# Determining the Target Deposit Insurance Fund: Practical Approaches for Data-Poor Deposit Insurers

John P. O'Keefe
*Federal Deposit Insurance Corporation*
and
Alexander B. Ufier
*Federal Deposit Insurance Corporation*

May 2017

# Determining the Target Deposit Insurance Fund:
# Practical Approaches for Data-Poor Deposit Insurers

John P. O'Keefe
Federal Deposit Insurance Corporation
550 17th Street, NW
Washington, DC 20429
Jokeefe@fdic.gov

And

Alexander B. Ufier
Federal Deposit Insurance Corporation
550 17th Street, NW
Washington, DC 20429
Aufier@fdic.gov

May 2017

**ABBREVIATIONS AND ACRONYMS**

| | |
|---|---|
| DIF | Deposit Insurance Fund |
| EAD | Exposure at Default |
| FDIC | U.S. Federal Deposit Insurance Corporation |
| FIRST | Financial Sector Reform and Strengthening Initiative |
| GDP | Gross Domestic Product |
| IADI | International Association of Deposit Insurers |
| LGD | Loss Given Default |
| PCA | Principal Component Analysis |
| PD | Probability of Default |

**Table of Contents**

## 1.  Introduction

The main public policy objectives of a deposit insurer are to reimburse depositors after bank failure, act as receiver for failed banks, and contribute to the stability of a financial system. To achieve these objectives and build public confidence in a deposit insurance system, deposit insurers must be ready to act quickly after a bank failure. Sound funding arrangements are essential aspects of such readiness, as they ensure prompt reimbursement of insured depositors and sufficient funds for the deposit insurer to unwind the institution. Depositor confidence depends, in part, on knowing that adequate funds for deposit insurance would always be available to ensure the prompt reimbursement of their claims. It is therefore considered a best practice to build credible ex-ante funding mechanisms that have the financial capacity to ensure that these obligations are met.

According to internationally accepted best practice by the International Association of Deposit Insurers (IADI), the appropriate measure of adequacy of a Deposit Insurance Fund (DIF) is the Target Fund Ratio (or Reserve Ratio). [1] The Target Fund Ratio is the ratio of the balance in the DIF to estimated insured deposits in the banking system. Each country is encouraged develop its own target level and funding path to achieve said target based on its financial obligations using relevant data and a transparent methodology. Each national target fund is likely to differ based on the level of financial development, banking concentration, and regulatory environment, in addition to meeting minimum demands placed on the country by other voluntary agreements such as European Union's Directive on Deposit Guarantee Schemes. [2] This target fund level should be reviewed regularly and the method to calculate it subject to validation in accordance with changing financial conditions. [3]

This paper presents a framework to help deposit insurers determine a Target Fund Ratio. The framework takes into consideration the role that credit and liquidity risks play in a bank failure. The goal of the paper is to show how deposit insurers might adapt the Target Fund Ratio framework to their economies and overcome the data limitations many jurisdictions face when attempting to determine deposit insurance losses. We have previously applied this framework to determining the Target Fund Ratio for deposit insurers in Nigeria, Zimbabwe, and the United States (O'Keefe and Ufier 2016a, O'Keefe and Ufier 2016b.)  We use data for the U.S. Federal Deposit Insurance Corporation (FDIC) in this paper. [4]

### 1.1.  Deposit Insurance Funding

There exists a vast literature on deposit insurance that examines all elements of deposit insurance schemes, with the most consequential question addressed by this literature being "how should the deposit insurer pay for bank-failure resolution and related insurance costs?" IADI has synthesized much of this literature and discusses (IADI, 2009) three funding options: 1) funding used to resolve a bank failure that is received *prior to* the bank's failure (ex-ante funding), 2) funding received *after* the bank's

---

[1] See IADI (2009, 2014).
[2] Art. 10 (2) of Directive 2014/49/EU.
[3] See "IADI Core Principles for Effective Deposit Insurance Systems," November 2014, p.29.
[4] We do not present target fund model results for the Nigeria Deposit Insurance Corporation (NDIC) and Zimbabwe Deposit Protection Corporation (DPC) in this paper.

failure (ex-post funding); and 3) hybrid approaches that combine ex-ante and ex-post funding. There are pros and cons to each option. Ex-ante funding can help avert delays compared with ex-post funding, with delays often being potentially expensive. Presence of a fund can improve public confidence. It is arguably fairer to fund ex-ante as failed banks contribute to the fund prior to failure as opposed to only collecting taxes from survivors. Risk-based premiums can be used to discourage risky behavior easily in ex-ante settings but less so in ex-post ones, and premiums can be adjusted to reduce pro-cyclicality in bank profits to spread resolution costs but cannot in ex-post regimes. However, ex-ante funding regimens come at the cost of lost capital to banks that may otherwise could have put it to better use outside the insurance fund, high burdens on individual banks if there are few banks compared with ex-post funding, administrative costs from managing the fund that would not exist were it collected ex-post, and moral hazard problems on both the banks and fund managers of having a large standing resolution fund (IADI 2009).

On a net, IADI (2009) concludes that the benefits of ex-ante funding outweigh the costs and that ex-ante funding of deposit insurance is preferred to ex-post, especially for recently established deposit insurance systems.[5] IADI (2009) states that most deposit insurance funding schemes combine elements of ex-ante and ex-post funding, as it is likely beneficial from a social welfare perspective to spread failure-resolution cost recovery over a long period before, during, and after a severe crisis. IADI (2009) states that the target deposit insurance fund should, at a minimum, be adequate to absorb insurance losses the insurer might incur under "normal" circumstances. As a result, this paper seeks to estimate the necessary size of an ex-ante deposit insurance fund and leaves ex-post deposit insurance schemes for future work.

### 1.2. Determining the Target Deposit Insurance Fund

IADI (2009) states that the majority of countries use their experience with bank-failure losses to determine the target deposit insurance fund. Given sufficient data on failure costs, a deposit insurer can estimate the empirical frequency distribution of losses and use that distribution to determine the level of losses the insurance fund should be able to absorb. This approach to determining the target deposit insurance fund is known as the Loss Distribution Approach. However, countries with limited experience closing failed banks will lack sufficient data to develop an accurate empirical loss distribution and may have difficulty estimating the likelihood of low-probability, high-loss events. As a result, practitioners must calibrate observed losses to an assumed probability distribution of losses, and results are highly sensitive to assumptions made in estimating the likelihood and size of low probability, high loss events. This approach is inherently backward-looking and cannot take into consideration recent changes in the banking industry profile as well as regulatory environment.[6]

A more forward-looking alternative to the Loss Distribution Approach is the Credit Portfolio Approach, which allows one to incorporate the effects of current economic conditions into deposit insurance

---

[5] IADI (2009) states that 80 percent of deposit insurance schemes at that time used ex-ante funding.
[6] Potential concerns include deregulation, changes in depositor preference, changes in deposit insurance assessment schemes, or any number of banking rule changes.

losses. This approach to modeling the target deposit insurance fund is based on the model of bond pricing by Merton (1974) and the loan portfolio model of Vasicek (1987, 1991, and 2002), hereafter the Merton-Vasicek Model. Merton (1974) develops a model for the pricing of corporate bonds that takes into account the possibility the issuing firm might default on payments. Merton (1974) presents the simple case of a corporation financed by a single bond and equity. In the model, bondholders have a claim on all of the corporation's assets should the corporation default on bond payments while equity holders receive nothing. Merton recognizes that since bond holders have a call option of the value of the firm's assets, bonds can be priced using the Black and Scholes (1973) option pricing framework. Under Merton's approach, a firm fails when the market value of firm's assets (call option value of the bond) falls below the nominal value of the firm's obligations to bond holders. Merton recognized this default model generalizes to failures occurring when the market value of a corporation's assets falls below the nominal value of the corporation's liabilities and all of the corporation's creditors can be viewed as having call options on the corporation's assets.

Vasicek (1987, 1991, and 2002) generalizes the Merton (1973) framework to model losses on loan portfolios. Vasicek assumes that obligors' asset value changes are determined by idiosyncratic and systemic risk factors. The systemic risk factor is common to all obligors (that is, the state of the economy). In the Vasicek model, changes in the value an obligor's assets are correlated with those of other obligors through the common risk factor. Finally, the correlation among obligors' asset value changes determines the correlation among obligor defaults. The possibility of correlated default is particularly important to models of the target deposit insurance fund.

The Credit Portfolio Approach assumes that the features of the financial safety net that can influence deposit insurance costs are captured in historical data and do not change over the forecast horizon. This approach has been used to model the target deposit insurance fund for many countries, including Colombia (Fogafin, 2013), Canada (CDIC, 2011), Singapore (Oliver, Wyman & Company, 2002), Nigeria (Katata and Ogunleye, 2014), (O'Keefe and Ufier, 2016a), and Zimbabwe (O'Keefe and Ufier, 2016b), supporting its use in a similar setting in this paper. As we shall show in the Section 2, The Credit Portfolio Approach allows for a forward-looking view of banking industry risk through separate estimates of bank probability of failure, correlation in failures, insurer exposure and losses given failure. This will provide estimates superior to the Loss Distribution Approach, with lower data prerequisites that can easily be applied and customized for numerous national settings.

The remainder of the paper is organized as follows. **Section 2** presents the proposed Target Fund Ratio framework in various states of the world. **Section 3** discusses estimation of the probability of bank failure, followed by estimation of losses given default in **Section 4**. **Section 5** provides a brief discussion of exposure at default and **Section 6** similarly considers failure correlations. **Section 7** provides information on model calibration and execution, and **Section 8** discusses results. **Section 9** discusses the framework's assumptions and inherent weaknesses, and **Section 10** concludes.

## 2. Proposed Target Fund Framework

This model employs a Merton-Vasicek based model, the Credit Portfolio Approach, to estimate deposit insurance losses. The model will allow deposit insurers to revise the target fund estimate as industry conditions change. This approach does not attempt to model the indirect influences of the financial sector safety net on deposit insurance costs; rather, it assumes that these effects are reflected in model input data. Default models, such as this model, describe expected losses as expressed by equation 1.

$$Expected\ Losses\ in\ state\ of\ world\ t = PD_t * LGD_t * EAD_t \qquad (1)$$

Where $EAD_t$ is the overall exposure at default in state of the world $t$, $LGD_t$ is the loss rate per default in state of the world $t$, and $PD_t$ is the probability of default in state of the world $t$. This model will generate failures $PD_t$ based on measures of default probabilities as well as correlations of defaults, and use rules developed from data on loss given default $LGD_t$ and exposure at default $EAD_t$ in a simulation to yield total expected losses and, as a result, a necessary fund level given a certain level of risk tolerance. Before discussing each component that together generates losses, we shall discuss differing states of the world which may affect all the components and how we estimate each of these components of the default model.

### 2.1. Identifying States of the World

In order to develop a robust estimate of deposit insurance fund adequacy, we consider how deposit insurance losses vary under different macroeconomic conditions as denoted by subscript $t$. Specifically, we consider three states of the economy—a severe economic downturn (crisis period), the average conditions over a business cycle (through the cycle), and current (normal) conditions—and calibrate the target fund simulation model to these states. In each of these states, we generate defaults from observed defaults and correlations of returns that contribute to $PD$ as well as to select different parameters for $LGD$ and $EAD$.[7] In order to identify these periods, we analyzed U.S. macroeconomic economic data over the period 1983:Q4–2016:Q1 and identified quarters of the worst economic performance, employing general macro-economic indicators and measures of bank condition in this analysis. Our approach is to first identify the combination of economic indicators, for example, civilian unemployment rate, gross domestic product, that best explain variation in the economic data for the United States and subsequently study how the economy, as characterized by these indicators, changes over time. Specifically, we use **Principal Component Analysis (PCA)** to reduce analysis to a single composite variable—the first principal component. Further information about principal components analysis and extensions to this approach that can refine period selection can be found in appendix A.

#### 2.1.1. Constructing Principal Components

We used the following measures to differentiate U.S. crisis from non-crisis periods*: GDP growth, Civilian Unemployment Rate, Labor Force Participation Rate, Net Exports as a share of GDP, Inflation as*

---

[7] These three views of the economy are designed to show variation in potential deposit insurance losses and are similar in spirit to the views of the economy used in mandatory capital stress-tests for U.S. banks.

*measured by the Consumer Price Index, and Nonperforming Bank Loans as a share of total loans*. We use principal components analysis to create six principal components from these six variables. We focus on the first principal component in this analysis, *PC1*, which explained 39 percent of the overall variation in the chosen economic data. Table 1 presents the variable weights for six key economic indicators for the period 1983:Q4–2016:Q1. These factor weights suggest that higher (lower) values of $PC_1$ imply worse (better) economic conditions.[8]

**Table 1**
**Macroeconomic Variables Used to Explain U.S. Economic Conditions**
**(1983:Q4–2016:Q1)**

| Variable | Variable Weight for First Component[9] |
|---|---|
| GDP Growth | -0.24 |
| Labor Force Participation Rate | -0.50 |
| Net Exports, % of GDP | -0.03 |
| Civilian Unemployment Rate | 0.57 |
| Consumer Price Index | 0.27 |
| Nonperforming Bank Loans, % of Loans | 0.54 |

We recover the values for the first principal component for the United States between 1983:Q4 and 2016:Q1 using the weights as illustrated by equation 2, and then sort years from best to worst using the principal component.

$$PC_{1,2009:Q1} = (-0.24) * GDP\ Growth_{2009:Q1} + \cdots + (0.54) * NPL/Loans_{2009:Q1} \qquad (2)$$

### 2.1.2.  Identifying Crisis Periods

After sorting years by relative level of economic stress, the second step in crisis period identification is to determine a cutoff value of the first principal component to distinguish between crisis and non-crisis periods. For this, we use a ***Bai and Perron break test*** to find a single break in the data series for $PC_1$ when arranged from highest (here, the worst) to lowest (here, the best) $PC_1$. Note that we are not

---

[8] A country may see a reversed scale from what is shown here, with higher values meaning better performance and lower values meaning worse performance. It will cause more interpretation problems if signs were mixed— for example, unemployment rate and GDP growth having the same direction of weights—and require deeper investigation of variables included in the principal components.
[9] If each of these weights is squared, then each column will add up to 1.

arranging quarters chronologically, but by value of their principal component. We identified a break point in the $PC_1$ series at size-ranked observation 104 of 130, which corresponds to a $PC_1$ value of 0.44. We identify values with higher $PC_1$ values than the cutoff as crisis periods. We observe that the crisis period quarters happen to be in two distinct bands, as shown in Figure 1. As additional support for the $PC_1$ approach, we find the worst $PC_1$ (2.03) occurred in 2009:Q3, which corresponds closely to the height of the most recent U.S. financial crisis.

**Figure 1**

**First Principal Component: U.S. Macroeconomic Indicators
(1983:Q4 - 2016:Q1)**
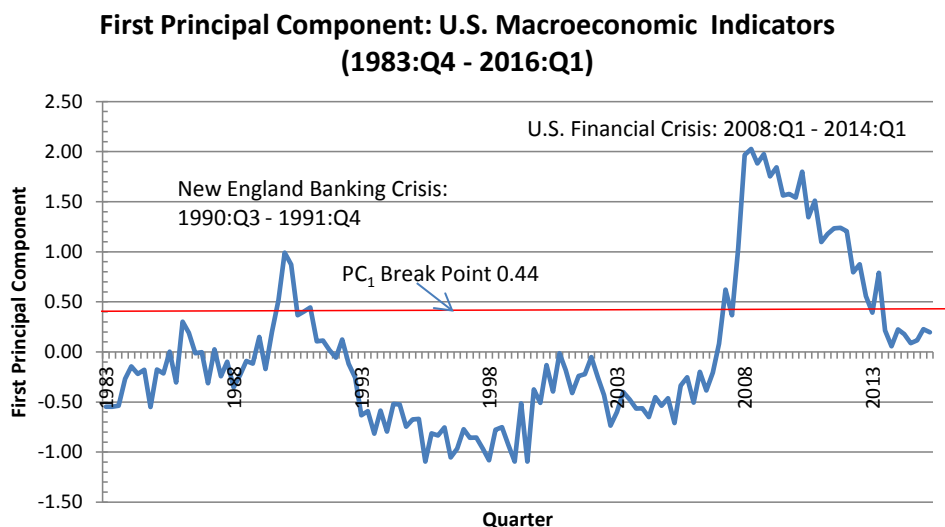


Based on our analysis of U.S. economic data for the period **1983:Q4–2016:Q1,** there are two distinct crisis periods. The first occurred during **1990:Q3–1991:Q4,** which largely coincides with the New England banking crisis. The second occurred during **2008:Q1–2014:Q1,** which generally coincides with the recent U.S. and global financial crisis and slow economic growth thereafter. The start of these crisis periods roughly correspond to those identified by the National Bureau of Economic Research (NBER), a private nonprofit research group with expertise in identifying U.S. business cycles that U.S. academic and government economists cite widely. The first NBER period is July 1990–March 1991 and the second period is December 2007–June 2009. It is important to point out that the NBER methodology differs from ours and is focused on "peak-to-trough" business cycles while ours is focused on the severely adverse economic downturn periods.[10] Our periods likely last considerably longer as our model includes nonperforming loans and unemployment, which tend to lag general measures of economic performance such as the GDP. We will use the data from both of these periods to form our estimates for **crisis period** parameters.

### 2.1.3. Calibrating to Other Periods

In addition to identifying crises periods, we wish to calibrate the Target Fund Model to conditions over a full business cycle, as well as current economic conditions. The NBER states that of the 11 business

---

[10] Business cycle dates are available at the NBER website, http://www.nber.org/cycles/cyclesmain.html

cycles it identified for the period 1945–2009, the average time from one trough to the next was 70 months, or just under six years, and the longest cycle from previous trough to peak was 120 months, or 10 years. To ensure that we capture as much of a full business cycle as possible, we use the most recent 10-year period **2006:Q1– 2016:Q1** as our **through-the-cycle period**. Finally, we use the two-year period, **2014:Q1–2016:Q1** as our **current period**.   Table 2 combines our findings for U.S. economic state identification.

**Table 2. Crisis Period and Business Cycle Identification**

| Economic State | Periods |
|---|---|
| Crisis | 1990:Q3–1991:Q4 <br> 2008:Q1–2014:Q1 |
| Through-the-Cycle | 2006:Q1– 2016:Q1 |
| Current | 2014:Q1–2016:Q1 |

This model explicitly treats each of these periods as different data generating processes, as opposed to assuming that there is a single data-generating process and crises, for example, are particularly low draws from the asset returns process. The crisis parameters would be assuming a distribution of returns calibrated only on the worst years, current times calibrated on average years at the center of a single distribution, and through the cycle calibrated on all years. Differing approaches to generating default probabilities and segmenting data-generating processes can produce different results, and regulators should carefully consider their calibrations to match their own business cycle experiences.

## 3.   Probability of Bank Failure

This section focuses on the $PD$ element of the default model, here the probability of bank failure, which Section 6 builds on by considering the correlation of returns and thus failures among different financial institutions. This $PD$ constitutes the most heavily modeled portion of the target fund framework, and will encompass credit failures $PD_C$, liquidity failures $PD_l$, and systemic failures $PD_s$, each coming from asset return simulations:

$$PD = \ PD_C + \ PD_l + PD_s \tag{3}$$

### 3.1.  Types of Failures in Simulation Study

The 2007–2009 global financial crisis showed that the interaction of credit and liquidity risks, coupled with systemic market shutdowns, could lead to catastrophic deposit insurance losses. We begin by discussing our conceptual approach to simulating bank failures caused by credit risk $PD_C$, followed by descriptions of the interaction of credit and other risks, liquidity and systemic risk, through the simulation.

#### 3.1.1.   Credit Failures

For the purpose of this discussion, obligor default is synonymous with bank insolvency or failure. As stated previously, in a Merton-Vasicek Model, obligors are assumed to default when their wealth or total asset value falls below that of their outstanding liabilities. Equation 4 expresses an asset's one-

period gross return as a weighted average of systemic and idiosyncratic risk measures. In equation 4, $R_i$ is the one-period asset return, $w_i$ is the weight placed on a single systemic risk factor, $X$, and $n_i$ is the weight placed on idiosyncratic risk factor, $E_i$. The systemic risk factor is something faced by all actors—high unemployment, asset price collapses, or changes in a government policy that affect bankruptcies may affect the credit quality of loans held by all banks, for example. The idiosyncratic risk factor is specific to the bank—several of its lines of business may be doing particularly well or poorly. All obligors face the same systemic risk. While $X$ can be a set of several risk measures, Gordy (2000) shows that these risks can be reduced to one systemic risk factor. Conversely, each obligor $i$ has different idiosyncratic risk, $E_i$.[11]

$$R_i = w_i * X + n_i * E_i \tag{4}$$

Without loss of generality, the Merton-Vasicek Model assumes that $X$ and $E_i$ are standard normal random variables. Hence, asset returns, $R_i$, are also distributed as standard normal random variables.[12] As we shall see in subsequent sections, the use of standard normal random variables greatly simplifies quantification of insurance losses.[13] Obligor default occurs when the change in the value of their assets is less than or equal to some critical value, $C_i$:

$$w_i * X + n_i * E_i \leq C_i \tag{5}$$

A more common representation of the asset return model is shown in equation 6.

$$R_i = \sqrt{\rho} * X + \sqrt{1 - \rho} * E_i \tag{6}$$

In equation 6, the term $\rho$ is the correlation between firms' asset returns and is assumed to be identical across any two firms. We next describe the asset return and failure simulation process in general terms. Specifics on model calibration are presented in sections 6 and 7.

### 3.1.2. Monte Carlo Simulations of Credit Failures

To create a loss distribution for a nation's banking sector, we must first create a frequency distribution of bank failures using a Monte Carlo simulation of asset returns. Rather than comparing simulated bank asset returns and ending asset values to those of liabilities, the Monte Carlo simulation takes a more straightforward approach to simulating failure events. Failures are assumed to occur whenever a randomly chosen asset return is more negative than that implied by the bank's expected failure probability.

---

[11] This discussion of the asset return process is based largely on Gordy (2000). Gordy shows that one can view the asset return generation process as being driven by a latent variable that is also determined by systemic and idiosyncratic risks.

[12] Standard normal random variables are normalized by subtracting the mean value of the variable and dividing this difference by the standard deviation. Hence, a standard normal random variable has a mean of zero and standard deviation of one.

[13] Note that equation 4 does not include a time subscript since the default model is a one period model.

Using the assumptions of the Merton-Vasicek Model, the asset return associated with an expected failure probability can be obtained by taking the inverse of the cumulative standard normal density function, evaluated at that failure probability, as shown is equation 7:

$$R_i = \Phi^{-1}(Expected\ Failure\ Probability_i) \qquad (7)$$

Using this approach, we are assured that the simulated failure rate for each bank out of a large number of random draws of asset returns equals the expected failure probability. We use three sources of information on expected failure probabilities—a logistic regression model of bank failure, bank failure rates associated with banks' issuer default ratings, and actuarial failure rates.

We use the Merton-Vasicek Model assumptions to randomly sample asset returns. Specifically, we generate asset returns by taking random draws of values of the idiosyncratic and systemic risk factors in equation 6. Next, we use an estimate of the correlation in bank failures based on bank stock return correlations to weight the risk factors and sum the weighted terms to get a single random draw of the asset return. As shown in equation 8, bank failure is assumed to occur whenever the simulated asset return is more negative than that implied by the failure probability estimate (worse than the stated critical value $C_i$.) As stated at the beginning of this section, equation 8 only refers to credit failure events.

$$If\ R_i < \Phi^{-1}(Expected\ Failure\ Probablity_i)\ then\ Bank\ i\ Fails \qquad (8)$$

We calibrate the systemic risk factor to an economy using the mean and standard deviation of the annual GDP growth rate. Since the idiosyncratic risk factors are standard normal random variables, we generate failure events by random draws from the weighted sum of a normal random variable and a standard normal random variable and using expected failure probabilities to determine the failure threshold for asset returns.

### 3.1.3. Liquidity Failures

Banks rely on a variety of short-term funding sources, and interruption in funding can make it impossible for banks to continue operations. This was the case during the 2007–2009 U.S. financial crisis, when interbank lending and loan securitization markets froze as a result of heightened uncertainty about banks' conditions. Without the immediate provision of liquidity from the central bank and other support programs, many of the largest banks in the United States and other countries faced failure.

Because of the existence of these liquidity programs, observed failure rates during this crisis were lower than they otherwise would have been. Had these institutions failed, higher costs would have accumulated to the deposit insurer. Additionally, if the deposit insurer were funding some of these emergency programs, they would have incurred additional costs. Ignoring these near-failures due to liquidity would potentially underestimate the liability that could accumulate to the deposit insurer in financial distress. Thus, we expand failures beyond just credit defaults to include the possibility of liquidity defaults, $PD_l$. We consider the possibility of liquidity failures by assuming that banks will lose a significant portion of uninsured deposits and other short-term funding if their asset returns place them "near" credit failure status and no further government guarantees are forthcoming. At this point, fire

sales of assets to meet liquidity demands may drive the bank to failure. The near-credit-failure threshold is admittedly subjective and regulators can consider conditions for their country, but this provides a useful overlay to increase bank default risk. We assume a near-credit-failure event occurs whenever the asset loss is 90 percent or more of that which would cause a credit failure, excluding the previously discussed credit failures, as shown in equation 9.

$$If\ 0.90 \leq \frac{R_i}{\Phi^{-1}(PD_i)} < 1.0\ and\ R < 0\ then\ bank\ i\ experiences\ a\ liquidity\ failure \quad (9)$$

In simpler terms, equation 9 increases bank failure rates via directly tightening the default threshold to account for the possibility that liquidity failures may occur in weakly capitalized banks, such as self-fulfilling runs and asset fire sales.

### 3.1.4. Systemic Failures

In addition to the credit and liquidity risks banks face, there is the possibility of a systemic event that disrupts the operations of all banks. One might model systemic risk as arising from a loss of confidence in short- and long-term interbank lending for all banks, including lending by banks outside the country to banks in-country. All interbank lending might cease at the point where borrowing lost due to all individual credit and liquidity failures exceeds a critical threshold. Taking into consideration the importance of interbank borrowing to each bank, if the lost funding exceeds an assumed threshold, banks that rely significantly on interbank funds might all fail due to the shutdown of that market. An example of how one might model systemic failures follows:

> We wish to model the systemic risk arising from a loss of confidence in short- and long-term interbank lending for all U.S. banks, including lending by non-U.S. banks to U.S. banks. We assume all interbank lending ceases at the point where borrowing lost due to all individual credit and liquidity failures is at least 30 percent of total interbank borrowing. We also consider the importance of interbank borrowing to each bank. If the lost funding is at least 10 percent of the bank's assets, the bank is assumed to fail due to the market wide loss of interbank funds.

Unfortunately, U.S. banks do not report sufficiently detailed information on lending to and borrowing from other banks in the United States and elsewhere to include systemic failures in our Target Fund Ratio analysis. This is not necessarily the case for other jurisdictions, however, and we recommend incorporating systemic risk in the Target Fund Ratio framework.

## 3.2. Estimating Probabilities of Failure

Moving beyond the distinct components that will compose default probabilities, we next consider data sources for those probabilities of defaults. We enumerate three approaches to estimating bank failure probabilities below: statistical models (usually logistic regressions), credit rating agency studies, and actuarial failure rates.

### 3.2.1. Statistical Models of Bank Failure

Deposit insurers that have extensive experience closing insolvent banks can use this information to develop statistical models of bank-failure prediction. The most commonly used approach to modeling

bank failure is logistic regression, in which the dependent variable is a binary (0, 1) indicator of the occurrence of bank failure within a specific time period, usually one year. The most informative explanatory variables for bank failure prediction will vary across countries. However, the bank-failure prediction literature finds bank financial measures of capital adequacy, asset quality, management quality, earnings strength, liquidity and sensitivity to market prices (hereafter, CAMELS attributes) are frequently informative explanatory variables. For example, we estimated a stepwise logistic regression of the determinants of bank failure within a given one-year period, using the CAMELS attributes as explanatory variables. Specifically, we used measures of the CAMELS attributes as of quarter-ends 2014:Q1, 2015:Q1 and 2016:Q1 as explanatory variables in the logit model and related these covariates to the incidence of failure in the year following each of these quarter-ends. The potential explanatory variables were those used by the FDIC's off-site bank monitoring model, SCOR.[14]

---

[14] See Collier, Charles, Sean Forbush, Daniel Nuxoll, and John O'Keefe (2003).

**Table 3. Stepwise Logistic Regression of Determinants of U.S. Bank Failures**
**(Forecast Horizon is One Year)**

| Independent Variables* | 2014:Q1 to 2016:Q1<br>Estimated Coefficient (Standard Error) |
|---|---|
| Equity | -0.6958*** |
| | (0.1166) |
| Loans Past due 30 Days or More | 0.4448*** |
| | (0.1160) |
| Loan Loss Reserves | 0.5919** |
| | (0.2212) |
| Income Before Taxes | -0.8811* |
| | (0.3541) |
| Loans and Long-term Securities | -0.1083*** |
| | (0.0300) |
| Liqud Assets | -0.0736** |
| | (0.0261) |
| Provisions for Loan Losses | -2.2281* |
| | (1.0077) |
| Gross Charge-offs | 1.7021* |
| | (0.7495) |
| Intercept | 6.7699** |
| | (2.4539) |
| Pseudo R-squared | 0.6358 |
| N | 19,105 |
| * p<0.05, ** p<0.01, *** p<0.001 | |
| *Note: All variables are measured as a percentage of gross assets. | |

Table 3 shows the estimated coefficient signs for the explanatory variables are as expected. Increases in loans past due 30 to 89 days, loan-loss reserves, and loan charge-offs increase the likelihood of failure while increases in equity capital, income before taxes, loans and long-term securities, liquid assets and loan-loss provisions decrease the likelihood of failure.

A deposit insurer can select the appropriate period over which to estimate the logistic regression to provide estimates of default that reflect different periods of economic conditions—current period, through-the-cycle and crisis period conditions—and apply these coefficient estimates to subsequent period financial data to obtain out-of-sample predictions of banks' failure probabilities. For example, in this study we used the above logit model estimates (Table 3) and year-end 2016 financial data to predict bank failure probabilities for 2017.

If a country has too few explicit bank closings with which to estimate a logistic regression, it may still be possible to model the likelihood that banks become critically undercapitalized. Models considering capitalization levels can use a variety of capital adequacy measures such as equity plus reserves-to-book assets and tier 1 plus tier 2 capital-to-risk weighted assets and observe when a threshold is breached, although the exact measure and capital level are up to the individual deposit insurer. Thresholds for determining when a bank becomes critically undercapitalized can be based on regulatory capital requirements or expert judgment. For example, a 2 percent threshold for equity capital-to-book assets that is in line with U.S. prompt corrective action bank closure policies. An "in-substance" failure could be said to occur when the aforementioned capital measure drop below 2 percent, but the regression remains the same.

There are two limitations to the statistical bank-failure prediction model. First, government support—such as credit guarantee or liquidity programs that affect the profit and indirectly capital position of banks—to the industry during crisis periods may make industry condition appear better than would be the case without government support. Second, government capital injections will improve bank capital adequacy and reduce the occurrence of observed failures, directly improving the capital position of banks.

### 3.2.2. Rating Agency-based Forecasts of Bank Failure

To counter the aforementioned weakness in the statistical bank-failure model, one could alternatively estimate failure probabilities with forecasts based on banks' credit ratings. Banks that issue publicly traded debt receive credit ratings from rating agencies. Fitch, Moody's, and Standard and Poor are the three best-known credit rating agencies that rate both the default risk of individual securities and issuers.

According to FitchRatings (2014, 2013b, 2011), Fitch credit ratings are designed to rate debt issues and issuers vulnerability to default, where default refers to failure to meet interest and principal payments on securities. Since we are primarily interested in banks versus all securities, we focus on Fitch Issuer Default Ratings (IDRs) for banks. Fitch IDRs rate banks' ability to service outstanding debt and are credit risk ratings. IDRs do not take into consideration market, liquidity, and other risks except to the extent that these risks affect the ability of the bank to make debt payments.

Fitch bank IDRs have two components: 1) the default vulnerability of the issuer assuming "ordinary support" from internal and external sources, and 2) the likelihood of receiving extraordinary support. Ordinary support includes support from parent organizations, shareholder support, as well as external support, such as regular access to a central bank for liquidity. Extraordinary support includes support from external sources that one would expect to be forthcoming should the bank become in danger of default, such as the possibility of a collapse of the financial system. Extraordinary support includes liquidity, guarantees, and capital injections. Fitch states that extraordinary support that was forthcoming in the past is not necessarily assumed to be available in the future. Hence, not all the government programs used to manage the 2007–2009 global financial crisis are assumed by Fitch analysts to be available in future when they rate banks' likelihood of receiving extraordinary support. Since Fitch IDRs

are measures of default risk, regardless of the source of a bank's financial support, IDRs are the higher of a bank's individual rating and support rating.[15] Fitch states that IDRs are not designed to be predictors of the numeric probability of default, but rather are ordinal risk measures. As a consequence, the observed default rates for across all IDR ratings bands vary over economic cycles. As with other measures of default, regulators must choose available data carefully to assign default probabilities to differing periods.

FitchRatings (2013a) reviews the experience of bank issuers of debt globally and presents cumulative *failure rates* for one- to three-year horizons by IDR. Fitch points out that issuer default and issuer failure are not the same. An issuer may be able to make debt payments; but if that ability is contingent on the bank receiving extraordinary support, Fitch classifies the bank as "failed" even though it's not in default. More generally, when computing historical issuer failure rates, Fitch includes banks that were non-viable without external support among the failed banks. Table 4 lists the current, average long-term, and global financial crisis period one-year bank failure rates from the 2013 Fitch study.

**Table 4. Fitch Credit Ratings and Global Bank Failure Rates**[16]

| Individual Rating | Long-term IDR | Most Current Available | Long-term Average | Crisis Period Average |
|---|---|---|---|---|
| Fitch IR Bands | Fitch LT IDR Bands | 2011 failure rate (%) | 1990–2011 average annual failure rate (%) | 2008–2009 average annual failure rate (%) |
| A | AAA, AA+, AA | 0 | 1.05 | 30.0 |
| A/B | AA+, AA,AA-,A+,A | 0 | 1.03 | 9.60 |
| B | AA-, A+,A, A- | 0 | 0.77 | 6.26 |
| B/C | A, A-, BBB+, BBB | 0 | 0.90 | 4.55 |
| C | BBB+,BBB, BBB-, BB+ | 0.42 | 1.59 | 3.58 |
| C/D | BBB-, BB+, BB, BB- | 1.16 | 2.03 | 2.01 |
| D | BB, BB-,B+,B,B- | 4.60 | 2.96 | 2.09 |
| D/E | B+,B,B-,CCC | 1.72 | 3.93 | 7.93 |
| E | CCC,CC, C | 13.33 | 7.38 | 18.16 |
| All Banks | | 1.82 | 1.71 | 4.92 |

Note that the average bank failure rates in Table 4 do not always increase the poorer the Fitch individual ratings (IRs). Specifically, Table 4 shows that average failure rate for A-rated banks exceeds that for B-rated banks for the 1990–2011 period and the average failure rate for A, B, and C-rated banks exceeds that for D-rated banks for the 2008–2009 period. The non-monotonic relationship between Fitch IRs and bank failure rates is consistent with the definitions of IRs and bank failures in the Fitch 2013 study, as Fitch classified some banks as failed due to reliance on extraordinary support even though these same

---

[15] Fitch ratings of issuer default risk have evolved over time; however, there has not been any fundamental change of the way Fitch sets IDRs. Specifically, Fitch replaced its Individual Ratings (IRs) with Vulnerability Ratings (VRs) in 2011. The VRs consider the same core risks as IRs, but use a more granular rating scale than did IRs.
[16] See "Global Bank Rating Performance Study: 1990–2012", FitchRatings, November 27, 2013, p. 9.

banks made debt payments. The largest banks, therefore, were most likely to receive assistance as they were systemically important and also likely to have the best credit rating, generating this pattern.

### 3.2.3. Actuarial Bank Failure Rates

Countries can estimate directly bank failure rates based on the global banking industry or on their domestic industry. This will require a calculation of actuarial tables. To accommodate short-term and long-term perspectives in target fund design, we include three bank-failure forecast horizons in the target fund framework—one-, two-, and three-year cumulative failure rates.[17] As an example, we obtained historical failure rates from the FitchRatings (2013a) study on global bank failure rates between 1990 and 2011. Sources may also include the central bank or other regulators tracking business activity. Table 5 presents historical cumulative failure rates from the study.[18]

**Table 5. Cumulative Bank Failure Rates From the FitchRatings (2013) Study**

| Economic State | Period | One Year | Two Year | Three Year |
|---|---|---|---|---|
| Crisis Period | 2008-2009 | 4.92% | 7.29% | 7.70% |
| Through-the-Cycle | 1990-2011 | 1.77% | 3.66% | 5.61% |
| Current Period | 2011 | 1.82% | 2.61% | 8.59% |

Table 6 presents one- , two-, and three-year cumulative failure rates for U.S. FDIC-insured banks for the three economic states we identified. Clearly, if a country has a significant history of bank closings, country failure rates are preferred to external failure rates. A shortfall of industry average failure rates is that one cannot differentiate banks in terms of failure risk and one failure rate is applied to all banks.

**Table 6. Cumulative Bank Failure Rates for the U.S.**

| Economic State | Periods | One Year | Two Year | Three Year |
|---|---|---|---|---|
| Crisis Period | 1990:Q3–1991:Q4 2008:Q1–2014:Q1 | 1.10% | 1.93% | 2.38% |
| Through-the-Cycle | 2006:Q1– 2016:Q1 | 0.65% | 1.27% | 1.87% |
| Current Period | 2014:Q1–2016:Q1 | 0.13% | 0.18%* | 0.20%* |
| *Rates truncated since failure data only exist through 2017:Q1. | | | | |

---

[17] In the event of three years of failure versus one year of failure, we are not taking three-versus-one draws from the distribution, but a "total" three-year result with a certain cumulative failure rate versus a one- year result with a certain failure rate.

[18] See "Global Bank Rating Performance Study: 1990-2012," Special Report, FitchRatings (November 27, 2013).

## 4. Loss Given Default

This section discusses the determinants of Deposit Insurance Fund (DIF) loss rates as a percentage of failed-bank assets.[19] Sections 4.1 and 4.2 discuss the features of a deposit insurer that influence DIF losses. Section 4.3 describes the key cash inflows and outflows that determine DIF losses, and Section 4.4 presents information on U.S. FDIC losses on bank closings between 1984 and 2016. While the examples of insurance loss determinants given in this section may not apply to all insurers, the section provides information on how deposit insurers generally should approach the task of determining loss given default. The model here will use data to create a rule for loss given default, and does not model or simulate explicitly in the calculation of losses as it does default events. Regulators may choose a single value for loss given default or select differing values to reflect all current conditions in the country.

### 4.1. Failure Resolutions

The bank failure-resolution process has three main elements. First, the deposit insurer makes payments to insured depositors using the resources of the DIF. Assuming that depositors are paid fully and promptly—sensible performance goals on their own—this payout process should not vary much across deposit insurers. Second, the insurer is entitled to receive reimbursement from asset liquidations based on the subrogated rights of insured depositors. Third, the deposit insurer reimburses all other bank creditors using the proceeds (recoveries) from failed-bank asset liquidations and/or proceeds from other forms of failure resolution. These last two can be significant sources of variation in loss rates across deposit insurers.

#### 4.1.1. Priority of Claimants

The primary determinant of deposit insurance losses lies in how asset recoveries are disbursed. The FDIC Act states that the FDIC's subrogated claim has priority over that of uninsured depositors and other creditors. Among claimants, deposits have preference over all other non-secured, non-preferred claimants. If a deposit insurer has first claim on assets, even a relatively low recovery rate will mean very few losses for the insurer. Not all deposit insurers have the same claim structure, however. If the deposit insurer is *pari passu* with other claimants, losses are likely to be high even with a relatively high recovery rate.

#### 4.1.2. Structure of Losses

Table 7 summarizes the key cash flows associated with bank-failure resolutions for the DIF.  Note that all recoveries, including recoveries from appointed agents and the courts, are included in the recoveries listed in Table 7. Deposit Insurers often record recoveries from failed-bank resolutions by bank asset type. In Table 7 we use three broad categories of bank assets—Risk (for example,, loans), Physical (for example, fixed assets), and Investment (for example,, securities)—to illustrate this point.

---

[19] Failed-bank assets are measured the quarter-end prior to failure. This loss rate base was chosen since one will only know reported bank assets prior to closing for the purpose of projecting losses.

**Table 7. Failed-bank Recoveries and Claims Payment**

| Cash Inflows: | After Bank Closure |
|---|---|
| Recoveries on Risk Assets, Physical Assets and Investments | Recoveries made by DIF<br>- Risk asset repayments/collateral sales<br>- Physical asset sales<br>- Investment asset sales |
| | Recoveries made by appointed agents |
| | Recoveries from court cases/litigation |
| **Cash Outflows:** | Insured Depositor Claims |
| Disbursements for creditor claims and liquidation expenses | Receivership Expenses<br>- Liquidation Expenses<br>- Asset Management<br>- Appointed Agent Expenses |
| | Uninsured Creditor Claims |
| Secured Claims | Are paid directly from collateral |

### 4.2. Deposit Insurance Losses

Equation 10 shows net recoveries on assets for an individual failed bank, *j*, as the sum of recoveries over the life of the receivership (periods 0 to T) minus receivership expenses.

$$\text{Net Recoveries}_j = \sum_{t=0}^{T} Recoveries_t - \sum_{t=0}^{T} Liquidation\ Expenses_t \quad (10)$$

After receivership expenses and preferred claims, the FDIC has the next claim on recoveries equal to the subrogated claim of insured depositors. Hence the FDIC's net cash flow is always less than or equal to zero, that is, never a profit.

$$Net\ Cash\ to\ FDIC_j = Net\ Recoveries_j - Preferred\ Claims_j - Insured\ Deposits_j \quad (11)$$

Should net recoveries exceed insured deposits and preferred claims, the FDIC would distribute the excess to uninsured claimants.

### 4.3. FDIC Loss Rates

Tables 8 and 9 present information on FDIC net loss rates as a percentage of failed-bank assets for the crisis, through-the-cycle, and current periods identified previously. Insurance losses take into consideration recoveries from asset liquidations and/or bidder payments for failed banks, receivership expenses, preferred and secured liabilities, and FDIC's subrogated claim. These rule-based values are then used with failure simulations to determine net losses for each simulated year. We computed loss rates on failed-bank assets for five bank asset-size groups to control for the historical relationship between bank size and deposit insurance loss rates—loss rates tend to decline as bank size increases.[20]

---

[20] Possible reasons for the inverse relationship between bank size and failure-resolution costs are the market monitoring of large, publicly traded banks, continuous on-site supervisory presence at the largest banks, and greater portfolio diversification and franchise value of large compared with small, community banks. An

An alternative approach would be to compute loss rates by asset types, for example, risk assets, physical assets, and investments. However, these types of loss rates were not available for this study.

**Table 8.  FDIC Loss Rates on Failed-Bank Assets**

| Asset Size | Crisis Period | Through-the-Cycle | Current Period |
|---|---|---|---|
| <= $100 M | 23.8% | 29.1% | 20.1% |
| $100 M to $500 M | 24.4% | 24.7% | 16.0% |
| $500 M to $1 B | 22.5% | 22.3% | 7.0% |
| $1 B to $10 B | 18.4% | 18.8% | 12.0% |
| Over $10 B | 13.1% | 15.4% | --- |

**Table 9.  Number of Failed Banks by Asset Size Group**

| Asset Size | Crisis Period | Through-the-Cycle | Current Period |
|---|---|---|---|
| <= $100 M | 250 | 129 | 16 |
| $100 M to $500 M | 292 | 262 | 9 |
| $500 M to $1 B | 69 | 63 | 1 |
| $1 B to $10 B | 65 | 56 | 1 |
| Over $10 B | 11 | 9 | --- |

## 5.  Exposure at Default

Estimating deposit insurance exposure at default is relatively straightforward compared with other parameters necessary to estimate a deposit insurance fund target. Data on deposits and bank liabilities should be available from quarterly bank financial statements that banks file with their regulators. Estimates of insured deposits are often reported by banks as well, sometimes directly to the deposit insurer and other times to the central bank. The accuracy of self-reported insured deposits varies with the complexity of deposit insurance coverage rules, with more complex rules yielding less reliable estimates. The percentage of deposits that are insured will vary with bank type within the country, and insurance exposures depend heavily on the deposit insurance thresholds relative to average depositor wealth levels as well as wealth distributions. Thus, the resulting exposure at default parameter will not be explicitly modeled in the simulation, but rather determined as a rule from available data.

### 5.1.  The U.S. Case

U.S. insured banks with assets over $1 billion are required to report an estimate of insured deposits quarterly to their primary federal regulator. Based on U.S. bank data as of December 2016, insured deposits as a percentage of domestic deposits decrease as bank asset size increases. Among banks with assets over $10 billion, insured deposits as a percentage of domestic deposits were 61 percent, and among banks with assets between $10 billion and $1 billion, the percentage of insured deposits was 74 percent. While we do not have self-reported insured deposits for banks with assets under $1 billion, the

---

examination of the determinants of large versus small-bank failure-resolution costs, however, is beyond the scope of this paper.

FDIC does have information on insured deposits at closing for 161 banks that failed between January 1984 and December 2016.  This sample is a small selected fraction of the 1,859 banks that failed during this period. However, as the purpose of this exercise is to bound the cost of the deposit insurer, we find insured deposits were an average of 97 percent of total deposits for these 161 failed banks. In the U.S. Target Fund Ratio estimates, we use the self-reported insured deposit shares for banks with assets over $1 billion and assume the percentage of deposits that are insured is 97 percent for banks with assets under $1 billion.  Countries with higher income inequality usually have a higher proportion of uninsured deposits, and regulators may elect to segment exposure at default by institution size or economic conditions as they see fit, or may instead choose to use only a single proportion for exposure given default across all banks and periods.

## 6.  Correlation of Bank Failures

A major contribution of this paper is going beyond default probabilities discussed in Section 3 to model the correlation of defaults through the correlation in asset returns, $\rho$. Obtaining correlations of bank failures to combine with overall probabilities of bank failure allows regulators to simulate a more realistic distribution of defaults. We discuss two primary approaches that can be used to obtain correlations in the movement of bank values and thus their proximity to failure.

### 6.1. Stock Return Data

Pricing data for publicly traded banks will incorporate all publically available information and possibly some private information as well about the valuation of the company. Correlations obtained from these data can be aggregated based on desired periods to generate correlation inputs for the simulation model. Regulators could estimate pairwise Pearson correlations for each pair of bank stock returns, and then take the average of these correlations to get an overall industry average correlation.

Table 10 shows the mean pairwise correlation in quarterly stock returns for all publicly traded U.S. insured banks for the three economic periods previously identified. Overall, return correlations are low, but do increase with economic stress, as expected. This is potentially due to the U.S. banking sector having numerous banks of varying size, product mix, geographic coverage, and complexity.[21]

**Table 10. Bank Quarterly Stock Return Correlation**

| Period | Mean Correlation |
|---|---|
| Crisis | 0.094 |
| Through-the-Cycle | 0.090 |
| Current | 0.049 |

---

[21] An alternative approach to using mean pairwise stock return correlations for all bank stocks is to compute average pairwise average correlations by industry segments, based on asset size, business orientation (for example, wholesale versus retail banking) or other bank characteristics. For simplicity, we use the overall pairwise average correlations in this paper.

### 6.2. Book Equity

Alternatively, one could derive correlation using book equity in a similar process. Banks that are required to report financial statements to the central bank would report returns on equity, and regulators could estimate pairwise Pearson correlations for each pair of bank returns on equity, and then average these correlations for an overall correlation in returns on equity. While every bank will have a value using this approach—even smaller private banks—they will not be subject to the same amount of public scrutiny and information gathering that stock return data are subject to, and thus this measure of asset correlation is generally of worse quality. Regulators should choose carefully between a larger number of low-quality equity measures from book equity data and a smaller number of higher-quality equity measures from common stock data.

## 7. Model Calibration

Estimating the national level bank-failure loss distribution using the Monte Carlo simulation model requires estimates of four parameters as discussed above—probability of default, loss given default, exposure at default, and correlation of default. For this example, we lay out the simulation options again in brief and note the selections we made.

### 7.1. Probability of Default (PD)

Deposit insurers should keep records on the number of bank closings during their history to use as a basis for simulating defaults. However, countries that lack long-term data must use other methods for estimating the probability of default. Options for all these data environments are presented below:

#### 7.1.1. Statistical Predictions

Statistical predictions of undercapitalization may be used as when failure information is sparse. In this approach, regulators estimate the likelihood of banks becoming critically undercapitalized (for example, less than 2 percent equity and reserves-to-assets ratio in the U.S. case) using available bank financial data, usually with a logistic model. This is discussed in section 3.2.1.

#### 7.1.2. Issuer Default Ratings

Credit ratings have been used to model bank failure risk in many jurisdictions where actual closings are infrequent or when data are unavailable to make statistical predictions of undercapitalization or closing. This is discussed in section 3.2.2.

#### 7.1.3. Industry Failure Rates

Failure rates based on actual closings may be available for some periods but not others. Records may be missing in some cases, and in other cases the variance in closures may be artificially high if banks are closed periodically as part of major government consolidation initiatives rather than when they become insolvent. This is discussed in Section 3.2.3. This is the measure used for this U.S. simulation, with

differing values for each of the three economic periods $t$ and from one- to three-year horizons, shown in Table 6, and contributes to the credit as well as liquidity probabilities of failure.

### 7.2. Loss Given Default (LGD):

Estimating loss given default requires access to information about recoveries from past asset liquidations among differing economic conditions $t$ as discussed in Section 4. Losses given default are not explicitly modeled in the simulation, but rather are determined by a rule from historical experience. Each country must choose these values based on its experience and institutional background. This simulation uses differing values of LGD for each of the three economic periods and by bank asset size, as shown in Table 8.

### 7.3. Exposure at Default (EAD)

Countries should have access to estimates of share of insured deposits as well as overall asset size from their bank's reporting as discussed in Section 5. This will allow regulators to create a rule-based value for the share of insured deposits in each bank, and regulators can elect to have it vary by period or across banks at their discretion.  Exposure at default varies by individual bank in this simulation, but is constant across all three economic periods. In the U.S. Target Fund Ratio estimates, we use the self-reported insured deposit shares for banks with assets over $1 billion and assume the percentage of deposits that are insured is 97 percent for banks with assets under $1 billion.

### 7.4. Correlation of Default

Regulators can either use publicly available stock returns or figures reported to the regulators on book equity to generate a measure of default correlation as discussed in Section 6. For this simulation, we use stock market data and overall pairwise return correlations by economic period, as shown in Table 10.

### 8. Model Results

Using the above inputs across the three differing sets of economic conditions—current, through-the-cycle, and crisis period—regulators can estimate losses from bank failures. Crisis conditions are likely to generate the highest required reserve ratio, and are likely to be the binding target for deposit insurers.

We used 500 random joint draws of systemic and idiosyncratic risk factors in the Monte Carlo simulations to generate failure events across each of these three periods of conditions over one-, two- and three-year horizons.  The greater the number of simulations, the greater the ability of the model to detect high-loss, low-probability events. Since there were about 5,857 FDIC-insured banks as of December 2016, we limited the number of random draws of the risk factors to 500.  The simulations resulted in over 2.9 million bank-simulation failure-loss results, from which we derive the FDIC's cumulative loss distribution.[22]

---

[22] The Excel simulation model execution time for bank-simulation events will vary with the capacity of the computer used to run the simulations. Our simulation run times was about five hours. Countries with vastly

It is common in these scenarios to have the vast majority of simulations result in few or no failures, with a few simulations yielding large numbers of failures. After identifying the failure events, each failed bank will impose costs to the insurer equal to the product of the loss given default rule and the exposure at default of that bank. These losses per bank are then summed to estimate total losses to the deposit insurer for that particular random draw.

## 8.1 Desired Fund Size

The aggregate amount of deposit insurance losses an insurer wishes to be able to absorb over a specific time horizon is a public policy choice. As a benchmark, over the past 40 years U.S. Aaa and Aa rated municipal bonds have made payments of interest and principal 99.97 percent of the time.[23] The 99.97 percent confidence level is also commonly used as a benchmark for U.S. banks' economic capital models and the Basel II capital requirements.[24] The 99.97 percent confidence level implies a loss level that is exceeded once in every 3,333 Monte Carlo simulations. The 99.97 percent loss threshold is, however, at odds with the U.S. experience with deposit insurance. The Federal Savings and Loan Insurance Corporation became insolvent, the National Credit Union Share Insurance Fund narrowly avoided bankruptcy by capitalizing a portion of member credit unions' capital and the FDIC twice became book-equity insolvent due to high failure-loss reserves that were not needed thanks to improvements in the economy as well as government support programs during previous banking crises. For these reasons, we chose a confidence level more in line with the experience for the U.S. Target Fund Ratio estimate—a 99.8 percentile confidence level—that ensures the target fund is exceeded only once in 500 trials. The confidence level we selected is consistent with previous research on the adequacy of the FDIC's insurance fund in non-crisis periods.[25]

Table 11 presents the results for estimates of the Target Fund Ratio necessary to absorb insurance losses at the 99.8 percent confidence level for three economic states where all results are based on U.S. historical bank failure for PD in section 7.1, insurance loss rates for the LGD rule as mentioned in in 7.2, bank balance sheets to summarize exposure as in section 7.3, and average pairwise correlation in stock returns as a measure of failure correlation mentioned in 7.4. We assume rigorous enforcement of FDIC's

---

smaller numbers of banks than the United States, for example, 20 to 30 banks, can run 50,000 simulations in minutes.

[23] See "Safety of Investment Grade Bonds - Examining Credit Ratings and Default Rates of Municipal and Corporate Bonds" by Stephen J. Huxley and Brent Burns, Asset Dedication White Paper Series (February 2011).

[24] There is inherently a tradeoff between selecting periods of the economy to use to calibrate default probabilities and the confidence level. Assuming that the economy uses only one data generating process, one would need to look at a higher confidence level than if one were to consider the economy uses multiple data generating processes instead and looking at the data generating process for the bad states of the economy, to get the same level of safety.

[25] Schuermann and Kuritzkes (2005) use a Merton credit loss model of the FDIC's Bank Insurance Fund (BIF), estimated as of year-end 2000 and find that the BIF was adequate to cover losses up to the 99.85 percentile level but note that under different, stressed market conditions the confidence level was 96 percent. See Til Schuermann and Andrew Kuritzkes, Deposit Insurance and Risk Management of the U.S. Banking System: What is the Loss Distribution Faced by the FDIC?" *Journal of Financial Services Research* 27:3 217–242, 2005.

least costly resolution rule by assuming losses cannot exceed the value of insured deposits. <u>To avoid false precision, we round Target Fund Ratio estimates to the nearest full percentage point.</u> Using a one-year bank failure horizon and limiting insurance losses to insured deposits, the Target Fund Ratio estimates under current, through-the-cycle and crisis period conditions are 3, 4 and 5 percent of insured deposits respectively.

**Table 11. Target Fund Ratio as a Percentage of Insured Deposits**
**(Target for 99.8% Confidence Level)**

| Cumulative Failure Rate | Current Period | Through-the-Cycle | Crisis Period |
|---|---|---|---|
| One Year | 3% | 4% | 5% |
| Two Year | 3% | 4% | 5% |
| Three Year | 4% | 7% | 7% |

The FDIC's current Target Fund Ratio is 2 percent of estimated insured deposits, a target which has been reaffirmed annually. The FDIC did not arrive at its Target Fund Ratio using a credit risk modeling approach as was used here; rather, the FDIC based its Target Fund Ratio choice in part on an analysis of historical FDIC losses, income and insurance fund levels. In addition to historical analysis, the FDIC must consider specific statutory factors when selecting the Target Fund Ratio—the risk to the DIF in current and future years, economic conditions, the potential for sharp swings in insurance assessment rates and other factors the FDIC's Board of Directors deem appropriate. The FDIC published a historical analysis by Davison and Carreon (2010) which used data from the period 1950 to 2010 and a different model from this one that was based on aggregate data in an income and expense simulation model that reviewed the FDIC's historical losses and simulated insurance fund levels under alternative insurance premium and fund maintenance strategies, arriving around a 2% minimum fund estimate.[26]

It is thus difficult to directly compare our credit loss model estimates of the Target Fund Ratio with the FDIC's historical insurance fund analysis.   The credit loss model in this paper uses a point in time estimate of potential insurance losses over one-, two- and three-year failure horizons and does not incorporate funding from insurance assessments and FDIC investment income over a long horizon that Davison and Carreon (2010) take into consideration. Other countries may not have as much flexibility in directing investments for their deposit insurance funds or making special or prepaid assessments of the banking sector as the FDIC has, which would necessitate a more conservative fund target. Finally, the credit loss model cannot take into consideration certain statutory factors the FDIC must consider when setting the Target Fund Ratio, such as potential future changes in regulatory legislation.

## 8.2 Longer Horizons

The Target Fund Ratio estimates increase as we increase the bank failure horizon to allow the deposit insurer to weather longer crises, with the three year failure horizon Target Fund Ratio estimate reaching 7 percent under crisis period conditions. Table 11 shows the sensitivity of the Target Fund Ratio

---

[26] See FDIC (2010).

estimates to the bank failure horizon and the economic conditions FDIC operates under when liquidating failed-bank assets.[27]

## 9    Inherent Weaknesses of Model Assumptions

All approaches to estimating the target deposit insurance fund require one to make assumptions about which factors influence the target fund (i.e., drivers of insurance losses) and the manner in which these factors combine to influence the target fund. The Loss Distribution Approach relies on historical data on deposit insurance losses and is entirely a data-driven approach. Implicit in the Loss Distribution Approach is the broad assumption that past drivers of deposit insurance losses remain relevant in the future and that the manner in which these drivers combine to influence insurance losses remains much the same in the future. The Credit Portfolio Approach relies on less data than the Loss Distribution Approach and, therefore, the Credit Portfolio Approach must use explicit assumptions about the drivers of insurance losses and how these drivers combine to influence insurance losses. While it is still reliant on historical data, it can be used to generate simulations based on new conditions and incorporate data from sources other than the historical experiences of the host country.

As discussed previously, the Credit Portfolio Approach does not model the influence of the legal and regulatory environment on insurance losses and assumes the structure of the financial safety net, and deposit insurance regime in particular, remain unchanged from that reflected in the model input data. The Credit Portfolio Approach also makes strong assumptions about the process that generates bank asset value changes and, therefore, bank failures. The specific assumptions for asset returns are:

a.   assets value changes are driven by a linear combination of systemic and idiosyncratic risk factors (Merton-Vasicek Model),
b.   both risk factors are transformed to standard normal random variables (mean zero and standard deviation of one),
c.   idiosyncratic risk and systemic risk are distributed independently of one another,
d.   the idiosyncratic risk of any two obligors is distributed independently of one another,
e.   Idiosyncratic risk of all obligors in not serially correlated.

It is generally acknowledged by economists that firms' profitability, liquidity and capitalization are influenced by firm-specific factors and events (e.g., hiring of new corporate executives), as well as by general macroeconomic conditions, i.e., systemic factors. There is less agreement, however, on how to measure idiosyncratic and systemic risk factors and on the manner in which these factors combine to determine asset returns.

The strongest assumption of Merton-Vasicek Models is that asset returns are normally distributed. Financial securities returns are typically non-normally distributed and have return distribution with "fat tails" that allow for higher probabilities of large losses. While the normal return distribution assumption might lead to some underestimation of low probability, high loss events, we feel the calibration of the

---

[27] We recommend deposit insurers also conduct sensitivity analysis around the sensitivity of Target Fund Ratio estimate to changes in the Monte Carlo simulation model parameters—PD, EAD, LGD and failure correlation.

loss distribution to three states of the economy—current, through-the-cycle and crisis period—and the use of a high threshold for the loss confidence level, 99.8 percent, helps ensure the adequacy of target fund estimates.

**10 Conclusion**

Deposit insurers need not restrict themselves to one methodology for determining the target deposit insurance fund. Further, the target fund estimation has been the subject of many academic studies. For these reasons, deposit insurers can choose a Target Fund Ratio by drawing upon several sources of information. For example, the FDIC has studied the target fund question using a wide variety of sources of information—FDIC historical experience, simulations based on past FDIC losses, credit risk models developed by outside experts and academic literature on deposit insurance. The target fund framework presented herein describes a transparent process that can be undertaken by regulators to estimate the Target Fund Ratio even when faced by significant data challenges.

**References**

Basel Committee on Banking Supervision and International Association of Deposit Insurers. 2009. Core Principles for Effective Deposit Insurance Systems, (June 2009).

Black, Fisher and Myron Scholes. 1973. The Pricing of Options and Corporate Liabilities. *The Journal of Political Economy*, Vol. 81, No. 3 (May–June, 1973), pp. 637-654.

Calomiris, Charles W. 2010. The Past Mirror: Notes, Surveys, Debates—banking crises yesterday and today. *Financial History Review,* Vol. 17, No. 1 (2010), pp 3–12.

Canadian Deposit Insurance Corporation. 2011. Consultation Paper Premium Assessment Approach and Target Fund Level (June 2011).

Collier, Charles, Sean Forbush, Daniel Nuxoll, and John O'Keefe.  2003.  The SCOR System of Off-Site Monitoring. *FDIC Banking Review*, Vol. 15, No. 3.

Davison, Lee K. and Ashley M. Carreon. 2010. Toward a Long-Term Strategy for Deposit Insurance Fund Management. *The FDIC Quarterly*, Vol. 4, No. 4.

De Lisa, Riccardo, Stefano Zedda, Francesco Vallascas, Francesca Campolongo and Massimo Marchesi. 2011. Modelling Deposit Insurance Scheme Losses in a Basel 2 Framework. *Journal of Financial Services Research* Vol. 40, pp. 123–141.

Dodd-Frank Wall Street Reform and Consumer Protection Act. 2010. Pub. L. No. 111-203, § 929-Z, 124 Stat. 1376, 1871 (2010) (codified at 15 U.S.C. § 78o) [Bluebook R. 12.4].

Federal Deposit Insurance Corporation. 2010. Designated Reserve Ratio. *Federal Register*, Vol. 75, No. 243,  (December 20, 2010), pp. 79286–79293**.**

FitchRatings. 2014. Definitions of Ratings and Other Forms of Opinion (December 2014)

FitchRatings. 2013a. Global Bank Rating Performance Study: 1990–2012 (November 27, 2013)

Special Report

FitchRatings. 2013b. Ratings Reality: Explaining What Fitch's Ratings Do and Do Not Address Special Report (May 8, 2013)

FitchRatings. 2011. Viability Ratings: An Introductory Primer Special Report (July 20, 2011)

Fogafin. 2013. "A Methodology for Determining the Target Funding Level of a Deposit Insurer," Paper No. 4 (February 2013). (Fogafin is a state-owned institution that protects bank depositors in Columbia.)

Gordy, Michael B. 2002. A Risk-Factor Model Foundation for Ratings-Based Bank Capital Rules, Working Paper, Board of Governors of the Federal Reserve System.

Gordy, Michael B. 2000. A Comparative Anatomy of Credit Risk Models, Journal of Banking & Finance Vol. 24, pp. 119–149.

International Association of Deposit Insurers. 2009. "Funding of Deposit Insurance Systems" Guidance Paper Prepared by the Research and Guidance Committee International Association of Deposit Insurers, (May 6, 2009).

International Association of Deposit Insurers. 2011. "Evaluation of Deposit Insurance Fund Sufficiency on the Basis of Risk Analysis," Discussion Paper Prepared by the Subcommittee on DIF Sufficiency Research and Guidance Committee (2011).

International Association of Deposit Insurers. 2012. "Enhanced Guidance for Effective Deposit Insurance Systems: Reimbursement Systems and Processes," Guidance Paper Prepared by the Research and Guidance Committee International Association of Deposit Insurers (November 2012).

International Association of Deposit Insurers. 2014. "IADI Core Principles for Effective Deposit Insurance Systems," (November 2014).

Internal Monetary Fund and World Bank. 2013. Financial Stability Assessment Program: Crisis Management and Crisis Preparedness Frameworks Technical Note (May 2, 2013).

Katata, Kabir S. and R.W. Ogunleye. 2014. "Target Funding Ratio and Assessing the Adequacy of the Deposit Insurance Fund," Nigerian Deposit Insurance Corporation, Working Paper (2014).

Koyluoglu, H. Ugur and Andrew Hickman. 1998. A Generalized Framework for Credit Risk Portfolio Models. Working Paper (September 14, 1998).

Merton, Robert C. 1974. On The Pricing of Corporate Debt: The Risk Structure of Interest Rates. *Journal of Finance*, Vol. 29, No. 2. pp. 449–470.

Monetary Authority of Singapore. 2002. Deposit Insurance Scheme Consultation Paper (August 6, 2002).

Oliver, Wyman & Company. 2002. Deposit Insurance Scheme: Technical Addendum (for the Monetary Authority of Singapore) (August 6, 2002).

O'Keefe, John and Alex Ufier. May 2016a. Nigeria: A Methodological Approach for Development of a Target Deposit Insurance Fund Model. Prepared for the Nigeria Deposit Insurance Corporation and World Bank Group. Available at the World Bank Group Open Knowledge Repository: https://openknowledge.worldbank.org/handle/10986/25776.

O'Keefe, John and Alex Ufier. June 2016b. Zimbabwe: A Methodological Approach for Development of a Target Deposit Insurance Fund Model. Prepared for the Zimbabwe Deposit Protection Corporation and World Bank Group.

Thomas, Hugh and Zhiqiang Wang. 2005. Interpreting the Internal Ratings-Based Capital Requirements in Basel II. *Journal of Banking Regulation* Vol. 6, pp. 274–289.

Vasicek, Oldrich A. 2002. Loan Portfolio Value. *Risk* (December 2002), pp. 160–162.

Vasicek, Oldrich A. 1991. Limiting Loan Loss Probability Distribution. Technical Document, KMV Corporation (August 9, 1991).

Vasicek, Oldrich A. 1987. Probability of Loss on Loan Portfolio. Technical Document, KMV.

Vijaya Krishnan. 2010. Constructing an Area-based Socioeconomic Index: A Principal Components Analysis Approach. Working Paper, Early Child Development Mapping Project, Community-University Partnership, Faculty Extension, University of Alberta, Edmonton, Alberta, Canada (May 2010).

Vincent, Kyle and Jason M. Sutherland. 2013. A Review of Methods for Deriving an Index for Socioeconomic Status in British Columbia. Working Paper, UBC Centre for Health Services and Policy Research, Vancouver, British Columbia, Canada (April 2013).

Vyas, Seema and Lilani Kumaranayake. 2006. Constructing socio-economic status indices: how to use principal components analysis. Oxford Journals, Medicine & Health, *Health Policy and Planning*, Vol. 21, No. 6, (October 9, 2006) pp. 459–468.

Zhang, Lei, Weisheng Dong, David Zhang and Guagming Shi. 2010. Two-stage Image Denoising by Principal Component Analysis with Local Pixel Grouping. *Pattern Recognition*, Vol. 43 (2010), pp.1531–1549.

**Appendix A—Principal Components Analysis used for Macroeconomic Crisis Periods**

## 1. Principal Component Analysis

Principal component analysis can most easily be explained through an example of its application to, for example, risk measurement. Suppose one has year-end 2015 data on bank-level observations for several bank profitability and efficiency measures—return on assets, net interest income-to-assets, expenses on fixed assets-to-total revenue, and noninterest expense-to-total revenue. Principal component analysis finds that linear combination of the underlying variables that best explains the total variation in the data and is orthogonal (uncorrelated) with the original variables.

More formally, let **X** be a matrix containing data on the bank financial ratios we wish to summarize in an index. The columns of **X** are different bank observations and the rows are the different financial ratios. If we measure our variables as deviations from means, the matrix product **X'X** becomes the **variance-covariance** matrix of **X.** In addition, if we normalize the deviations from means by the standard deviations, then **X'X** becomes a matrix of pairwise correlation coefficients for the different financial ratios.

PCA transforms a dataset of correlated variables into a dataset of uncorrelated variables, the principal components. There are as many principal components as there are variables in the original dataset. PCA, however, selects that orthogonal row vector **C** (aka, eigenvector) that maximizes the amount of variance in the original dataset explained by the principal components. The product of the data row vector **X'** and column eigenvector **C** is the first principal component:[28]

$$PC_1 = \mathbf{X'C} \tag{1A.}$$

PCA assumes the underlying data are quantitative measures or ordinal measures. PCA is scale dependent. Hence, unless all variables are measured in the same units (for example, percentages, dollars), the data should be normalized as described previously. In equation 2A, $PC_1$ is the first principal component and is the sum of the products of the variable weights or factor loadings $c_1, c_2, \ldots, c_N$ based on the eigenvector and the value for the corresponding underlying economic variables $x_1, x_2, \ldots, x_N$ for that observation, here quarter t.[29]

$$PC_{1,t} = (c_1) * x_{1,t} + \cdots + (c_N) * x_{N,t} \tag{2A.}$$

Principal component analysis ranks these transformed variables based on the amount of variance in the entire dataset the principal component explains, hence the first principal component explains more variance than the second principal component and so on for the remaining principal components. Another property of principal components is that they are all independent (uncorrelated) of one another, with the result that each principal component explains different characteristics of the dataset.

---

[28] More specifically, to find the first principal component, one solves the constrained maximization problem of finding that eigenvector, **C**, that maximizes the variance-covariance matrix (**C'X'XC**) such that **C'C** = **I,** where I is the identity matrix.

[29] The sum of the squared factor loadings will equal one.

While there are as many principal components as there are underlying raw variables, the first one or two principal components usually explain a majority of the variance of the dataset. This latter result means one can obtain a great deal of the information in a dataset using just the first one or two principal components (dimension reduction).

To know how to interpret the principal component values across banks, one can estimate the Spearman rank order correlation coefficient between the principal component and the underlying variables. Typically one will find some variables to be more highly correlated with the principal component than are other variables and that the correlations change as one uses the second, third, and remaining principal components. These correlations also provide a way to validate the informational content of the principal component.

**2. Two-Stage Principal Component Analysis**

If one has, for example, five measures of a single bank attribute, such as asset quality, one can replace these variables with an average value. However, it is not clear how to weight the individual variables used by this average. One way to determine the weights for the individual asset quality measures is to find the first principal component for the five asset quality measures and then use this principal component as a variable in a second principal component analysis, which we next describe.[30]

In the two-stage PCA, each of the key desired attributes, for example, the six CAMELS attributes, is individually modeled with separate principal components analyses. Next, all first principal components from the first stage PCA are used as variables in a second-stage PCA. Equation 3A shows the second-stage PCA in which the weights, $a_i$, for the six CAMELS $PC_1$ are determined by the principal components procedure discussed previously. The resulting first principal component is a composite CAMELS attribute index.

$$PC_{1 \text{ composite},t} = (a_1) * PC_{1,capital,t} + \cdots + (a_6) * PC_{1,sensitivity\ to\ market\ prices,t} \qquad \text{(3A.)}$$

The advantage of the two-stage PCA is that there is no intermediate variable selection step required and all key variable types, for example, CAMELS attributes, are maintained through the final step.

The two-stage principal component analysis of banks' CAMELS attributes is one way in which analysts can measure banks' condition using the widely used CAMELS attributes even when supervisory ratings of banks based on onsite safety and soundness exams are not available. The first-stage PCA provides principal components (indexes) for each of the six CAMELS attributes (that is, substitutes for CAMELS component ratings) and the second-stage PCA provides a first principal component for bank overall condition (that is, substitutes for the composite CAMELS ratings).

---

[30] Vincent and Sutherland (2013) discuss the use of the two-stage PCA in the construction of socioeconomic indexes. Two-stage PCA is also used in pattern recognition models as a way to further reduce the noise in the video signals as discussed in Zhang, Dong and Shi (2010).

To evaluate the potential of the first principal component to measure bank riskiness, we compare the predictive accuracy of two bank-failure prediction models. **The first model** is a standard logit regression of the determinants of bank failure during a one-year period as a function of prior year-end bank financial condition. We measure bank financial condition using 12 financial ratios that are used by the FDIC's Statistical CAMELS Offsite Rating (SCOR) model.[31] The 12 ratios capture each of the six CAMELS attributes and are heavily weighted toward asset quality measures since asset quality is a primary driver of bank safety and soundness. We estimate stepwise logit regressions annually to determine the most predictive variables, and use parameter estimates to estimate out-of-sample failure probabilities for banks in the following year. **The second model** is a one-stage PCA of all 12 SCOR financial ratios using the same year-end data used in the logit model out-of-sample forecasts. We estimate models annually using data on all U.S. insured banks and thrifts between 2008 and 2014, a period that includes the most recent U.S. financial crisis. For brevity we do not present all logit model estimates and results here. However, representative results for the 2009 logit model estimates and 2010 PCA factor loadings used in risk rankings are shown in tables 1A and 2A. In table 1A the logit model coefficient estimates show increases in equity capital and liquid assets reduce the likelihood of failure, while increases in other real estate owned and nonaccrual assets increase the likelihood of failure, as expected. Table 2A shows the factor loadings for the SCOR model ratios also have an intuitive relationship with the risk index, $PC_1$. The factor loadings for equity capital, liquid assets and income before taxes are negatively related to $PC_1$, while all remaining SCOR ratios (primarily asset quality measures, loan loss measures and noncore funding) are positively related to $PC_1$. These factor loading signs suggested bank riskiness increases with $PC_1$.

In terms of in-sample explanatory power of the two models, the first principal component explained 34 percent of total variance in the data and the first three principal components explain 58 percent of total variance. These results suggest the logit model should outperform PCA in short-term failure prediction.

---

[31] The 12 SCOR model financial variables are equity capital, loan-loss reserves, loans past due 30-89 days, loans past due 90 days or more, nonaccrual loans, other real estate owned (includes repossessed real estate), loan and lease charge-offs, provisions for loan losses, income before taxes, noncore funding, loans and long-term securities (maturities over 5 years). Liquid assets are the sum of cash balances, securities, federal funds and repurchase agreements sold. Noncore funding is the sum of time deposits over $100,000, foreign deposits, federal fund and repurchase agreements purchased, demand notes issued to U.S. Treasury, and other borrowed money. All financial variables are measured as a percent of the bank's gross assets (assets plus loan-loss reserves). For further details see Collier, Forbush, Nuxoll, and O'Keefe (2003).

**Table 1A. Stepwise Logit Regression of the Determinants of Bank Failure**

| Independent Variables* | Year-end 2010 Estimated Coefficient (Standard Error) |
|---|---|
| Equity | -1.0792*** |
| | (0.1168) |
| Liquid Assets | -0.0580* |
| | (0.0258) |
| Other Real Estate Owned | 0.1122* |
| | (0.0486) |
| Nonaccrual Loans and Leases | 0.1018* |
| | (0.0421) |
| Intercept | 2.4547* |
| | (0.9877) |
| Pseudo R-squared | 0.7199 |
| N | 7,490 |
| * p<0.05, ** p<0.01, *** p<0.001 | |
| *Note: All variables are measured as a percentage of gross assets. | |

**Table 2A. Factor Loading (Eigenvector) for First Principal Component**

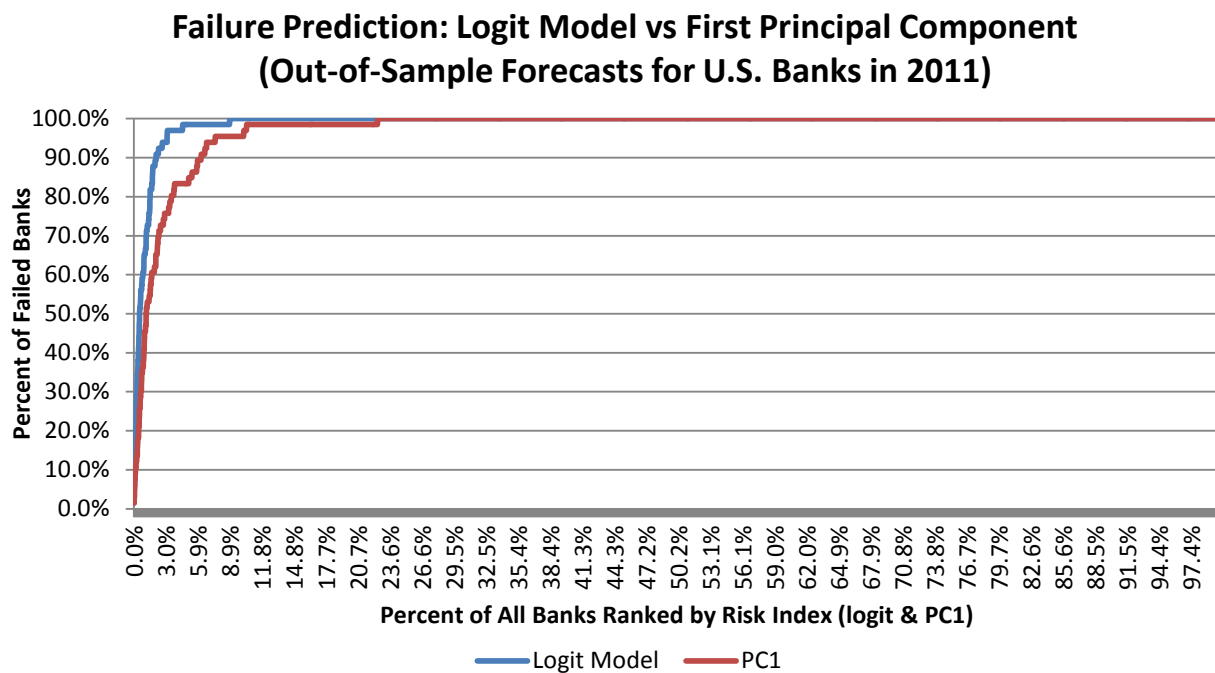| SCOR Ratios | First Principal Component Factor Loading |
|---|---|
| Equity Capital | -0.1859 |
| Loans PD 30-89 | 0.2035 |
| Loans PD 90+ | 0.0554 |
| Nonaccrual Loans and Leases | 0.3804 |
| Other Real Estate Owned | 0.3059 |
| Liquid Assets | -0.2604 |
| Noncore Funding | 0.1650 |
| Charge-offs | 0.3589 |
| Income Before Taxes | -0.3273 |
| Loan Loss Reserves | 0.3878 |
| Loan Loss Provisions | 0.4156 |
| Loans and long-term Securities | 0.1689 |

Figure 1A shows comparative model results for out-of-sample bank failure prediction for 2011.[32] In Figure 1A, we compare the percentage of 2011 bank failures that are correctly identified by the ranked indexes—logit model failure probability and first principal component. The logit model correctly identifies 82 percent of failed banks in the first 1.56 percent of all 7,490 risk-ranked banks while the first

---

[32] All model estimates and forecasts are available from the authors upon request.

principal component correctly identifies 58 percent of failed banks.[33] We obtained similar results for 2012 through 2015. While we expected the logit model to be more accurate than PCA in risk ranking banks, deposit insurers in many jurisdictions do not have a sufficient number of historical bank failures with which to estimate a logit model of bank-failure prediction.[34] We believe PCA can provide a useful alternative to empirical risk measures that are based on probability distributions, require significant historical data on failure events, or rely on bank risk ratings from credit rating agencies or government safety and soundness examinations of banks. All deposit insurers should have access to bank financial statements and have a sufficient understanding of bank risk drivers, for example, SCOR model variables, with which to use PCA, however.

**Figure 1A.**

## Failure Prediction: Logit Model vs First Principal Component
## (Out-of-Sample Forecasts for U.S. Banks in 2011)



## 3. Interpretation of First Principal Component

Section 2 demonstrated the ability of the first principal component to risk-rank banks. If one normalizes the financial data used in PCA, that is, subtract the mean and divide the difference by the standard

---

[33] There were 92 bank failures in 2011. Banks file quarterly financial reports with their primary federal regulators that are used to obtain the SCOR financial ratios. Since 26 banks failed in the first quarter of 2011, prior to filing financial reports for year-end 2010, our sample includes 66 of the 2011 bank failures.

[34] Our tests of PCA's relative predictive power is obviously biased toward the logit model since we obtained a best fit logit model based on the FDIC's long-standing early warning system SCOR. While we did not conduct an exhaustive search for the "best" failure prediction model, the SCOR model contains explanatory variables common to published literature on the determinants of bank failures. Further, we did not conduct a second-stage PCA in the interests of simplicity; however, we anticipate a second-stage PCA would further enhance the predictive accuracy of the approach.

deviation, one obtains a standard normal variable that has a mean of zero and standard deviation of one. If normality can be reasonably assumed, most statistical textbooks contain the information on the distributions of standard normal random variables (aka, Z scores) that can be used to determine the likelihood of various values. For example, the Z score distribution indicates that 95 percent of scores will fall between +/- 1.96 and 99.7 percent of scores between +/- 3. The Z score distribution is also assumed constant over time, and implicitly this assumes one can compare first principal components not only across banks, but also over time.

Like an issuer default rating, the default frequency for any $PC_1$ range (bucket) will vary with economic conditions, and in general rise with economic stress. Where deposit insurers lack information on issuer default ratings, CAMELS ratings, and other formal ordinal risk rankings, it might be possible to determine the default frequencies for banks in several comparable jurisdictions over time and map these to a countries $PC_1$ buckets. These default rates could serve as a means to calibrate a bank's $PC_1$ to the failure risk they present to the deposit insurer.