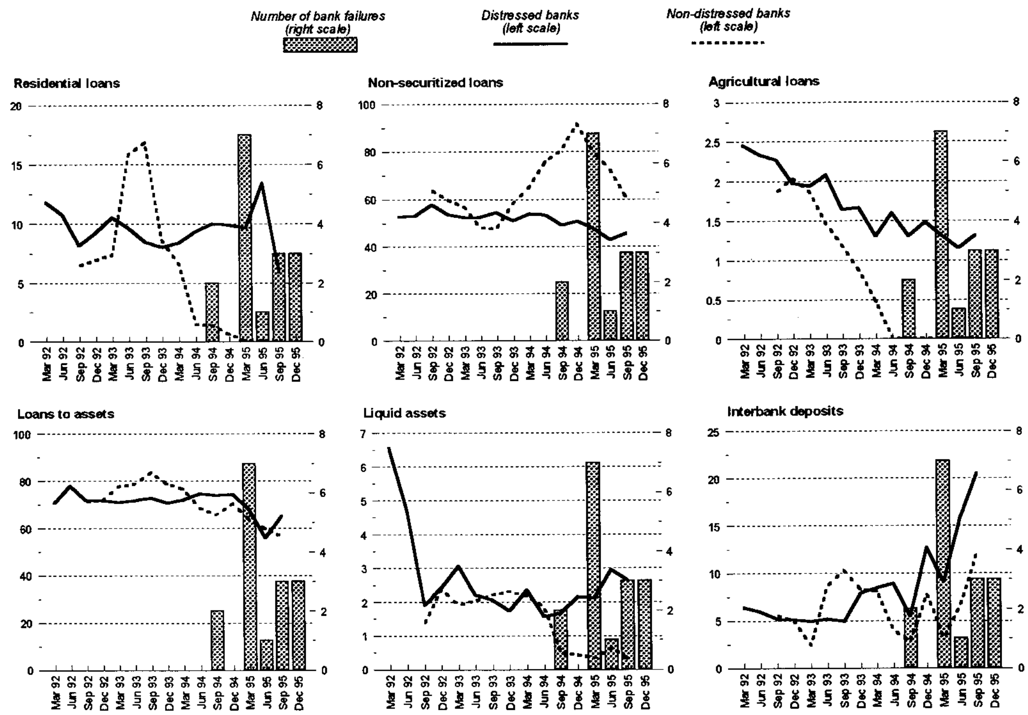
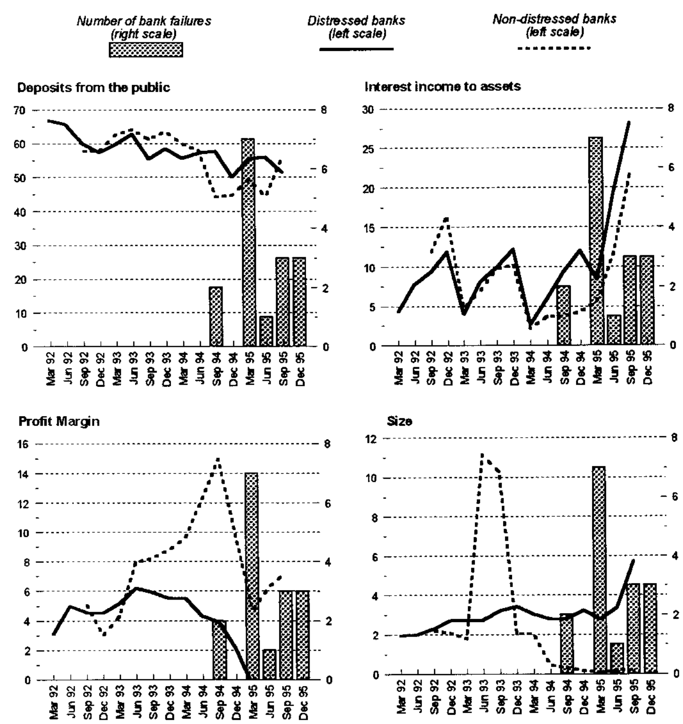


Figure 26 (concluded) Distressed Banks vs. Non-Distressed Banks - Mexico



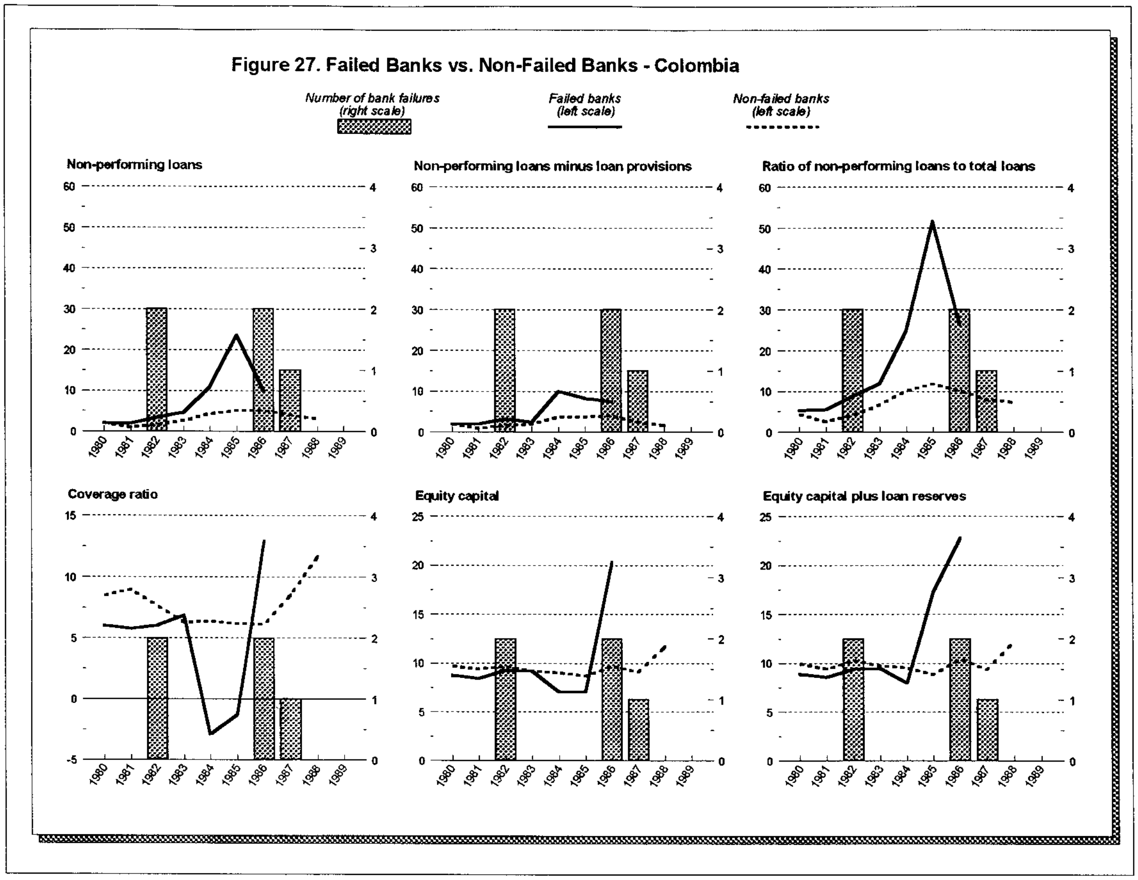


Figure 27. Failed Banks vs. Non-Failed Banks - Colombia
Number of bank failures (right scale)
Failed banks (left scale)
Non-failed banks (left scale)
Non-performing loans
Non-performing loans minus loan provisions
Ratio of non-performing loans to total loans
Coverage ratio
Equity capital
Equity capital plus loan reserves

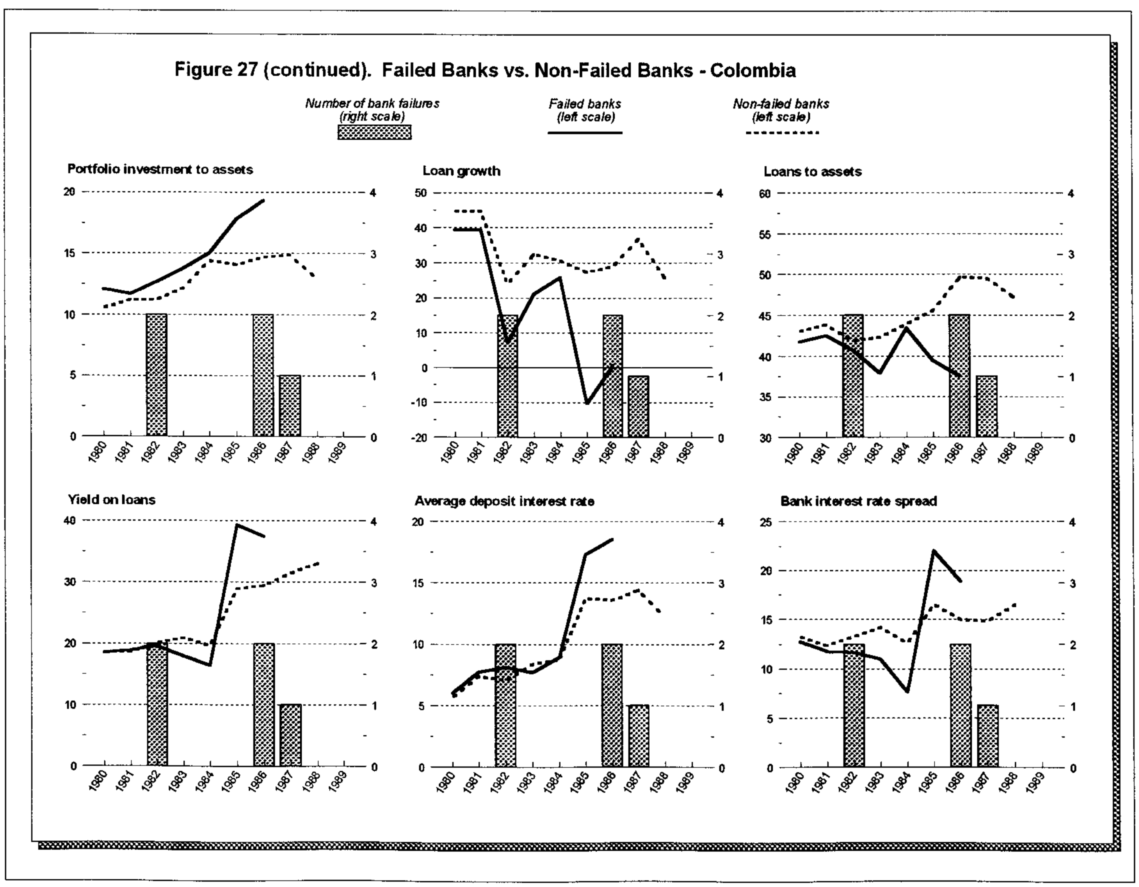


Figure 27 (continued). Failed Banks vs. Non-Failed Banks - Colombia
Number of bank failures (right scale)
Failed banks (left scale)
Non-failed banks (left scale)
Portfolio investment to assets
Loan growth
Loans to assets
Yield on loans
Average deposit interest rate
Bank interest rate spread

Figure 27 (continued). Failed Banks vs. Non-Failed Banks - Colombia

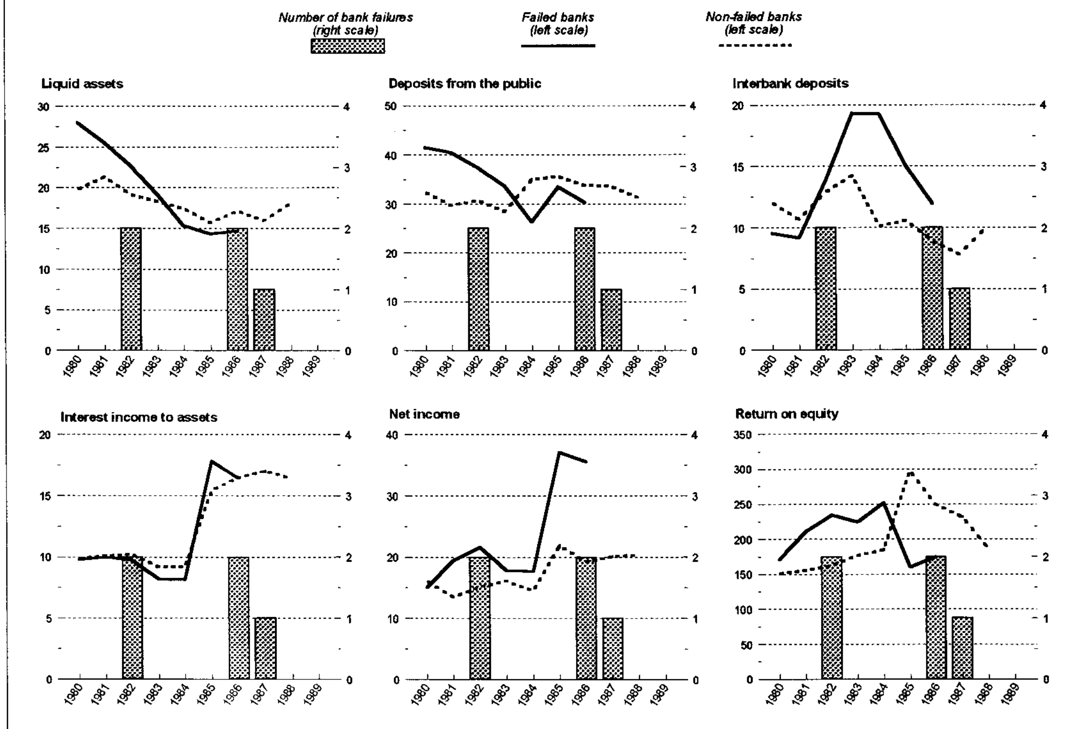


Figure 27 (concluded). Failed Banks vs. Non-Failed Banks - Colombia

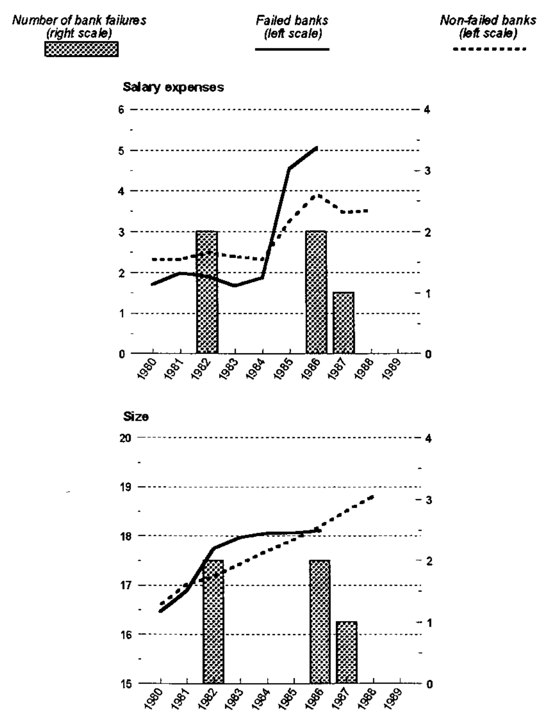


Figure 28. Distressed Banks vs. Non-Distressed Banks - Colombia

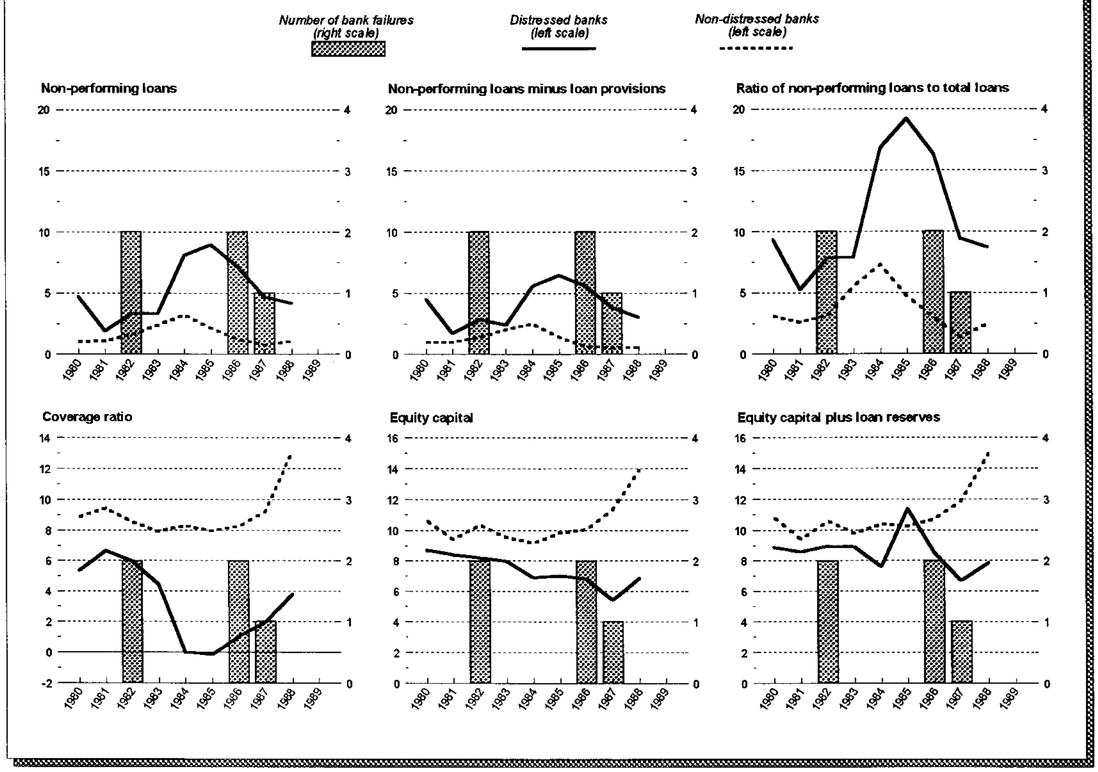


Figure 28 (continued). Distressed Banks vs. Non-Distressed Banks - Colombia

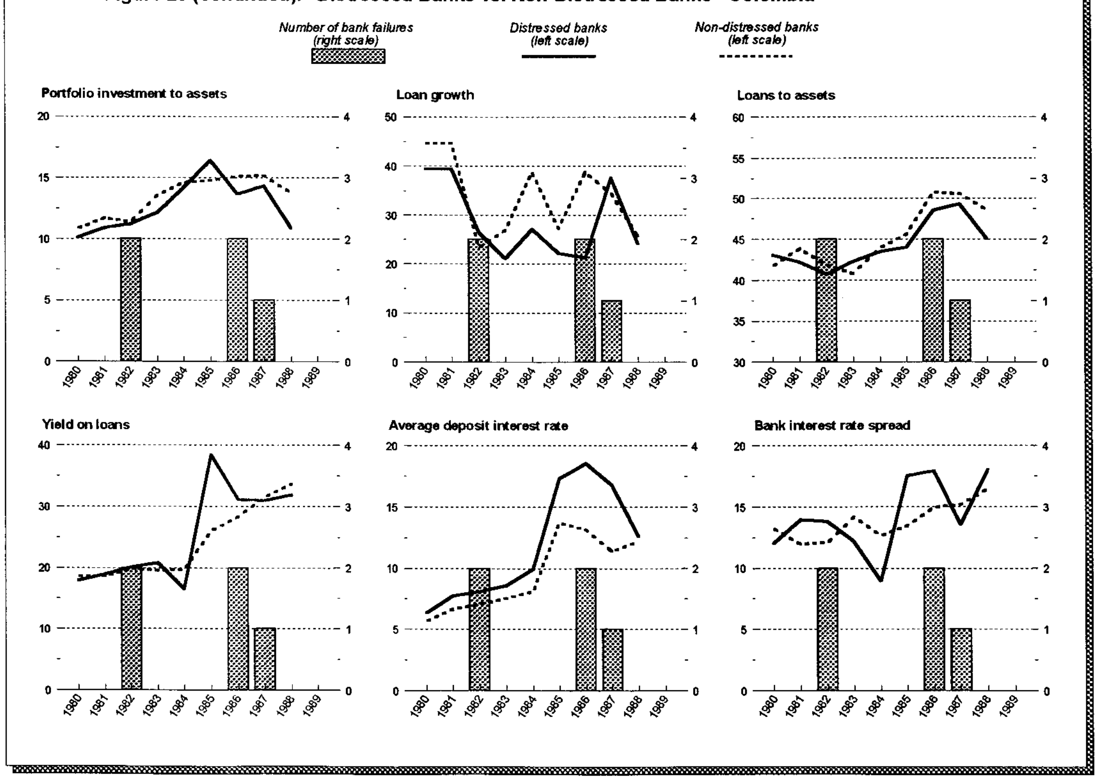


Figure 28 (continued). Distressed Banks vs. Non-Distressed Banks - Colombia

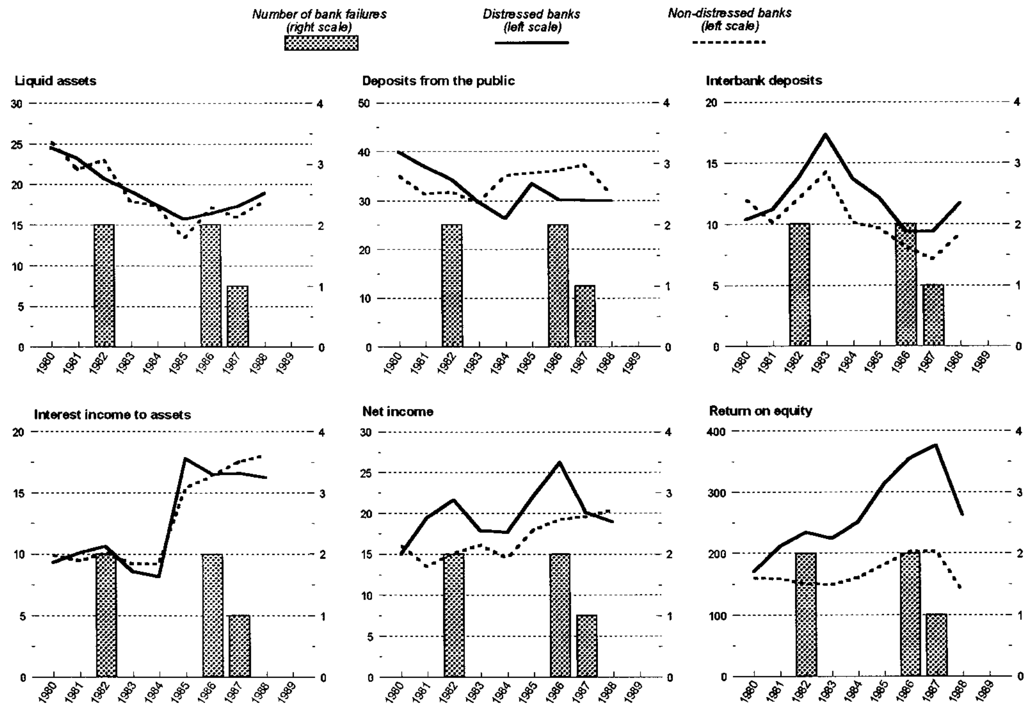
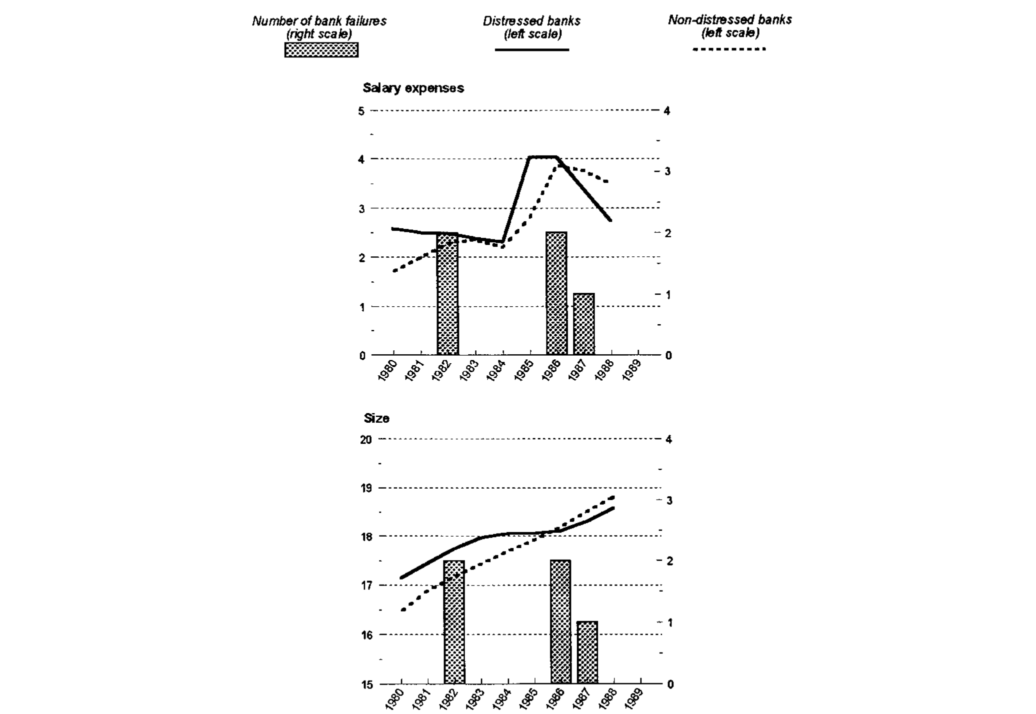


Figure 28 (concluded). Distressed Banks vs. Non-Distressed Banks - Colombia



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