Capitalization of the Bank Insurance Fund

Kevin P. Sheehan
Financial Economist
Federal Deposit Insurance Corporation
Division of Research and Statistics
550 17th Street, NW
Washington, DC 20429
Phone: 202-898-7366
Fax: 202-898-7149
E-mail: kesheehan@fdic.gov

FDIC Working Paper

98-1

Abstract: A two-state Markov-switching model is estimated to characterize the time series behavior of disbursements from the Bank Insurance Fund (BIF). The estimated model is used to project future disbursements, and these projected disbursements are used to estimate the likelihood of insolvency as well as the likelihood of the BIF falling below two different minimum reserve ratios. The simulation results confirm that the current funding arrangement—an assessment rate of 23 basis points with a 1.25 percent required reserve ratio—is sufficient to maintain BIF solvency if one assumes that the prior history of losses is a good indicator of future losses.

The comments and suggestions of Barry Kolatch, Steven Seelig, James Marino, Lynn Shibut, and Daniel Nuxoll are gratefully acknowledged. The views expressed are those of the author and not necessarily those of the Federal Deposit Insurance Corporation.

1 Introduction

The FDIC is required to maintain Bank Insurance Fund (BIF) reserves of at least 1.25 percent of insured deposits; as of year-end 1996 the actual reserve ratio was 1.34 percent. In light of the BIF's loss experience in the late 1980s and early 1990s, questions have been raised about the adequacy of these levels. At the same time, however, given the currently robust financial state of the banking industry, questions have also been raised about the need for these levels.

This study, assuming losses similar to those experienced in the past, simulates the BIF's future reserve levels and examines the implications of different assessment rates and required reserve ratios. The results indicate the extent to which the FDIC may have to balance two possibly conflicting objectives when it makes decisions affecting its ability to sustain funding losses from a future banking crisis. One of the two objectives is the desire to minimize assessment rates. The other is the desire to avoid breaching a specified minimum fund level.

Currently assessment rates are to some extent a function of the ratio between BIF reserves and insured deposits at any given time. If the ratio drops below 125 basis points, the FDIC is required by law *either* to assess the industry to bring the fund back to this minimum level *or* to adopt a restoration plan whereby the annual assessment rate is at least 23 basis points. (The FDIC could ask Congress to relax this requirement and afford the agency greater flexibility in setting premium levels of less than 23 basis points.)

But while the FDIC is required to maintain a fund of at least 125 basis points, a crisis may cause the fund to fall below this level. This matters because the FDIC would like not only to avoid the possibility of insolvency but also to retain public confidence.

To help ensure public confidence, it may be desirable for the FDIC to keep the reserve ratio above a certain minimum ratio—for example, 50 or 75 basis points.

These issues are examined by constructing a model (the Markov-switching model) that projects future disbursements under certain conditions. The projected disbursements are used to estimate the BIF's likelihood of insolvency as well as the likelihood of the BIF falling below two different minimum reserve ratios. These probabilities are estimated across a range of assessment rates for a number of different required reserve ratios. (Note that the analysis does not explicitly address what effect recent bank consolidation will have on the solvency of the BIF.)

2 Overview of Methodology

This paper uses a Monte-Carlo simulation to analyze the adequacy of the Bank Insurance Fund. I generate sequences of future disbursements and then combine these projected disbursements with a recovery rate and an assessment schedule to track the level of the bank fund over time. Using these simulated disbursement sequences, I quantify the probability of insolvency for alternative funding schemes. More specifically, I simulate a thousand sequences of disbursements, and the proportion of sequences that exhaust the Bank Insurance Fund determines the probability of insolvency.

When a bank fails, cash is paid out of the insurance fund to cover insured-deposit losses. However, this drain on the fund is offset by the sale of failed-bank assets and by premium income collected from banks. Historically, annual fund disbursements have ranged from 0 basis points (in 1962) to 105 basis points (in 1991), and the recovery rates from the sale of the failed-bank assets have averaged about 65 percent. Assume, for example, a large annual fund disbursement of 100 basis points. With a recovery rate of 65 percent, the sale of failed-bank assets would reduce this large gross disbursement to 35 basis points. Premium income would further offset the gross disbursement. In fact, if banks were assessed an average premium of 23 basis points, the drain on the fund would be reduced to 12 basis points.

The simulation approach can be illustrated by drawing on the example above. Consider a bank fund balance at the beginning of period t of 100 basis points and assume a simulated fund disbursement of 100 basis points, a recovery rate of 65 percent, and an assessment of 23 basis points. At the end of the period, the fund balance would be reduced by 12 basis points. Given this drain on the fund, the fund balance at the beginning of period $t+1$ would be 88 basis points. After simulating a new fund disbursement for period $t+1$, one would determine the fund balance for the beginning of period $t+2$ in the same way. This process would continue, with the simulation algorithm tracking the level of the insurance fund across a sequence of simulated disbursements.

Using this approach, I can quantify the probability of insolvency (and the probabilities of falling below different minimum reserve ratios) under the current funding arrangement—an assessment rate of 23 basis points with a 1.25 percent required reserve ratio—as well as under alternative funding schemes. These probabilities allow me to address in a meaningful way the adequacy of different funding arrangements.

I generate sequences of future fund disbursements and use these projected disbursements, along with a recovery rate and an assessment schedule, to track the level of the bank fund over time. I argue that the probability of bank failure is higher during a banking crisis than during noncrisis periods and capture this difference by using a model that allows for a data-generating process that changes over time. To simulate sequences of future disbursements I use a Markov-switching model, whose construction I explain below.

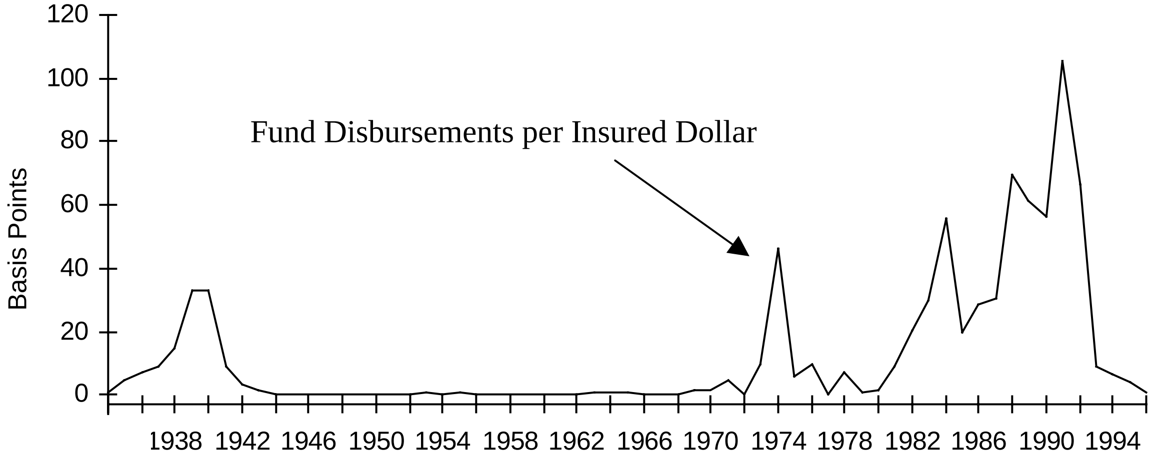
The model projects future disbursements on the basis of two different sets of historical data, one for the 63-year period 1934–1996, the other for the more volatile 25-year period 1972–1996. By projecting disbursements on the basis of these two different sets of historical data, I am able to analyze the adequacy of a funding arrangement under two very different assumptions. The first simulation, based on disbursements from the 63-year period 1934–1996, assumes *low* future losses. In contrast, the second simulation, based on disbursements from the 25-year period 1972–1996, assumes *high* future losses. In fact, the average simulated disbursement for the second simulation increases by more than 100 percent.[1]

3 Markov-Switching Model

Using data from the 1996 *FDIC Annual Report* (tables 108 and 110), I began by constructing a time series for historical fund disbursements, which is plotted in figure 1. Observe that the behavior of disbursements has changed markedly over the history of the

[1]Shaffer (1991) also used a simulation to analyze the adequacy of the Bank Insurance Fund. My analysis differs from Shaffer's work in two important ways. First, Shaffer assumed that disbursements were drawn from a stationary distribution. By using a Markov-switching model, I allow for different states of nature associated with banking crises. Second, Shaffer investigated some historical assessment rates—e.g., the historical assessment rate of 8.33 basis points. I analyze the current statutory framework that requires both lower and higher premiums based on the level of the fund, as well as some possible alternative assessment rates.

Figure 1



Bank Insurance Fund. Before the mid-1970s, disbursements were uniformly small and close to zero, whereas since the mid-1970s disbursements have been larger and much more variable. The behavior of the series changes quite dramatically, and this change may be the result of significant changes in government policy or in the economic environment.

How could one model this dramatic change in the disbursement time series? Consider the statistical model

$$d_t = \mu + \varepsilon_t \,, \qquad (1)$$

where $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$. This model characterizes the sample of data as random deviations about an average disbursement μ. However, the average disbursement appears to have increased some time after the mid-1970s. Indeed, these different time periods may represent distinct phases whose features would be more accurately modeled by an equation representing a data-generating process that changes across time. For the data before the mid-1970s, one might specify the model as

$$d_t = \mu_1 + \varepsilon_t, \tag{2}$$

while data after the mid-1970s might be described by

$$d_t = \mu_2 + \varepsilon_t, \tag{3}$$

where $\mu_1 < \mu_2$.

Equations (2) and (3) define my statistical model as

$$d_t = \mu_{s_t^*} + \varepsilon_t. \tag{4}$$

The model assumes two states and these states are specified by the variable s_t^*, which takes on either the value 1 or 2. When $s_t^* = 1$, the model reduces to the model in equation (2). (Setting $s_t^* = 1$, $\mu_{s_t^*} = \mu_1$.) With the model in equation (2) specifying a small average disbursement, $s_t^* = 1$ identifies the state of small disbursements. When $s_t^* = 2$, the model reduces to the model in equation (3). (Setting $s_t^* = 2$, $\mu_{s_t^*} = \mu_2$.) With the model in equation (3) specifying a large average disbursement, $s_t^* = 2$ identifies the state of large disbursements.

The model in equation (4) is a plausible description of the data in figure 1. The model allows the mean disbursement to vary across states that evolve according to a first-order Markov transition process,

$$
\begin{aligned}
p(s_t = 1 | s_{t-1} = 1) &= p_{11} \\
p(s_t = 2 | s_{t-1} = 1) &= p_{12} \\
p(s_t = 1 | s_{t-1} = 2) &= p_{21} \\
p(s_t = 2 | s_{t-1} = 2) &= p_{22} ,
\end{aligned}
\qquad (5)
$$

where $p_{11} + p_{12} = p_{21} + p_{22} = 1$. The model maintains the assumption that time series data may display periodic changes in their observed behavior, and it accounts for such changes through switches in states, where the mean disbursement of the state is allowed to differ.

The statistical model characterizes the historical disbursements as the random movement between states of small and large disbursements. The state of small disbursements appears to have characterized the historical data before the mid-1970s; the state of large disbursements appears to have characterized the historical data for some time after the mid-1970s; recently there appears to have been a shift back to the state of small disbursements.

I assume that this movement between states is random, and the likelihood of moving between states is defined by the transition probabilities in equation (5), where p_{ij} defines the probability of moving from state i to state j. More specifically, p_{11}

defines the probability of remaining in the state of small disbursements from one period to the next; p_{12} defines the probability of moving from the state of small disbursements to the state of large disbursements; p_{21} defines the probability of moving from the state of large disbursements to the state of small disbursements; and p_{22} defines the probability of remaining in the state of large disbursements from one period to the next.

The specification (5) is quite general. As Hamilton (1993, pp. 235–36) observes,

> A change in regime [state] could be represented as a *permanent* change in the value of μ, rather than the cycling back and forth between states 1 and 2 that seems implicit in [(5)]. However, the specification [(5)] allows the possibility of a permanent change as a special case if $p_{21} = 0$. [That is, once the system moves into the state of large disbursements it will never return to the state of small disbursements. In other words, $p_{21} = 0$ identifies a permanent increase in the average disbursement.] Alternatively, we could have p_{21} quite close to zero, with the implication that in a sample of given size T we would likely see only a single shift [to the state of large disbursements], though at some point in the future we should see a return to … [the state of small disbursements. In this case, p_{21} identifies a temporary increase in the average disbursement.] This second parameterization has … [much] appeal—[a temporary increase in the average disbursement characterizes the large disbursements of a banking crisis.]

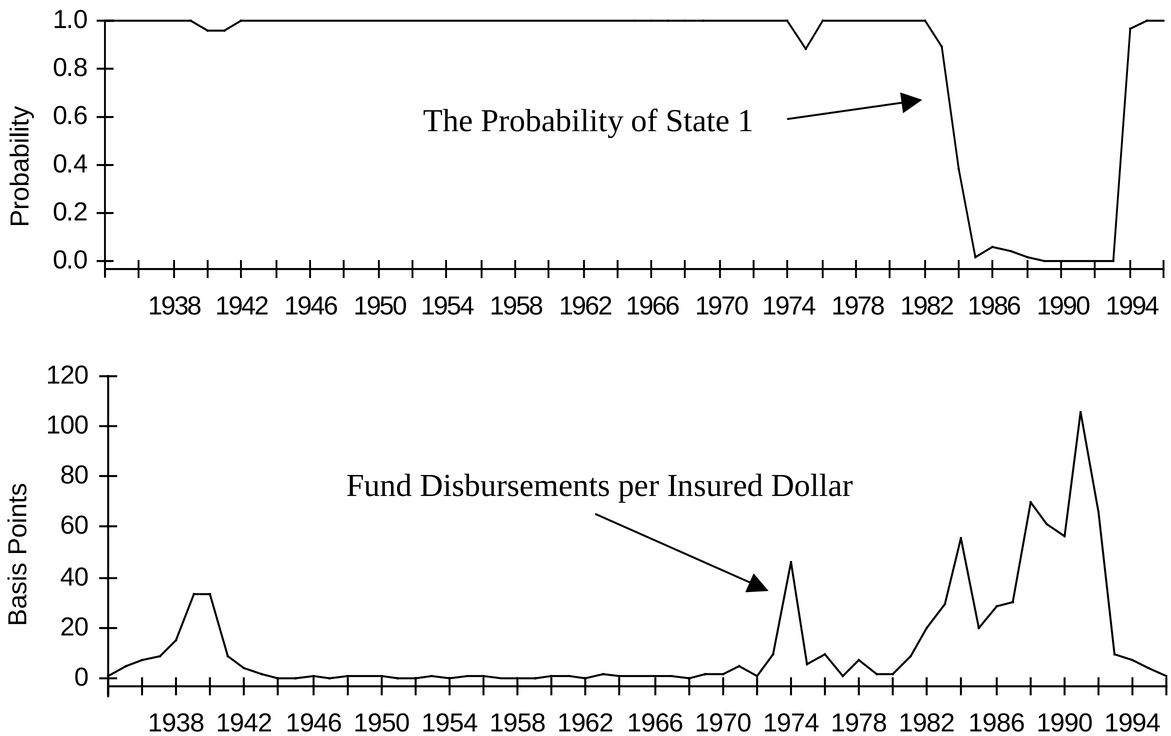
In other words, the model allows for the possibility of a banking crisis; moreover, it identifies the crisis and determines the dates associated with its beginning and end. Significantly, the statistical features and identification of the crisis are not imposed exogenously on the data but, rather, endogenously by the estimation procedure.

> By specifying the probability law rather than imposing particular dates a priori, we allow the data to tell us the nature and incidence of … [the crisis]. Thus we view $\lambda \equiv [(\sigma^2, \mu_1, \mu_2, p_{11}, p_{22})']$ as a vector of population parameters that characterize the probability density $[p(d_1, d_2, \ldots, d_T; \lambda)]$ of the observed data. Our tasks are then to find the value of the parameter λ that best describes the data, form an inference about when the … [crisis] occurred, and use these parameters and inference to forecast the series and test economic hypotheses. (Ibid., p. 236.)

3.1 Estimates Using Data from 1934–1996

The two-state Markov-switching model is estimated using historical disbursement data for the period 1934–1996. The model specifies a process that moves to and from states of small and large disbursements; however, these states are not directly observable. Because they are not directly observable, I make an inference about which regime was more likely to have been responsible for producing each value of the historical disbursements. The upper panel of figure 2 plots the probability of being in state 1 at each point in the sample. These probabilities allow us to infer the identities of the states, and a probability value close to one identifies the state with near certainty. Observe that the probability of state 1 is uniformly close to one for the years before 1984 and the

Figure 2



period 1994–1996; by inference, the probability of state 2 is uniformly close to one during the period 1984–1993.[2]

State 1 defines the state of small disbursements. With probability of state 1 uniformly close to one during the periods 1934–1983 and 1994–1996, the model

[2] The probability of being in a state is referred to in the literature as a smoothed probability. Smoothed probabilities are not to be confused with transition probabilities. A smoothed probability is a measure of the likelihood of *being in a state*; in contrast, a transition probability is a measure of the likelihood of *moving between states*. The smoothed probabilities play an important role in estimating the parameters of the model. The estimation algorithm weights the observations by the smoothed probabilities; the estimated mean disbursement for regime *j* is then the weighted average of all observations in the sample, where the weight for the observation d_t is proportional to the probability that date *t*'s disbursement was generated by regime *j*. The more likely an observation is to have come from regime *j*, the bigger the weight given that observation when one is estimating μ_j. The estimated transition probability $\hat{p}_{ij}$ is essentially the number of times state *i* seems to have been followed by regime *j*, where this count is estimated using the smoothed probabilities. For a detailed description of the estimation procedure, see Hamilton (1993).

identifies small disbursements with these two separate periods. For this state of small disbursements, the model estimates the mean disbursement to be 6 basis points and the average duration to be 43 years. The transition probability of remaining in this state of small disbursements from one period to the next is estimated to be $\hat{p}_{11} = 0.977$.

State 2 defines the state of large disbursements. With the probability of state 2 uniformly close to one during the period 1984–1993, the model identifies large disbursements with this single period. It estimates the mean disbursement for this state of large disbursements to be 49 basis points and the average duration to be 8 years. The transition probability of remaining in this state of large disbursements from one period to the next is estimated to be $\hat{p}_{22} = 0.877$.

The results are summarized in table 1. An interpretation of these results is that the model is describing the Bank Insurance Fund as either in crisis or not in crisis. More specifically, disbursements during the periods associated with state 1 were generally small and of no consequence to the solvency of the Bank Insurance Fund. These periods identify a fund that is not in crisis, despite the fact that during the years 1939, 1940, and 1974 disbursements were quite large.

It is true that disbursements were large during these particular years; nevertheless, these isolated large disbursements were not a problem. A long sequence of large disbursements, however, does put the insurance fund in jeopardy. The period 1984–1993 represents ten consecutive years of large disbursements that threatened the solvency of the fund. Disbursements during this period were 55, 19, 29, 30, 70, 61, 56, 105, 66, and 9 basis points, respectively. Given the size of the disbursements and the length of the episode, this period identifies an insurance fund in crisis.

Table 1

Data-Generating Process
(Data from 1934–1996)

	State 1	State 2
Time Periods	1934–1983 1994–1996	1984–1993
Mean Disbursement	6	49
Average Duration	43 years	8 years

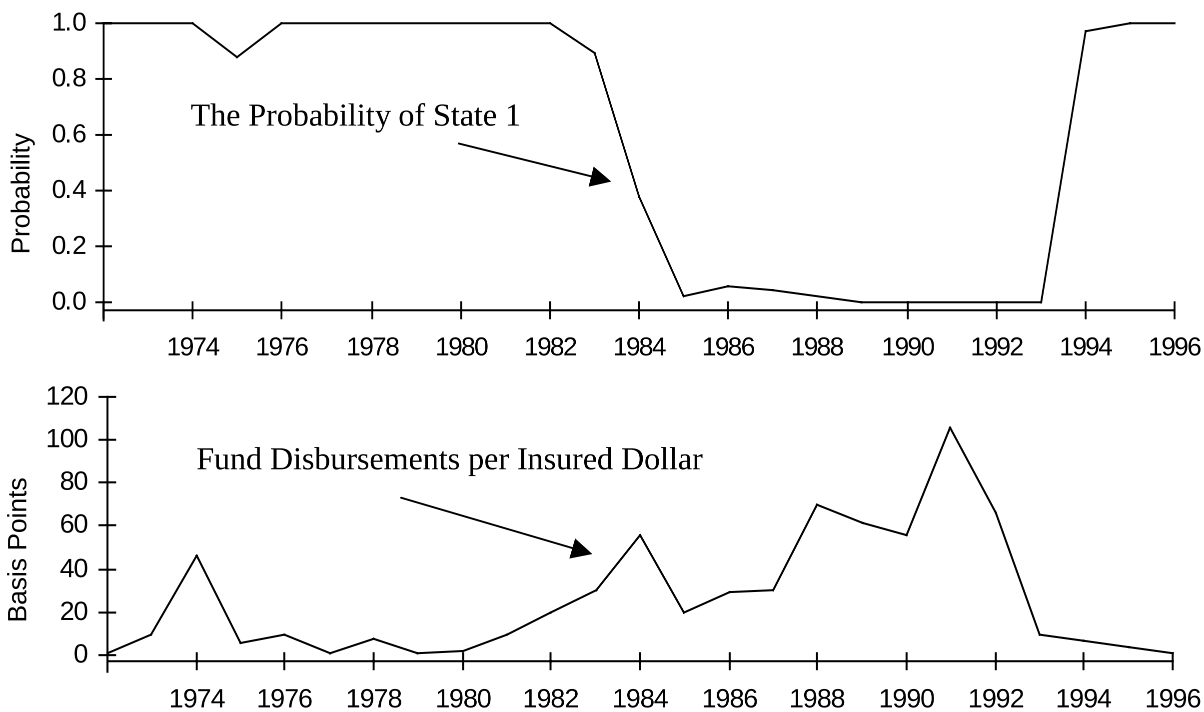
To sum up: the model accurately characterizes the 63-year history of the Bank Insurance Fund. It identifies most years with small disbursements; the estimated average duration of this state corresponds nicely with the long period of small disbursements before 1984. It also identifies a single period of stress that corresponds nicely with the recent banking crisis. The estimated average duration of this state coincides with the length of the crisis; significantly, the model captures the severity of the crisis by estimating a mean disbursement that is eight times larger than the average disbursement of the noncrisis state.

3.2 Estimation Using Data from 1972–1996

The model is now estimated using disbursement data for the subperiod 1972–1996. The upper panel of figure 3 plots the probability of being in state 1 at each point in the sample. Observe that the probability of state 1 is uniformly close to one for the years before 1987 and for the period 1994–1996; by inference, the probability of state 2 is uniformly close to one during the period 1988–1993.

State 1 is again the state of small disbursements. With the probability of state 1 uniformly close to one during the periods 1972–1987 and 1994–1996, the model identifies small disbursements with these two periods. For this state of small

Figure 3



disbursements, the model estimates the mean disbursement to be 16 basis points and the average duration to be 15 years. The transition probability of remaining in this state of small disbursements from one period to the next is estimated to be $\hat{p}_{11} = 0.931$.

State 2 defines the state of large disbursements. With the probability of state 2 uniformly close to one during the period 1988–1993, the model identifies large disbursements with this single period. It estimates the mean disbursement for this state to be 55 basis points and the average duration to be 6 years. The transition probability of remaining in this state of large disbursements from one period to the next is estimated to be $\hat{p}_{22} = 0.825$. (See table 2 for a summary of results.)

Table 2

Data-Generating Process
(Data from 1972–1996)

	State 1	State 2
Time Periods	1972–1987 1994–1996	1988–1993
Mean Disbursement	16	55
Average Duration	15 years	6 years

4 Simulation Model

We now explore the implications of different funding arrangements for the long-term solvency of the Bank Insurance Fund. For each funding arrangement—a funding arrangement is defined by the assessment rate and the required reserve ratio—I examine the fund's survival properties by using a simulation based on historical disbursement data. More specifically, I quantify the probability of insolvency (and the probabilities of falling below two different minimum reserve ratios) by generating sequences of future fund disbursements.

4.1 The Simulation Algorithm

The simulation algorithm is laid out in equation

$$TA_t = (1+i)TA_{t-1} + (1+\tfrac{i}{2})(\Pr em_t - (1-r)D_t)\,, \tag{6}$$

where TA_t defines total assets at the end of time t; i defines the net return on assets; $\Pr em_t$ defines assessments during time t; and $(1-r)D_t$ defines the net disbursements during time t, with r specifying the recovery rate. Each term of the equation—total assets, net return on assets, assessments, and net disbursements—is elaborated on in the pages that follow.

4.1.1 Total Assets

The FDIC determines the bank fund balance by reducing total assets by total liabilities. The fund balance in the simulation is determined in a similar manner. After using the model in equation (6) to simulate future values for total assets, we determine the bank fund balance by reducing the simulated total assets by total liabilities, where total liabilities are set equal to an amount reserved for troubled banks. More formally, the bank fund balance is specified by

$$BF_t = TA_t - R_t \, , \tag{7}$$

where BF_t, defines the bank fund balance at the end of time *t*; TA_t defines total assets at the end of time t; and

$$R_t = (1 - r) D_t \tag{7a}$$

defines a reserve for troubled banks set up at the end of period *t*. (Note that since the bank fund balance, BF_t, is expressed as a percentage of insured deposits, the variables TA_t and D_t are also expressed as a percentage of insured deposits.) More specifically, the amount reserved for the future losses of troubled banks (i.e., losses during period $t+1$) is set equal to the current period's net disbursement (i.e., losses during period t).

At the beginning of each period a number of banks are identified by the regulatory process as likely to fail, and an estimated liability for these anticipated failures is determined. To illustrate how reserving policy affects the solvency of the Bank Insurance Fund, consider the period 1984–1993. This period represents a decade of consecutive large insurance losses that threatened the solvency of the BIF. In fact, the BIF was technically insolvent at the end of 1991, but insolvency was due only in part to this long sequence of large losses. At the end of 1991, the FDIC reserved $15.427 billion for the expected losses of those banks identified by the regulatory process as likely to fail in the future. With assets depleted at that time, reserving such a large amount drove the BIF balance below zero. (That is, TA_t was less than $R_t = \$15.427$ billion in equation (7).) However, actual losses were $3.7 billion in 1992 and only $677 million in 1993, and if the amount reserved had been closer to these actual losses, the BIF would have remained in the black. (That is, TA_t would have been greater than R_t in equation (7).)

We capture this sort of phenomenon by including $R_t = (1-r)D_t$ in equation (7). This specification assumes adaptive reserving: the reserve for the next period's expected losses is set equal to the current period's actual losses. Under this specification, the model overreserves when a small disbursement follows a large disbursement and underreserves when a large disbursement follows a small disbursement. In a typical sequence of simulated disbursements, a period of small disbursements follows a period of large disbursements. As we move from a period of large disbursements to a period of small disbursements, the model incorrectly reserves for future large disbursements. In this case, the model overreserves, and this large reserve adversely affects the bank fund balance. However, after one period the model identifies the end of a banking crisis and then correctly reserves for future small disbursements.

In other words, in the model the FDIC is initially fooled; but after a short lag the FDIC identifies the end of a banking crisis and then reserves for future small losses. After one period, the model accurately reserves for future small losses, but since the reserve is set equal to the current period's losses, the amount reserved is never exactly equal to the future loss. One could not reasonably expect the FDIC to forecast future bank failures with certainty (perfect-foresight reserving), but one would expect these forecasts to be somewhat accurate, given the FDIC's access to Call Report and examination information. A reasonable approximation of this reality is an adaptive reserving specification.

4.1.2 Net Return on Assets

The simulation model assumes that asset earnings are sufficient to cover operating expenses and insured-deposit growth in addition to returning 2 percent during periods of small disbursements. (Since 1985 operating expenses have ranged from less than 1 percent to almost 2 percent of total assets. Insured deposits have grown at an annual rate of about 2.5 percent over the same period; however, the growth of deposits for 1990–1996 was flat, a fact that may reflect a permanent shift away from deposits into other financial assets, such as money market mutual funds.)

Asset earnings in excess of operating expenses and insured-deposit growth determine the net return on assets (i), assumed to be 2 percent during periods of small disbursements. But since one would anticipate smaller asset earnings during a crisis, a zero net return is assumed during periods of large disbursements. In the simulation, a period of large disbursements represents a banking crisis. Banking crises often correspond with declining values for bank assets. Thus, it is not unreasonable to assume that the FDIC may suffer some capital losses on existing assets in liquidation at the onset of a crisis and that, as the crisis persists, accretion in the value of assets in liquidation may be less than had been anticipated. Nevertheless, a zero net return assumes that the smaller asset earnings during a crisis are still sufficient to cover operating expenses and the growth of insured deposits.

In the simulation, only insurance losses can reduce the size of the fund. (The fund, measured as a percentage of insured deposits, will decline when money is paid out to cover operating expenses and/or when insured deposits increase, but in the simulation asset earnings cover these costs.) However, during a period of small disbursements, a 2 percent net return on assets will cover most insurance losses; in fact, this income will generally be greater than insurance losses. With income greater than insurance losses, the simulated fund grows during good times. However, during bad times (periods of large disbursements), the assumed smaller asset earnings preclude such growth.

4.1.3 Assessments

According to the Financial Institutions Reform, Recovery, and Enforcement Act of 1989 (FIRREA), if the level of the Bank Insurance Fund falls below 125 basis points of insured deposits, banks are assessed a premium. They are assessed rates that are sufficient to increase the reserve ratio to the designated reserve ratio within a year. If that cannot reasonably be done, they are assessed rates in accordance with a BIF recapitalization schedule designed to achieve the designated reserve ratio by the end of a

15-year period. Assessments over the term of the recapitalization schedule must be at least 23 basis points. I model the assessment schedule after this legislation.

In the model, premiums are assessed at the beginning of the period. Defining RR as the required reserve ratio and AR as the maximum assessment rate, $\Pr em_t = \max(0, \min(AR, RR - BF_{t-1}))$, where BF_{t-1} specifies the beginning fund balance. (In other words, the beginning fund balance is determined by the fund balance at the end of the prior period.)

The simulation assumes zero premiums when the fund balance is greater than the required reserve ratio. To illustrate, consider a required reserve ratio of 1.25 percent, a maximum assessment rate of 23 basis points, and a bank fund balance of 150 basis points. In this case, $\Pr em_t = \max(0, \min(23, 125 - 150)) = 0$ basis points. When the fund balance is less than the required reserve ratio by an amount smaller than the maximum assessment rate, the simulation assumes premiums equal to the deficit. To illustrate, consider a required reserve ratio of 1.25 percent, a maximum assessment rate of 23 basis points, and a bank fund balance of 120 basis points. In this case, $\Pr em_t = \max(0, \min(23, 125 - 120)) = 5$ basis points, and the reserve ratio increases to the designated ratio within the period. Finally, when the fund balance is less than the required reserve ratio by an amount greater than the maximum assessment rate, the simulation assumes premiums equal to the maximum assessment. To illustrate, consider a required reserve ratio of 1.25 percent, a maximum assessment rate of 23 basis points, and a bank fund of 100 basis points. In this case, $\Pr em_t = \max(0, \min(23, 125 - 100)) = 23$ basis points. The premium is set equal to the maximum assessment rate; nevertheless, the reserve ratio remains temporarily below the designated ratio as we assume the implementation of a recapitalization schedule, where assessments over the term of the recapitalization schedule are uniformly set equal to 23 basis points.

4.1.4 Net Disbursements

To simulate gross disbursements (D_t), the estimated transition probabilities are used. Here I illustrate the simulation of gross disbursements using the Markov-switching model estimated with data for the period 1934–1996.

The simulation randomly moves the disbursement process to and from states of small and large disbursements, where the estimated transition probabilities specify the likelihood of moving between the states. Our two-state Markov-switching model identified the final year of the historical disbursement data as a small disbursement. With the final year of the historical data identified as a small disbursement, the disbursement process either remains in a state of small disbursements during the first simulated year with a probability of $p_{11} = 0.977$, or the disbursement process moves to a state of large disbursements with a probability of $p_{12} = 0.023$.

If the disbursement process remains in a state of small disbursements, then the first simulated disbursement is randomly chosen from the set of historical disbursements identified as small disbursements. The set of small disbursements contains the historical disbursements from the periods 1934–1983 and 1994–1996; each element of the set is assumed to be equally likely. (If the disbursement process instead moves to a state of large disbursements, then the first simulated disbursement is randomly chosen from the set of historical disbursements identified as large disbursements, where each element of this set is also assumed to be equally likely.)

Once the first simulated disbursement is generated, the model then determines the state of the disbursement process for year two. Assuming that the first simulated disbursement is a small disbursement, the disbursement process either remains in a state of small disbursements during the second simulated year with a probability of $p_{11} = 0.977,$ or it moves to a state of large disbursements with a probability of $p_{12} = 0.023.$ Once the state of the process is determined, the second simulated disbursement is randomly chosen from the set of historical disbursements identified with the state. The algorithm continues until a sequence of 63 future disbursements is generated.[3]

In practice, some fraction of disbursements is subsequently recovered either through the liquidation of assets or by workouts. More generally, we assume that r percent of disbursements is recovered; $(1-r)D_t$ therefore defines net disbursements in the simulation model. These recoveries are assumed to equal 63 percent of gross disbursements in any given year—the average recovery rate for the period 1980–1995. This is somewhat smaller than the 65 percent average recovery rate over the history of the fund; the smaller recovery rate may be explained by the large sales of assets associated with the banking crisis of this period.[4]

---

[3] The model is capable of simulating sequences of any length. The number of disbursements in our analysis corresponds to the 63-year history of the fund, 1934–1996. That is, we use this history to simulate arbitrarily a sequence of equal length.

[4] The model in equation (6) assumes that all recoveries occur in the first year; however, we also ran the simulation assuming that recoveries occurred over a ten-year period, and estimated a recovery schedule based on the historical experience since 1986. Our estimates, however, showed that 90 percent was recovered in the first two years of the schedule; so not surprisingly, inclusion of this ten-year schedule had no effect on the results of the simulation.

4.1.5 Example of a Simulation

Assume that the first simulated disbursement is set equal to the small historical disbursement of 6 basis points. (With the simulated disbursement identified as a small disbursement, the net return on assets (*i*) is set equal to 2 percent.) We specified that 63 percent of gross disbursements is recovered either through the liquidation of assets or by workouts. Given a gross disbursement of 6 basis points, a recovery rate of 63 percent defines a net disbursement of 3.78 basis points.

In the simulation model, the variable TA_{t-1} defines prior assets. The algorithm begins by setting this variable equal to 136 basis points—total assets as of year-end 1996. The bank fund balance as of year-end 1996 was 134 basis points. Assume a required reserve ratio of 1.25 percent. Since the bank fund balance is greater than 125 basis points, the premium is set equal to 0 basis points. Now, given prior assets equal to 136 basis points, a net return of 2 percent, assessment income equal to 0 basis points, and a net disbursement equal to 3.78 basis points, equation (6) defines total assets at the end of the first simulated year as 134.90 basis points.

Once this value is simulated, one can determine the bank fund balance at the end of the first simulated year simply by reducing the simulated total assets (i.e., 134.90 basis points) by an amount reserved for troubled banks, where the reserve is set equal to the current period's net disbursement (i.e., 3.78 basis points). Reducing the simulated total assets by this amount defines a bank fund balance of 131.12 basis points at the end of the first simulated year. This process continues, with the simulation algorithm tracking the level of the insurance fund across a sequence of 63 simulated disbursements.

The simulation generates 1,000 different sequences of 63 disbursements. These simulated disbursement sequences are used to quantify a probability of insolvency. A single sequence of 63 simulated disbursements defines a simulation trial. If the fund balance is positive across an entire sequence of 63 simulated disbursements, then the trial is identified with bank fund solvency; if the fund balance falls below zero, the trial is identified with insolvency. The proportion of these trials that exhausts the Bank Insurance Fund determines a probability of insolvency—the probability that the FDIC requires additional funding sometime within a given 63-year period.

4.2 Simulation Results for a 1.25 Percent Required Reserve Ratio

This section reports the simulation results for a 1.25 percent required reserve ratio. I examine this reserve ratio across a range of different assessment rates by running two simulations. The first simulation uses disbursement data for the period 1934–1996; the second, disbursement data for the period 1972–1996.

4.2.1 Probabilities of Insolvency Using Data from 1934–1996

Solvency of the fund is critically dependent on the size of the maximum assessment. The simulation results report that the 1.25 percent required reserve ratio is sufficient to maintain FDIC solvency if the maximum assessment rate is 23 basis points.[5] (See table 3.) The Markov-switching model identifies large disbursements with the time period 1984–1993. The disbursements for a simulated banking crisis are chosen from this set of historical large disbursements, where the average across the set is 49 basis points. With an average large disbursement of 49 basis points, a recovery rate of

Table 3

Probability of Insolvency Using Data from 1934–1996

Maximum Assessment Rate (Basis Points)	Probability of Fund < 0 (%)	Probability of Fund < 50 (%)	Probability of Fund < 75 (%)
23.0	0.1	8.2	38.6
20.0	0.9	16.2	40.0
17.0	4.0	23.8	44.0
12.0	16.7	37.3	50.4
8.33	26.6	44.1	54.9

63 percent suggests an average net disbursement during a simulated crisis of 18.13 basis points. The drain on the fund *during a crisis* therefore averages about 20 basis points; however, this drain is offset by assessments of up to 23 basis points. Because assessments are large enough to neutralize the drain on the fund, the probability of insolvency is approximately zero.

This is not true for most of the other assessment rates examined. Although not allowed under current law, consider the historical rate of 8.33 basis points. With a maximum assessment of 8.33 basis points, premium income is not large enough to neutralize the drain on the fund. Assessments in this case cover less than half of the net disbursement during a crisis; consequently, a long sequence of large disbursements could bankrupt the fund. The probability of this event is found to equal 26.6 percent.

The simulated disbursements are not independent random draws from some specified distribution. Instead, the Markov-switching model randomly moves the

[5] The assessment rate of 23 basis points is also the current statutory minimum unless the designated reserve ratio can be restored within a year.

disbursement process to and from states of small and large disbursements. States of small disbursements tend to follow other small disbursements; states of large disbursements tend to follow other large disbursements. Because these states are serially correlated, a typical sequence of simulated disbursements consists of a long period of small disbursements followed by a shorter period of large disbursements.

We know the Bank Insurance Fund is vulnerable to a long sequence of large disbursements. Recall that the time period 1984–1993 represents ten years of consecutive large disbursements that threatened the solvency of the fund. The Markov-switching model estimates the duration of a crisis to be about eight years; therefore, we would expect to observe a crisis of this length in almost all of the 1,000 simulation trials. In other words, the typical simulated crisis would consist of eight consecutive large disbursements averaging 49 basis points. Given the size of these disbursements and the length of this episode, it is clear that the simulation provides a strong test for the solvency of the fund. (Note that the simulation also allows for the possibility of a much more severe crisis—i.e., a crisis longer than eight years with an average disbursement much larger than 49 basis points. In fact, a simulated crisis of this magnitude is almost certain to occur in at least one of the 1000 simulation trials.)

4.2.2 Probabilities of Insolvency Using Data from 1972–1996

The simulation results in table 3 indicate that the current funding arrangement—an assessment rate of 23 basis points with a 1.25 percent required reserve ratio—is sufficient to maintain FDIC solvency. But the analysis is premised on the assumption that the future will be something like the past. The past is the history of the Bank Insurance Fund, a history characterized by a long period of stability. Disbursements were close to zero for the time period 1940–1970. Since the past is dominated by this stability, the projections implicitly assume it is likely that the FDIC will again experience another thirty years of essentially no bank failures.

This assumption of stability is relaxed by truncating the data set. I now use parameter estimates from the Markov-switching model estimated with disbursement data for the subperiod 1972–1996. Since this set of historical data reflects a period of generally larger and much more volatile disbursements, the second simulation assumes high future losses. In fact, the average disbursement for the second simulation increases from 12.04 to 27.49 basis points. Yet despite the fact that simulated disbursements increase on average by more than 100 percent, the probability of insolvency remains quite close to zero for an assessment rate of 23 basis points. (See table 4.) With a probability so close to zero, the results again confirm that the current funding arrangement—an assessment rate of 23 basis points with a 1.25 percent required reserve ratio—is sufficient to maintain FDIC solvency.

Reducing assessment rates below 23 basis points would require a change in current law; however, if the FDIC were afforded greater flexibility in establishing premium levels when the fund drops below 125 basis points, the FDIC's ability to lower assessment levels in a time of crisis would depend on its willingness to assume risk. Consider a reduction of the assessment rate from 23 to 20 basis points. If the minimum assessment level is reduced slightly to 20 basis points, there is approximately a zero probability of the fund becoming insolvent under a low-loss assumption (table 3); however, under a high-loss assumption (table 4), a probability of 10.5 percent could not rule out the possibility of future FDIC insolvency.

Table 4

Probability of Insolvency Using Data from 1972–1996

Maximum Assessment Rate (Basis Points)	Probability of Fund < 0 (%)	Probability of Fund < 50 (%)	Probability of Fund < 75 (%)
23.0	3.2	48.9	88.2
20.0	10.5	65.8	91.2
17.0	27.2	76.9	93.9
12.0	57.2	87.8	95.7
8.33	74.2	93.1	97.1

4.2.3 Probabilities of Low Fund Balances

Although the current funding arrangement is sufficient to maintain FDIC solvency, it cannot guarantee large fund balances. Tables 3 and 4 both report the probabilities that the fund balance will fall below either 50 or 75 basis points. These probabilities are in general quite large; and in the second simulation, they increase substantially. For the current assessment rate of 23 basis points, the probability of a fund balance less than 50 basis points increases from 8.2 percent in the first simulation to 48.9 percent in the second; the probability of a fund balance less than 75 basis points increases from 38.6 percent to 88.2 percent.

4.3 Simulation Results for Alternative Required Reserve Ratios

Current law mandates a reserve ratio equal to 1.25 percent of insured deposits;[6] however, six alternative required reserve ratios ranging from as low as 100 basis points to as high as 150 basis points are examined. I examine each required reserve ratio across a

[6] If significant risk of substantial losses to the insurance fund is identified, the FDIC Board of Directors may raise the required reserve ratio for a particular year.

range of different assessment rates by running two simulations.[7] The first simulation uses disbursement data for the period 1934–1996; the second, disbursement data for the period 1972–1996. The results (presented in appendix A) give rise to three conclusions:

- Substantially reducing the required reserve ratio would depend on the FDIC's willingness to assume risk. Consider a smaller required reserve of 100 basis points. For an assessment rate of 23 basis points, the probability of insolvency under the lower-loss assumption (table A-1) is close to zero; however, under the higher-loss assumption (table A-2), a probability of 12.8 percent could not rule out the possibility of future FDIC insolvency.
- Increasing the required reserve ratio would not allow the FDIC to substantially reduce assessment rates. Consider a larger required reserve of 150 basis points and a smaller assessment of 12 basis points. The probability of insolvency is equal to 11.0 percent under the lower-loss assumption (table A-11); the probability of insolvency is equal to 43.4 percent under the higher-loss assumption (table A-12). Given these probabilities, a larger fund with smaller assessments would not be sufficient to maintain FDIC solvency.
- But increasing the required reserve ratio while maintaining the current assessment rate would substantially reduce the likelihood of small fund balances. With a 23 basis points maximum assessment rate, for example, the probability of the fund dropping under 50 basis points falls from 8.2 percent to 0.6 percent

[7] The simulations are run by assuming that total assets are initially equal to the required reserve ratio. To illustrate, consider a required reserve ratio of 100 basis points. Total assets and the beginning fund balance are both equal to the required reserve ratio of 100 basis points. The beginning bank fund balance is less than the 1996 ending fund balance of 134 basis points; however, in this case we assume a one-time rebate of 34 basis points. Alternatively, we assume a special assessment is collected if the required ratio is greater than the 1996 ending fund balance.

under the low-loss scenario and from 48.9 percent to 11.5 percent under the high-loss scenario. (Compare tables 3 and 4 with tables A-11 and A-12.)

5 Conclusion

A model (the Markov-switching model) was constructed that enabled us to project future disbursements under certain conditions. I used the projected disbursements to estimate the BIF's likelihood of insolvency as well as the likelihood of the BIF falling below two different minimum reserve ratios. These probabilities were estimated across a range of assessment rates for a number of different required reserve ratios.

The simulation results confirm that the current funding arrangement—an assessment rate of 23 basis points with a 1.25 percent required reserve ratio—is sufficient to maintain FDIC solvency if one assumes that the prior history of losses is a good indicator of future losses. More generally, the results indicate that for the current funding arrangement

- The likelihood of the BIF becoming insolvent is very small regardless of the loss assumption used. Under the lower-loss assumption, there is only a 0.1 percent chance of insolvency; under the higher-loss assumption, this probability increases slightly to 3.2 percent.
- But the likelihood of small fund balances is quite large. Under the higher-loss assumption, there is a 48.9 percent chance that the fund level will fall below 50 basis points. Under the lower-loss assumption, there is a 38.6 percent chance that the fund level will fall below 75 basis points; this probability increases to 88.2 percent under the higher-loss assumption.

If the FDIC were afforded greater flexibility in establishing premium levels when the fund dropped below 125 basis points, the FDIC's decision whether to lower assessment levels in a time of crisis would depend on its willingness to assume risk. More generally, the results indicate that

- If the minimum assessment level is reduced slightly from 23 to 20 basis points, there is close to zero probability of the fund becoming insolvent under a low-loss assumption; however, under a high-loss assumption, a probability of 10.5 percent could not rule out the possibility of future FDIC insolvency.
- If one of the FDIC's objectives were to maintain a minimum reserve ratio, moving the minimum assessment level below 23 basis points would be substantially more difficult. If the minimum assessment level is reduced to 20 basis points, for example, the probability of the reserve ratio dropping below 50 basis points almost doubles from 8.2 percent to 16.2 percent under the low-loss assumption and increases to 65.8 percent from 48.9 percent under the high-loss assumption.

With respect to changing the required reserve ratio: on the one hand, substantially reducing it would expose the FDIC to the possibility of future FDIC insolvency. On the other hand, increasing it would not allow the FDIC to reduce assessment rates substantially. However, increasing the required reserve ratio while maintaining the current assessment rate would substantially reduce the likelihood of small fund balances.

Let me conclude with a word of caution. If we assume that the prior history of losses is a good indicator of future losses, then the adequacy of the current funding arrangement is confirmed by the results. However, the adequacy of the current funding arrangement is very doubtful when one assumes future losses that are twice as large as historical losses. If we double the magnitude of the assumed future losses, the probability of insolvency for the current funding arrangement exceeds 50 percent.[8] (The probability of insolvency for the current funding arrangement is unaffected if we assume the same magnitude of losses but instead double the length of a crisis.) Running the simulation under this assumption of proportionately larger losses illustrates that the results in the paper are critically dependent on our assumptions concerning future losses.

[8] I ran the simulation after first doubling the historical disbursements. The simulation was run twice: once employing the revised historical data for the period 1934–1996 and then with the revised historical data for the period 1972–1996. Using the revised historical data for the period 1934–1996, the probability of insolvency was found to equal 54.7 percent. The probability of insolvency using the revised data for the period 1972–1996 was found to equal 94.8 percent.

APPENDIX

Required Reserve Ratio of 100 Basis Points

Table A - 1

Probability of Insolvency Using Data from 1934–1996

Maximum Assessment Rate (Basis Points)	Probability of Fund < 0 (%)	Probability of Fund < 50 (%)	Probability of Fund < 75 (%)
23.0	0.7	42.7	70.5
20.0	3.7	44.6	70.6
17.0	10.3	49.3	71.1
12.0	28.2	56.7	72.2
8.33	38.5	61.2	73.5

Table A - 2

Probability of Insolvency Using Data from 1972–1996

Maximum Assessment Rate (Basis Points)	Probability of Fund < 0 (%)	Probability of Fund < 50 (%)	Probability of Fund < 75 (%)
23.0	12.8	88.4	99.9
20.0	30.2	91.5	99.9
17.0	51.5	94.5	99.9
12.0	74.0	96.2	99.9
8.33	85.4	97.7	100.0

Required Reserve Ratio of 110 Basis Points

Table A - 3

Probability of Insolvency Using Data from 1934–1996

Maximum Assessment Rate (Basis Points)	Probability of Fund < 0 (%)	Probability of Fund < 50 (%)	Probability of Fund < 75 (%)
23.0	0.3	37.0	57.5
20.0	2.0	38.9	59.8
17.0	7.5	41.7	61.5
12.0	22.9	49.7	63.7
8.33	34.0	54.9	65.0

Table A - 4

Probability of Insolvency Using Data from 1972–1996

Maximum Assessment Rate (Basis Points)	Probability of Fund < 0 (%)	Probability of Fund < 50 (%)	Probability of Fund < 75 (%)
23.0	6.5	86.0	97.0
20.0	20.4	88.1	97.8
17.0	40.0	91.2	98.4
12.0	67.1	94.5	99.4
8.33	81.4	96.1	99.8

Required Reserve Ratio of 120 Basis Points

Table A - 5

Probability of Insolvency Using Data from 1934–1996

Maximum Assessment Rate (Basis Points)	Probability of Fund < 0 (%)	Probability of Fund < 50 (%)	Probability of Fund < 75 (%)
23.0	0.1	19.5	42.6
20.0	1.2	26.6	46.6
17.0	5.3	32.5	50.7
12.0	19.1	43.1	57.4
8.33	30.1	49.4	60.0

Table A - 6

Probability of Insolvency Using Data from 1972–1996

Maximum Assessment Rate (Basis Points)	Probability of Fund < 0 (%)	Probability of Fund < 50 (%)	Probability of Fund < 75 (%)
23.0	4.2	68.4	90.3
20.0	13.4	78.8	94.4
17.0	32.1	85.1	95.7
12.0	60.8	91.5	96.8
8.33	77.4	94.5	98.3

Required Reserve Ratio of 130 Basis Points

Table A - 7

Probability of Insolvency Using Data from 1934–1996

Maximum Assessment Rate (Basis Points)	Probability of Fund < 0 (%)	Probability of Fund < 50 (%)	Probability of Fund < 75 (%)
23.0	0.1	6.5	38.4
20.0	0.7	11.9	39.6
17.0	3.3	20.1	42.5
12.0	16.0	36.2	49.6
8.33	26.1	43.5	54.3

Table A - 8

Probability of Insolvency Using Data from 1972–1996

Maximum Assessment Rate (Basis Points)	Probability of Fund < 0 (%)	Probability of Fund < 50 (%)	Probability of Fund < 75 (%)
23.0	2.3	41.0	87.4
20.0	9.3	58.1	89.1
17.0	24.4	71.9	92.7
12.0	55.2	85.8	95.2
8.33	72.4	91.5	96.5

Required Reserve Ratio of 140 Basis Points

Table A - 9

Probability of Insolvency Using Data from 1934–1996

Maximum Assessment Rate (Basis Points)	Probability of Fund < 0 (%)	Probability of Fund < 50 (%)	Probability of Fund < 75 (%)
23.0	0.1	1.8	28.6
20.0	0.4	6.5	31.4
17.0	2.1	14.2	34.7
12.0	12.7	28.8	43.4
8.33	22.5	37.6	48.3

Table A - 10

Probability of Insolvency Using Data from 1972–1996

Maximum Assessment Rate (Basis Points)	Probability of Fund < 0 (%)	Probability of Fund < 50 (%)	Probability of Fund < 75 (%)
23.0	1.2	21.3	77.2
20.0	6.5	42.4	84.1
17.0	18.0	61.1	88.3
12.0	49.6	79.2	92.9
8.33	67.0	87.9	95.2

Required Reserve Ratio of 150 Basis Points

Table A - 11

Probability of Insolvency Using Data from 1934–1996

Maximum Assessment Rate (Basis Points)	Probability of Fund < 0 (%)	Probability of Fund < 50 (%)	Probability of Fund < 75 (%)
23.0	0	0.6	8.1
20.0	0.4	3.2	15.9
17.0	1.6	8.9	23.4
12.0	11.0	23.6	36.3
8.33	19.4	33.8	42.9

Table A - 12

Probability of Insolvency Using Data from 1972–1996

Maximum Assessment Rate (Basis Points)	Probability of Fund < 0 (%)	Probability of Fund < 50 (%)	Probability of Fund < 75 (%)
23.0	0.9	11.5	49.2
20.0	4.6	27.9	65.1
17.0	14.2	47.8	76.8
12.0	43.4	71.7	87.9
8.33	62.7	83.2	92.7

References

Federal Deposit Insurance Corporation. 1996. *Annual Report.* Washington, DC.

Hamilton, James D. 1989. A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle. *Econometrica* 57: 357–84.

———. 1990. Analysis of Time Series Subject to Changes in Regime. *Journal of Econometrics* 45: 35–70.

———. 1993. Estimating, Inference, and Forecasting of Time Series Subject to Changes in Regime. In *Handbook of Statistics, Vol.* 11, edited by G. S. Maddala, C. R. Rao, and H. D. Vinod. Elsevier Science Publishers.

Shaffer, Sherrill. 1991. Aggregate Deposit Insurance Funding and Taxpayer Bailout. *Journal of Banking and Finance* 15: 1019–37.