Options for Pricing Federal Deposit Insurance

*Eric P. Bloecher, Gary A. Seale, and Robert D. Vilim**

Editors Note:

The following article discusses some deposit insurance pricing options that are under consideration by the FDIC. The specific pricing examples are presented only to illustrate the general types of options being considered and should not be regarded as a comprehensive set. This article is intended to highlight the practical trade-offs posed by the choice among different types of pricing systems.

In April 2001, the FDIC released a document entitled "Keeping the Promise: Recommendations for Deposit Insurance Reform" (the recommendations paper), which laid out the Corporation's recommendations for merging the insurance funds, eliminating the designated reserve ratio as the trigger for charging premiums, considering rebates if the merged fund grows too rapidly, and indexing insurance coverage. The paper also recommended charging regular, risk-based insurance premiums to all banks,[1] and it included some examples of how the FDIC might enhance the current nine-cell premium matrix (see table 1 in the next section) to better price for risk.

Since the FDIC released the recommendations paper, our work has focused on further exploring the options for pricing deposit insurance. Generally, we have been reviewing three primary methodologies: expanded use of supervisory ratings, use of statistical models, and a combination of the two. Choosing a system for deposit insurance pricing involves trade-offs among a number of desirable attributes. We summarize the options being explored and discuss the trade-offs without offering a judgment as to which attributes of deposit insurance pricing are most desirable from a policy standpoint.

* All the authors are with the Division of Insurance and Research at the Federal Deposit Insurance Corporation. Eric P. Bloecher and Robert D. Vilim are senior financial analysts, and Gary A. Seale is a senior financial economist. The authors would like to thank John O'Keefe and Richard Jones for helpful comments, and Christine Brickman for research assistance.

[1] Throughout this article, the term *banks* refers to all FDIC-insured institutions.

After providing some historical background on FDIC premiums, we lay out the desirable attributes, or general requirements, of deposit insurance pricing; present the pricing options we have been considering, along with the relative merits of each option; and then describe pricing for two categories of banks that could be priced separately: new banks and large banks. The final section concludes with a brief summary of the trade-offs that need to be evaluated before a new deposit insurance pricing system is selected.

Historical Background

For most of the FDIC's history, deposit insurance coverage was funded by a premium system under which all insured institutions were charged an identical flat rate for deposit insurance. The rate was set by the Banking Act of 1935 as 1/12 of 1 percent of total domestic deposits.[2] Thus, deposit insurance premiums did not vary with the level of risk that an institution posed to the insurance fund.

After passage of the Banking Act, the banking industry stabilized quickly, and bank failures remained low through the 1940s. The rapid increase in lending after the war was not accompanied by the high loan losses that many had anticipated; instead, the FDIC was faced with the possibility that the insurance fund could grow unchecked. To address this issue, Congress passed the Federal Deposit Insurance Act of 1950, which provided for assessment credits to be distributed to banks in years when the FDIC's assessment income exceeded its losses and expenses. The credits were distributed on a pro rata basis, with the FDIC retaining up to 40 percent of the Corporation's net assessment income and banks receiving up to 60 percent. The system of credits was a way to control the growth of the insurance fund by allowing premium income to be reduced in periods with low failure rates, while the FDIC retained the ability to make full use of premiums during periods of higher failure rates.

Although many observers recognized from the beginning that the original pricing system had weaknesses, the full implications of flat-rate insurance assessments did not attract significant attention until the bank and savings and loan insurance funds experienced record losses in the late 1980s. Two main problems were identified. First, a flat-rate system provided an inducement for a bank or thrift to undertake higher-risk business strategies to maximize profits. These strategies could be pursued without the banks incurring additional insurance expense; failure costs generated by increased risk taking were instead passed on to the insurer (and perhaps the taxpayer). Second, in a flat-rate premium system, sound and well-managed institutions were subsidizing high-risk, poorly managed institutions: low-risk banks paid more for insurance than they should, whereas risky banks paid less. The subsidy funded by low-risk banks represented an economic burden that caused them to operate at a competitive disadvantage. These two problems pointed to the conclusion that a more equitable and economically supportable deposit insurance pricing system would require high-risk institutions to pay more than low-risk institutions.

The Federal Deposit Insurance Corporation Improvement Act of 1991 (FDICIA) required that a risk-based premium system be implemented by January 1, 1994. The FDIC implemented a risk-based system on January 1, 1993, a year early. Separate but identical assessment rate schedules were adopted for the Bank Insurance Fund (BIF) and the Savings Association Insurance Fund (SAIF). Institutions were assigned to one of nine risk categories by the use of capital ratios and other relevant information, mainly supervisory ratings. Originally, assessment rates ranged from 23 cents per $100 of assessable deposits for the lowest-risk institutions to 31 cents per $100 of assessable deposits for the highest-risk institutions. When the funds were recapitalized, premiums were lowered. The Deposit Insurance Funds

[2] This rate was calculated to be the annual assessment rate that would have been required to cover actual losses on deposits in banks that failed between 1865 and 1934, excluding "crisis" years when losses were unusually high.

Act of 1996 prohibits the FDIC from charging premiums to institutions that are well capitalized and highly rated by supervisors as long as the insurance fund is above 1.25 percent of insured deposits. Table 1 presents the current nine-cell matrix for the combined fund—that is, a hypothetical fund in which the BIF and SAIF are merged—and gives the number and percentage of banks in each cell as of year-end 2002. As the table indicates, over 90 percent of institutions are in the 1A category. Currently, these institutions are not assessed for deposit insurance.

Table 1

Matrix Distribution, Risk-Related Premium System
(Bank Insurance Fund and Savings Association Insurance Fund Combined, Year-End 2002)

	Supervisory Subgroup[b]		
Capital Subgroup[a]	**A (CAMELS 1 or 2)**	**B (CAMELS 3)**	**C (CAMELS 4 or 5)**
1–Well Capitalized	8,583 91.7%	523 5.6%	115 1.2%
2–Adequately Capitalized	113 1.2%	17 0.2%	14 0.1%
3–Undercapitalized	1 0.0%	0 0.0%	6 0.1%

Note: The figures in the cells refer to the number and percentage of all FDIC-insured institutions.

[a] Assignments to capital subgroups are made in accordance with section 327.4(a)(1) of the FDIC's Rules and Regulations. "Well capitalized" means a total risk-based capital ratio that equals or exceeds 10 percent, a Tier-1 risk-based capital ratio that equals or exceeds 6 percent, and a Tier-1 leverage capital ratio that equals or exceeds 5 percent. "Adequately capitalized" means not well capitalized and a total risk-based capital ratio that equals or exceeds 8 percent, a Tier-1 risk-based capital ratio that equals or exceeds 4 percent, and a Tier-1 leverage capital ratio that equals or exceeds 4 percent. "Undercapitalized" means neither well capitalized nor adequately capitalized.

[b] Assignments to supervisory subgroups are made in accordance with section 327.4(a)(2) of the FDIC's Rules and Regulations. Subgroup A consists of financially sound institutions that have only a few minor weaknesses; this subgroup generally corresponds to the primary federal regulator's composite CAMELS rating of 1 or 2. Subgroup B consists of institutions with demonstrable weaknesses that, if not corrected, could lead to a significant deterioration of the institution and an increased risk of loss to the relevant insurance fund; this subgroup generally corresponds to the primary federal regulator's composite CAMELS rating of 3. Subgroup C consists of institutions that pose a substantial probability of loss to the relevant insurance fund unless effective corrective action is taken. This subgroup generally corresponds to the primary federal regulator's composite CAMELS rating of 4 or 5.

Key Attributes of a Deposit Insurance Pricing Structure

Ideally, any pricing system adopted by the FDIC would possess some combination of five attributes: accuracy, simplicity, flexibility, appropriate incentives, and fairness.

Accuracy

Perhaps the most important consideration for any proposed pricing system is that the criteria used to rank or categorize banks accurately reflect the relative risk that institutions pose to the insurance fund. Accuracy is generally measured against the insurable event, which in this case is bank failure.[3] Banks that are in higher-premium categories should have a more frequent occurrence of failure than banks in lower-premium categories.

Additionally, for any pricing methodology that relies extensively on data provided by banks or other outside parties, the integrity of the data must be adequate. Reported data must be timely, accurate, and verifiable. They must be available to regulators early enough in the assessment cycle to allow for premiums to be calculated.

Simplicity

The methodology selected should be available to the public, insured banks, and other outside parties, and members of all three groups should find it comprehensible. Moreover, bankers should be able to compute their risk categories or ratings without undue difficulty—preferably, early in the assessment cycle. For some pricing systems, the FDIC may need to provide software or some other form of technical assistance to help bankers perform the calculations.

[3] For certain groups of banks or within certain time periods, data on failures are often insufficient to allow meaningful statistical comparisons. As a result, to compare the pricing methodologies considered here, we also use historical data on the frequency of examination rating downgrades.

Flexibility

The factors that are most predictive of bank failure can change over time. Moreover, we expect that the FDIC's ability to measure risk exposure will improve over time. Consequently, it is important that any pricing system allow for periodic changes in the risk-assessment criteria. Allowing for periodic changes will enable the FDIC to continually evaluate which factors are relevant at any particular time. Updates should be infrequent enough to allow banks a measure of stability for planning purposes, yet frequent enough to ensure that all the criteria remain relevant.

Appropriate Incentives

The measures of bank risk included in the pricing structure should provide incentives for bank management to act responsibly. While some measures of risk may perform well in statistical tests, their inclusion in a pricing system may not be appropriate because of the perverse incentives they create for sound bank management. For example, a measure that penalized banks for increasing levels of charge-offs might create an incentive for managers to avoid charging off loans simply to reduce their insurance premiums.

Fairness

Closely associated with the idea that the classification is to be correlated with risk is the idea that banks with similar characteristics should be treated in a like manner. Institutions with similar risk structures should pay approximately equal premiums.

Pricing Options for Well-Capitalized and Highly-Rated Institutions

A primary objective of deposit insurance pricing reform is to better differentiate among the best-rated institutions on the basis of risk, thereby reducing subsidies paid by low-risk institutions to riskier ones and moderating incentives for increased risk taking.[4] Pricing that incorporates greater sensitivity to risk would achieve the goal of making the deposit insurance system more equitable and economically efficient.[5]

The options currently being considered for banks (other than large banking organizations) include expanded use of supervisory ratings, use of statistical models (both in a continuous and discrete format), use of a combination of statistical models and supervisory ratings, and a scorecard that uses expert judgment in conjunction with a statistical model.

Expanded Use of Supervisory Ratings

A simple method of providing further risk differentiation within the best insurance category is to make expanded use of the CAMELS ratings.[6] This expansion could involve either the use of composite ratings alone or the use of composite and component ratings combined. If composite ratings alone are used, composite 1-rated institutions would pay a lower premium than composite 2-rated institutions. Table 2 presents examples of how the FDIC might use both the composite rating alone and the composite rating combined with the component ratings to subdivide the 1A

[4] Because of the statutory prohibition noted above, currently subsidies are paid only when the insurance fund is less than 1.25 percent of insured deposits. For purposes of this article, we concentrate on banks within the best insurance category (the 1A category). Institutions that are not well capitalized and highly rated are generally subject to a higher level of supervisory review and, in some cases, may be operating under specific enforcement actions.

[5] This article is concerned primarily with differentiating banks according to the risk they pose to the insurance funds, not with determining the absolute amounts that individual banks should pay for insurance (that is, not with determining the "break-even" or "actuarially fair" amounts). Actuarial pricing is the goal of most private insurers and as a general approach has much to recommend it, but adopting a strict actuarial framework would be impractical for the FDIC, mainly because if the FDIC were to charge the highest-risk institutions such a premium, the premium would be high enough to threaten these banks with failure.

[6] The CAMELS rating is assigned by a bank's primary regulator. The acronym stands for **C**apital, **A**ssets, **M**anagement, **E**arnings, **L**iquidity, and **S**ensitivity to market risk. A rating from 1 (the best) to 5 (the worst) is assigned for each of these component elements, and an overall composite rating based on the component ratings is then assigned to the bank.

insurance category. In option 1 of the table (composite ratings only), banks rated a composite 1 are placed in the lower-premium category (1A1) and banks rated composite 2 are placed in the higher-premium category (1A2). As of year-end 2002, 40.4 percent of institutions would have fallen in the 1A1 category and 59.6 percent of institutions would have fallen in the 1A2 category. In option 2 (composite and component ratings combined) the institutions rated composite 1 are placed in the 1A1 category as in option 1. However, composite 2-rated banks would be divided into two groups based on their component ratings: most would categorized into the 1A2 category, while those banks having weaker component ratings would be placed into the 1A3 category. Banks in the 1A3 category would pay the highest premium rates among the 1A banks.

Table 2

Options for Pricing Well-Capitalized and Highly-Rated Institutions Using CAMELS Ratings (Year-End 2002)

	Subcategories		
	1A1	**1A2**	**1A3**
Option 1: Using Composite Ratings			
Composite 1 Rated	3,501 40.4%		
Composite 2 Rated		5,169 59.6%	
Option 2: Using Composite and Component Ratings			
Composite 1 Rated	3,501 40.4%		
Composite 2 Rated *and* Sum of Components <= 12 *and* No More Than One Component Rated 3 or Worse		4,271 49.3%	
Composite 2 Rated *and* Sum of Components > 12 *or* Two or More Components Rated 3 or Worse			898 10.4%

Note: The table shows two options for subdividing the 1A insurance category using supervisory ratings. The 1A1 subgroup represents the least risk and the 1A3 subgroup represents the greatest risk. The figures in the cells refer to the number and percentage of 1A institutions.

Statistical Models

Pricing methods that rely on statistical models have been developed to provide options that incorporate objective financial data reported by banks. The two statistical models under consideration use reported financial data to rank banks in the 1A category. One is a failure-prediction model, and the other is a CAMELS downgrade-prediction model.

Failure-Prediction Model

The failure-prediction model is a statistical model that relates historical Call Report ratios to bank failures to determine an estimated failure probability for each bank.[7] This failure probability can be used to rank banks for pricing. Table 3 illustrates an example of a failure-prediction calculation for a hypothetical bank. Column A shows the coefficients produced by the model. These coefficients are the same for all banks and represent the relative weight placed on each ratio for determining a probability of failure. The hypothetical bank's financial ratios, which can be obtained from the Call Report, are in column B. These ratios are multiplied by the corresponding coefficients in column A to obtain the values in column C. The sum of these values produces a raw score, which is then transformed to obtain the estimated failure probability.[8] For the hypothetical bank, this probability is 0.39 percent.

The estimated probability of failure for each bank ranges between 0 and 100 percent. This value represents the likelihood of a bank's failing over a five-year period. Under a continuous pricing format, in which each institution receives an individual score, banks could be ranked according to their estimated failure probabilities and assessed according to their ranking.

[7] The model is a logistic model of the general form $\rho\{1 | X, \beta\} = e^Z/(1 + e^Z)$ where $Z = \alpha + \Sigma\beta_i x_i$, the number 1 represents bank failure within a specified period, and x_i represents the *i* th financial-ratio variable.

[8] The transformation follows the formula in the above footnote.

Table 4 shows how failure probabilities from the statistical failure model would have been distributed among all well-capitalized and highly-rated FDIC-insured banks for selected years between 1985 and 2002. Most banks would have had a low estimated probability of failure, especially after 1995. Thus, it is reasonable to assume that during periods of relative stability, most banks would pay an amount close to the average premium for that category.

Table 3

Failure-Prediction Model, Hypothetical Bank

Scoring Factor	Coefficient (Weight) (A)	Financial Ratio (B)	Score[a] (C)
Intercept	–3.91	N/A	–3.91
Nonaccrual Loans / Total Assets	35.47	.002	0.07
Loans Past Due 90+ Days / Total Assets	37.10	.010	0.37
ORE / Total Assets	30.46	.015	0.45
Loans Past Due 30–89 days / Total Assets	30.45	.005	0.15
Pretax Net Operating Income / Average Assets	–15.17	.030	–0.45
Noncore Funding / Total Assets	5.20	.120	0.62
Equity & Reserves / Total Assets	–21.69	.130	–2.82
Total Score			**–5.52**

Note: This table demonstrates how the results of the failure-prediction model can be used to create an individual expected-failure probability for each institution.

[a] The raw score is the product of columns A and B. Via the formula in note 7, the total score produces the expected probability of failure (Pr(default)) through the transformation.

$$\Pr(\text{default}) = \frac{e^{-5.52}}{(1 + e^{-5.52})} = 0.39\%$$

Figures 1 and 2 show how the failure-prediction model would have performed historically in identifying both CAMELS downgrades (figure 1) and failures (figure 2). In figure 1, we used Call Report data at each year-end to rank banks according to their expected failure probabilities; we then divided the rank listing into three numerically equal groups and, for each group, calculated the percentage of banks that were actually downgraded from a CAMELS 1 or 2 to a CAMELS 3, 4, or 5 over the subsequent five-year period. As the figure shows, the group with the highest expected failure rate consistently has the highest percentage of banks downgraded. Likewise, banks in the middle group of the three consistently have a higher percentage of downgrades than banks in the group with the lowest expected rate of failure.

Figure 2 shows the percentage of banks in each of the three groups that actually failed over the subsequent five-year period. This figure, too, shows a consistently higher failure rate for the group of banks having the highest expected failure rate. The distinction is not as clear for the middle and lowest thirds, however, primarily because of the low overall number of failures in these groups, especially after 1992. (This problem of the low overall number of actual failures distorting the percentages after 1992 is common to all the pricing systems evaluated here.)

Table 4

Continuous Pricing Distribution of Well-Capitalized and Highly-Rated Institutions Based on Projected Failure Probabilities

	Projected Range of Failure Probability									
	<= 0.5	0.5–1.0	1.0–1.5	1.5–2.0	2.0–2.5	2.5–3.0	3.0–3.5	3.5–4.0	4.0–4.5	> 4.5
2002	42.3%[a]	28.1%	12.7%	5.8%	3.0%	2.0%	1.3%	0.9%	0.7%	3.2%
2000	42.5	27.4	12.6	5.6	3.5	2.3	1.3	0.9	0.7	3.3
1995	55.5	27.2	8.5	3.0	1.8	1.0	0.7	0.4	0.3	1.6
1990	36.5	29.7	12.8	6.6	3.9	2.2	1.7	1.1	0.9	4.7
1985	28.6	27.4	14.1	7.4	5.2	3.0	2.2	1.7	1.4	8.9

Note: Data are as of year-end.

[a] The percentages are those of 1A institutions in each of the failure-probability ranges. These percentages are based on the model shown in table 3.

CAMELS Downgrade-Prediction Model

The **S**tatistical **C**AMELS **O**ff-site **R**ating (SCOR) model is similar to the failure-prediction model but was designed specifically to estimate the likelihood that a bank will receive a CAMELS downgrade over the next year. The FDIC currently uses this model for the off-site risk monitoring of banks. The model produces an expected CAMELS rating for the bank, which is expressed as a number between 1.00 (the best) and 5.00 (the worst). The SCOR rating could be used to rank banks by risk for pricing purposes. In historical tests of downgrades and failures, SCOR performs much like the failure-prediction model, producing results very similar to those shown in figures 1 and 2.

Continuous versus Discrete

Separate from the choice of whether supervisory ratings or statistical models should be used to rank institutions is the question of whether a discrete or continuous format should be used. The failure-prediction model and the SCOR model produce a continuous ranking. (After each bank receives an individual score based on the results of the models, premium amounts are established on the basis of the relative ranking of each bank.) However, it is possible to create a discrete pricing structure by superimposing a fixed number of categories on the results of the models; for example, to create figures 1 and 2 we arbitrarily divided the banks into three groups with an equal number of institutions in each group. But the groups do not necessarily have to be of equal size. Rather, groups could be established that minimized the difference in expected failure probabilities between the best and worst banks in each group. Doing this is desirable, since grouping makes it inevitable that some banks will pay a somewhat higher premium than their expected failure probabilities will warrant, while others will pay a somewhat lower premium.

Discrete formats may offer greater simplicity than continuous formats, but they also create the potential that small changes in a measured variable could produce large changes in the deposit insurance premium ("cliff effects"). The existing nine-cell matrix is an example of a discrete format with cliff effects; however, it is based on well-established and generally accepted thresholds.

Figure 1

Relationship between Probability of Failure and Actual CAMELS Downgrades within Five Years of Failure-Probability Calculation

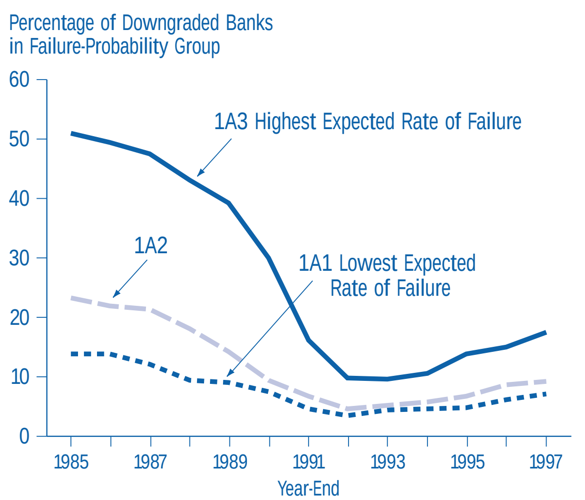
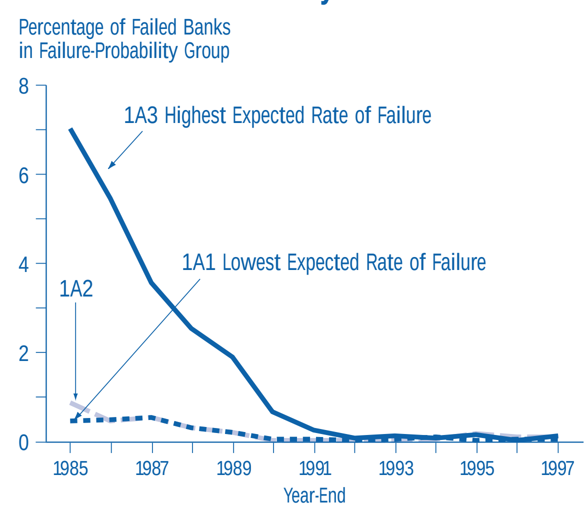


Figure 2

Relationship between Probability of Failure and Actual Failures within Five Years of Failure-Probability Calculation



For example, there is widespread understanding of the difference between a CAMELS 2-rated institution and a CAMELS 3-rated institution, and there is even different supervisory treatment for the two. Additionally, the capital thresholds are the same as the thresholds established by regulation for purposes of Prompt Corrective Action.

The problem of creating cliff effects can be mitigated by the use of a more graduated pricing structure. Any of the statistical methods could achieve this result. However, the greater the number of categories created, the more stringent the requirements that are placed on the specified system. If too many categories are created, the distinctions between them become less clear, and fairness becomes an issue. This is also the case with continuous pricing systems, when the number of categories is essentially equal to the number of banks. The methodologies described above could be used to create as many or as few pricing categories as required to achieve an acceptable trade-off, but it is important that expected failure rates be progressively higher for successively higher risk-pricing categories.

Combination of Supervisory Ratings and Statistical Models

Although using statistical models to price deposit insurance premiums might be appealing because of their reliance on objective financial data reported by banks, strictly applying a statistical model would inevitably result in some CAMELS 1-rated institutions paying more than some CAMELS 2-rated institutions. Since banks rated a composite 2 fail more frequently than banks rated a composite 1, it would seem logical to make the case that the 2-rated institutions in general should pay a higher premium for deposit insurance.

An alternative that addresses this concern is to combine supervisory ratings with one of the statistical models. A combined approach would preserve the CAMELS rating by initially classifying banks according to whether they were ranked CAMELS 1 or 2 and would then use the statistical models to create subcategories.

There are a number of potential possibilities for combining supervisory ratings and statistical models. Table 5 illustrates one way in which a pricing system might operate using CAMELS ratings and SCOR. In the table, we divide the 1A insurance category as of year-end 2002 into three subcategories. All CAMELS 1-rated banks are placed in the 1A1 category. CAMELS 2-rated banks with a SCOR value of less than 1.25 also are placed in the 1A1 category. The remaining CAMELS 2-rated banks are classified as either 1A2 (SCOR rating anywhere from 1.25 to 1.75) or 1A3 (SCOR rating higher than 1.75). The distributions shown in Table 5 would vary depending on the threshold values chosen for the SCOR ratings.

Combined approaches tend to perform much like the statistical methodologies in identifying downgrades and failures. Banks that are in higher-premium groups are more likely to be downgraded or to fail than banks in lower-premium groups.

Table 5

Option for Pricing Well-Capitalized and Highly-Rated Institutions Using CAMELS and SCOR Ratings (Year-End 2002)

	Subcategories		
	1A1	**1A2**	**1A3**
All Composite 1 Rated *and* Composite 2 Rated with SCOR Rating < 1.25	3,618 41.7%		
Composite 2 Rated with SCOR Rating >= 1.25 *and* <= 1.75		2,767 31.9%	
Composite 2 Rated with SCOR Rating > 1.75			2,285 26.4%

Note: SCOR values are calculated from December 31, 2002, Call Report data, and these values are combined with December 2002 exam ratings. The 1A1 subgroup represents the least risk and the 1A3 subgroup represents the greatest risk. The figures in the cells refer to the number and percentage of 1A institutions.

Scorecard

The scorecard uses an expert system to develop gradations of risk for each variable in the failure-prediction model, thus lessening the cliff effects. The original example of a scorecard appeared in the recommendations paper in April 2001. Since then, we have held numerous meetings with other regulators, industry groups, and academics to solicit ideas on the scorecard. The comments received from these groups led us to make adjustments to correct for criteria that unduly penalized a particular class of banks. Other changes were designed to improve the estimation techniques that had been used to create the original scorecard. The most significant change is that the failure-prediction model was reestimated for banks in the 1A insurance category only, rather than for the entire industry.

Table 6 shows the most recent version of the scorecard. In this example, the 1A category of the current pricing matrix (table 1) is divided into three subcategories. The scoring framework allows banks to be classified as 1A1 (least risk), 1A2, or 1A3 (most risk). The noncore-funding adjustment factor at the bottom of the table is included to address the unique funding strategies used by large banks and is discussed more fully below. This version of the scorecard places greater emphasis on asset-quality measures than the original scorecard. This version also includes more gradations of risk within each of the three subcategories. The modified scorecard does maintain the net income, noncore funding, and equity elements of the original scorecard, but the weight placed on these measures has been reduced, as would be more appropriate for CAMELS 1- and 2-rated banks. Also, the equity measure has been changed to include loss reserves.[9]

[9] This equity measure, which includes loss reserves, performed better in statistical tests than equity alone. In addition, we believe that including loss reserves could create a disincentive to charge off loans purely to avoid higher nonperforming-asset scores.

Table 6

Scorecard
(Weightings Based on Well-Capitalized and Highly-Rated Institutions Only)

		Range of Scores	Maximum Score
Scoring Factor			
Nonaccrual Loans / Total Assets	< 0.5%	30	30
	= 0.5–1.0%	26	
	= 1.0–1.5%	23	
	= 1.5–2.0%	21	
	= 2.0–2.5%	20	
	> 2.5%	0	
Loans Past Due 90+ Days / Total Assets	< 0.5%	25	25
	= 0.5–1.0%	22	
	= 1.0–1.5%	20	
	= 1.5–2.0%	18	
	= 2.0–2.5%	13	
	> 2.5%	0	
ORE / Total Assets	< 0.5%	20	20
	= 0.5–1.0%	16	
	= 1.0–1.5%	14	
	= 1.5–2.0%	12	
	= 2.0–2.5%	11	
	> 2.5%	0	
Loans Past Due 30–89 Days / Total Assets	< 0.5%	14	14
	= 0.5–1%	12	
	= 1–1.5%	10	
	= 1.5–2%	9	
	= 2–2.5%	8	
	> 2.5%	0	
Pretax Net Operating Income / Average Assets	> 0.5%	7	7
	= 0–0.5%	4	
	< 0%	0	
Noncore Funding / Total Assets	<= 40%	3	3
	> 40%	0	
Equity & Reserves / Total Assets	> 7.0%	1	1
	<= 7.0%	0	
Total			**100**
Application of Scoring Framework			
If institution is 1A and total score is >= 97, classify as			1A1
If institution is 1A and total score is < 97 and >= 87, classify as			1A2
If institution is 1A and total score is < 87, classify as			1A3
Adjustment Factor if Noncore Funding / Total Assets > 40%			
Market Adjustment for Standard and Poor's AA– or Better		3	
Market Adjustment for Standard and Poor's A– to A+		1	
Market Adjustment for Standard and Poor's BBB+ or Worse		0	

Table 7 shows the distribution that would have resulted under this structure. It is clear that the distribution can shift significantly over different periods. Although 43 percent of the banks would have been classified in the best category at the end of 2002, only 24 percent would have been in this category in 1985. Thus, a certain amount of migration into and out of categories can be expected as the banking industry passes into and out of periods of stress.

Table 7

Distribution of Well-Capitalized and Highly-Rated Institutions Based on the Scorecard (1985–2002)

Year	Subcategories 1A1	1A2	1A3
2002	43.5%	38.6%	17.9%
2000	44.5	38.0	17.6
1995	45.5	42.2	12.3
1990	30.0	43.3	26.7
1985	23.8	41.4	34.9

Note: For each selected year, 1A institutions are scored on the basis of their reported financial ratios at year-end and are then placed into one of the three subcategories demarcated in the section of table 6 called "Application of Scoring Framework".

Relative Merits of Proposed Pricing Options

To recap, the pricing options presented here for banks (other than large banking organizations) include expanded use of supervisory ratings, use of statistical models (both in a continuous and discrete format), use of a combination of statistical models and supervisory ratings, and a scorecard that uses expert judgment in conjunction with a statistical model. How do these options fare relative to the desirable attributes outlined earlier?

Accuracy

We can compare accuracy, or the ability to differentiate risk, through the use of power curves for each of the deposit insurance pricing options discussed. Figure 3 is a power curve that represents how well each of the options performs in identifying failures. The horizontal axis of the figure shows the percentage of total institutions scored by each method. The institutions are sorted left to right, from those having the worst score (most likely to fail) to those having the best score. The vertical axis shows the cumulative percentage of total failures identified. The point identified on the figure shows that the first 10 percent of the institutions ranked according to SCOR values contained 62 percent of the total failures. The closer the curve is to the upper-left corner of the graph, the more accurate the particular method is at identifying failures. The diagonal line essentially represents a system with no predictive power, where the number of failures identified is proportional to the percentile of observations.

A failure identification score can be developed by measuring the area between an option's respective curve and the diagonal line. Based upon this score, the CAMELS-downgrade model has the most predictive power (37.05), followed by the failure-prediction model (35.66), the scorecard (28.49), and finally the supervisory-based structure (16.74).[10]

Simplicity

The supervisory ratings approach has an advantage over the other options when considering simplicity because of the level of familiarity with and acceptance of the CAMELS rating system. The CAMELS rating system is well understood and accepted by the banking industry, and broad agreement exists as to what each of the five ratings means in terms of a bank's condition. In contrast, the statistical models are more complicated than other methods. They also are less

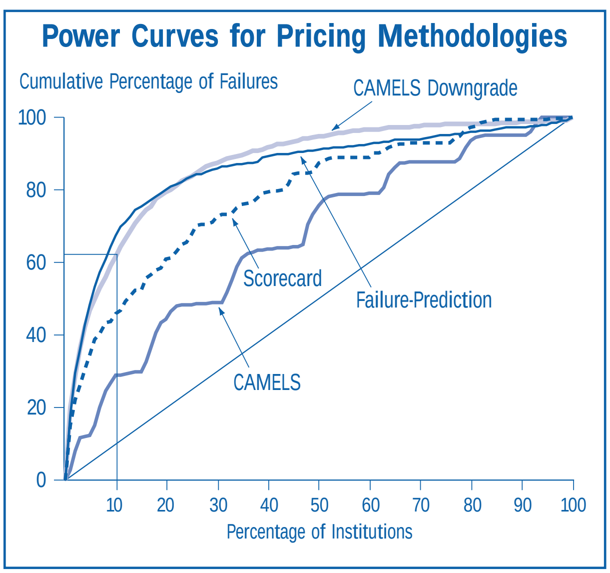
[10] This is not to say that supervisory ratings are inaccurate. Rather, CAMELS ratings provide a relatively broad measure of risk. They are good at separating healthier institutions from those showing more pronounced financial weaknesses, but are not specifically designed to differentiate among better-rated institutions. The statistical models, on the other hand, were developed to fit the historical failure and CAMELS downgrade data. In a sense, they are designed to excel at tests of historical accuracy (ex post). It is not clear that statistical models would fare as well relative to CAMELS ratings going forward (ex ante), where the task is to identify emerging risk factors that may or may not be reflected in historical experience.

transparent to insured institutions because the mechanics of the models are not observable. The scorecard represents an attempt to simplify the purely statistical approaches by combining an expert system with the failure-prediction model.

Flexibility

The supervisory ratings approach also holds an advantage over the other options in terms of flexibility. When examiners assign a CAMELS rating, they have access to and can analyze a wide range of data, including information about management, underwriting, and various intangible factors. Statistical models and scorecard can never completely reflect the current financial condition of a bank because they rely on Call Report information and because they cannot be tailored to reflect the unique aspects of individual banks. With a supervisory ratings approach, changes in virtually any factor predictive of bank failure, as well as improvements in supervisors' ability to measure risk exposure, would automatically be incorporated into the deposit insurance pricing system. To achieve flexibility, the statistical models and scorecard would need to be updated with some frequency to ensure that they continue to reflect the factors most closely associated with risk, thus making them more difficult to implement.

Figure 3



Appropriate Incentives

A supervisory approach also would best avoid perverse-incentive problems because examiners would verify on-site that operating results were achieved through safe and sound management practices. Supervisory and insurance ratings would therefore be closely aligned. Purely statistical approaches could create unintended incentive problems because they rely completely on Call Report data. The scorecard was designed to reduce the possibility of perverse incentives inherent in the statistical approach. The expert system incorporated into this approach would allow choices to be made regarding the factors used and threshold values to avoid these problems.

Fairness

Even though a goal of each of the pricing options is to treat banks equitably, almost always there will be cases in which the classification of a particular bank may be seen as unfair. The combined supervisory ratings and statistical models approach was developed, in part, to address a fairness issue. A purely statistical approach probably would result in some CAMELS 1-rated institutions paying higher premiums than some CAMELS 2-rated institutions. A combined approach could prevent this outcome.

Another way to evaluate fairness is in terms of an option's objectivity. The statistical models are the most objective since they rely completely on a bank's reported data. The scorecard would be the next most objective, followed by the supervisory ratings approach, which would rely a great deal upon examiners' judgment.

Pricing Options for New Banks

A separate pricing system is being considered for new institutions because of their special characteristics. Risks in new institutions often result from the fact that these institutions operate with unproven business plans in markets served by established competitors. The risks inherent in new institutions are not easily identified by the methods that can be useful for detecting risk in seasoned institutions. For instance, new institutions typically have high capital-to-asset ratios and low levels of problem assets compared with their seasoned-institution counterparts, yet new institutions have generally displayed a higher failure rate than seasoned institutions. As a result, pricing structures that rely on financial ratios would be less effective in identifying risk in new institutions.

No consensus exists as to when a new bank takes on the characteristics of a seasoned institution. For purposes of deposit insurance pricing, we define new banks as those existing for five years or less. Figure 4 shows that at the end of this five-year period, failure rates of new institutions approach failure rates of seasoned institutions. Moreover, five years should allow new institutions enough time to confirm the viability of their business plans. Conversely, using a period longer than five years could discourage bank formation because of the relatively higher premiums to be paid by new institutions.

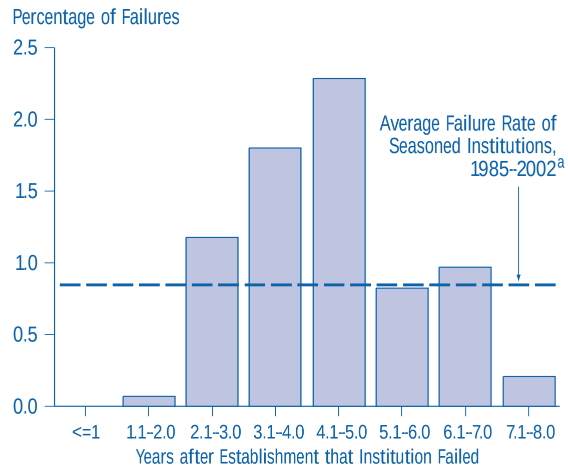
Two options for setting the assessment rate for new institutions are currently being considered. They are based on the premise that, although new banks should pay a risk premium that reflects their historical failure experience, the premium should not be so high as to discourage new firms from entering the industry. The two options are (1) automatically charge new institutions the highest rate paid by well-capitalized, highly-rated banks, or (2) charge new institutions a separate rate. The difference between the two lies in the maximum rate that could be charged to these new institutions.

In the second option—charging new institutions a separate rate—the assessment rate for these new institutions could be based on the historical risk profile of new institutions as a group, and the rate could be capped so that these new institutions would pay a rate lower than the rate paid by institutions that are less than well capitalized and not highly rated. As in option 1, new institutions that fall outside the best insurance assessment risk class would pay the same rate as other institutions in their particular class.

Figure 4

Years to Failure for Institutions Established between 1985 and 1994

(Failure Data through 2002)



[a] Seasoned institutions are institutions that have been in operation for at least five years.

Pricing Options for Large Banks

Large banks also have special characteristics, which may not be captured by the more traditional approaches to risk assessment. This unique status is explicitly acknowledged by FDICIA, which allows for separate pricing based on institution size. Although a pricing system that relies primarily on financial ratios derived from Call Report data may be suitable for small and medium-sized banking institutions, it may not be the best approach to identifying and equitably charging for risk in larger, more complex institutions.

In the long term, Basel II holds some promise for pricing large bank risk because it incorporates default probabilities derived from the institutions' own internal credit-risk models.[11] Such a system will not be possible before the Basel II capital guidelines are implemented (the scheduled date is 2007). In the meantime, information derived from the financial markets—alone or in combination with supervisory information—may provide a more accurate way to evaluate and price risk in large and complex organizations than an accounting-based system.

Developing a pricing system specifically for large and complex banking organizations will first require establishing criteria to select the institutions that would be subject to such an alternative system. The simplest and most commonly used criterion for delineating the group of large and complex banking organizations is asset size. Another criterion could be market capitalization, or a measure of complexity such as market participation or foreign operations.

Aside from the criterion used to define large banks, the ability to implement a pricing system that relies upon financial market data depends upon the availability of market data for these larger institutions. Equity data are generally available for most large banking companies. However, other market data, such as subordinated debt price quotes, are not available for several large banks.

Pricing Framework Based on Supervisory Ratings

A simple method for categorizing large, well-capitalized and highly-rated institutions according to risk is the method already proposed for small and medium-sized banks: creating two or more subgroups based on CAMELS ratings. Using supervisory ratings to set assessment rates for large institutions is appealing for several reasons. Large banking organizations are subject to frequent and thorough on-site review. Continuous supervision programs, which provide real-time and continuous evaluations of risk, have been established by the Office of the Comptroller of the Currency, the Federal Reserve Board, and the FDIC. Also, ratings assigned by regulators to large banks reflect information from a variety of sources, including the financial markets.

Pricing Framework Based on Market Measures of Risk

As the scale and complexity of the banking industry has increased, interest in using market information as a regulatory tool has grown. Regulators already use market signals extensively to monitor bank risk, and a variety of market indicators hold promise for pricing deposit insurance for large and complex institutions. These include price data such as stock price volatility and subordinated debt yield spreads; credit ratings assigned by companies such as Moody's, Standard and Poor's (S&P), and Fitch; and estimated default frequencies calculated using option pricing-type models such as the one developed by KMV Corporation.[12] A combination of these measures—and others that might prove suitable—could provide a more robust and balanced pricing tool for large banks than one based entirely on either

[11] As the requirements of Basel II are formalized and as institutions opt to adhere to them, we would expect the FDIC to incorporate information about the bank's internal credit rating systems, operational risk, and market risk into its pricing of deposit insurance.

[12] KMV's model calculates a company's probability of default from its stock price volatility, current capital structure, and value of its assets.

supervisory ratings or financial ratios. A disadvantage of relying entirely on market measures is that the insurer would forgo the benefits of information gleaned by examiners with access to confidential information.

A key issue is whether the data used for insurance pricing should originate at the bank or the parent holding-company level. In general, data related to the depository institution are of greater value to the insurer, since they reflect the consensus opinions of investors about the condition and performance of the entity having the most direct access to the federal safety net. Data related to the depository institution are all the more important in light of the increasing diversification of financial holding companies into business lines unrelated to banking; market information about a parent company may not accurately reflect the performance of an insured subsidiary.

Unfortunately, market data are often unavailable at the insured-institution level. The equity and debt instruments that would provide information useful for deposit insurance pricing are more typically issued by the parent holding companies of banks. This practice may compel the use of holding-company data for pricing.

Measuring the Predictive Ability of Market Factors

Because so few large institutions have failed, insufficient data are available to establish statistical relationships between the probability of bank failure and market measures in the same way failure was correlated with Call Report data to develop the failure-prediction model. To establish the usefulness of market measures as predictive factors, therefore, we tested three market measures against supervisory downgrades from CAMELS 1 or 2 to CAMELS 3 or lower over the period from 1987 through 1999 for the largest 25 banks as of year-end 1999.

Figure 5 shows the degree to which stock price volatility has predicted downgrades. We calculated a coefficient of variation for stock price (as a measure of volatility) and grouped the institutions by high, medium, or low volatility. The bars in the figure show the percentage of banks in each category that were downgraded to a composite 3 rating or worse within two years of our calculation. The results show a relationship between stock volatility and supervisory downgrades, indicating that stock price volatility may be an effective way to differentiate institutions for pricing purposes.

Figure 6 shows how well S&P credit ratings perform in predicting CAMELS composite downgrades. These aggregate results show a certain degree of differentiation between higher and lower investment-grade ratings, and a significant differentiation between investment- and noninvestment-grade ratings.

Figure 5

Aggregate CAMELS Downgrades in Relation to Stock Price Volatility for Top 25 Institutions
(Coefficient of Variation, 1987–1999)

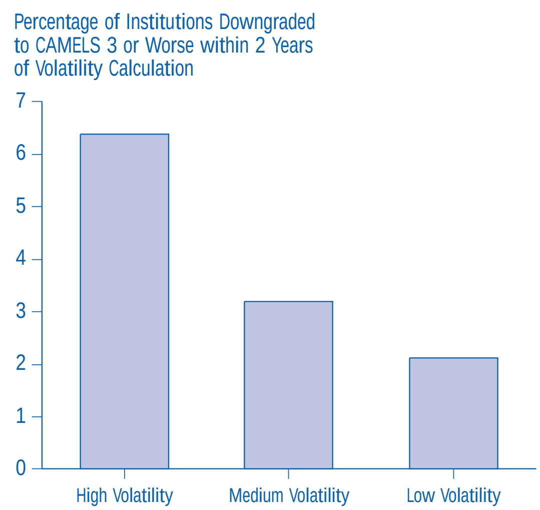


Figure 7 shows how KMV-estimated default frequencies perform in predicting downgrades during subsequent two-year periods. Again, a correlation is evident between the market measure and higher probabilities of downgrades.

Methodology for Assigning Scores

A large-bank pricing system using market measures could be constructed in a number of ways. One would be to use an individual measure—for example, credit ratings—on its own. Currently, S&P credit ratings for the parent companies of the 50 largest insured institutions range from AA– to BBB–. Given this fairly wide distribution, assessment rates could be assigned either to each credit rating category individually or to larger groups made up of more than one rating category. Alternatively, a combination of market measures could be weighted and summed to produce a single score per institution.

Pricing Framework Based on Combination of Supervisory and Market Measures

Another way to create subcategories in the best insurance group would be to use supervisory ratings in combination with a select set of market measures of bank risk. Such a system could take the form of either an integrated system in which supervisory ratings and market measures were combined and equally represented or a system in which market measures would serve as trip wires to adjust insurance classifications based mainly on supervisory ratings. An integrated system would require a method of weighting the various factors—composite ratings and market measures—to produce a single score.

A pricing system with trip wires might incorporate any of the market measures mentioned above (or others, such as price-to-book ratios) to adjust institution scores after the institutions had initially been categorized by supervisory ratings. For example, banks might be placed into separate CAMELS 1 and CAMELS 2 categories, and CAMELS 2-rated institutions that had relatively poor credit ratings might then be relegated to a third category. In table 8, the composite 2-rated group is subdivided into two categories: those with S&P credit ratings of A– or better (the 1A2 group) and those with ratings worse than A– (the 1A3 group). Similarly, high subordinated debt yield spreads, high stock price volatility, or low price-to-book ratios might serve as the secondary means of differentiation.

Figure 6

Aggregate CAMELS Downgrades in Relation to Credit Rating for Top 25 Institutions
(Coefficient of Variation, 1987–1999)

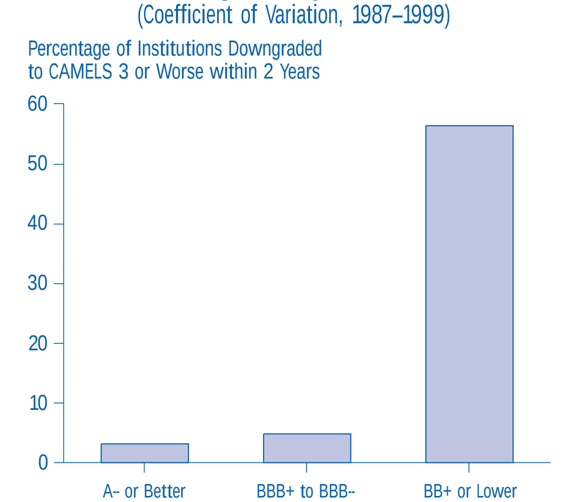
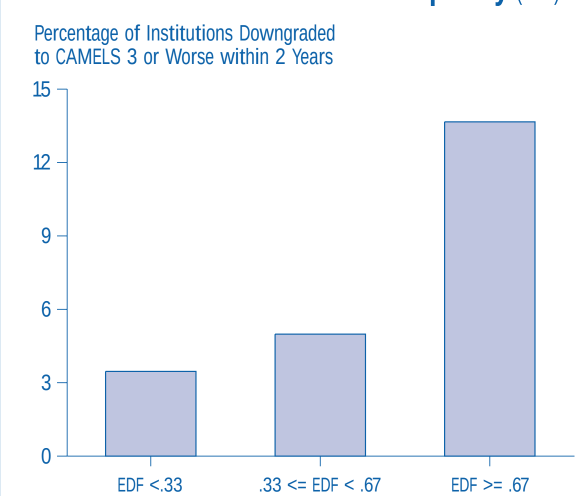


Figure 7

Aggregate CAMELS Downgrades in Relation to KMV for Estimated Default Frequency (EDF)



Pricing with a Scorecard

The disadvantages of using a financial ratio-based pricing system for large banks are discussed above. However, it may be possible to modify the scorecard approach in ways that would eliminate unintended adverse effects on large banks. Larger institutions tend to be penalized by the noncore funding component of the scorecard because they often operate with higher levels of wholesale funding and lower levels of capital than the smaller institutions that compose the bulk of observations used to calibrate the scorecard risk weights. To compensate, selected market measures could be incorporated into the scorecard either to replace certain of its elements as measures of risk or to offset elements that unduly penalize large banks. One approach we explored is the use of credit ratings.

For example, the lowest section of table 6 (see page 9) shows the part of a revised scorecard that includes an adjustment for institutions' S&P credit ratings. The rating adjustment relates to a bank's noncore funding score: banks that have ratings of A– or better receive an upward scoring adjustment to reflect their enhanced ability to obtain capital in the debt markets. Table 9 shows the effect of the rating adjustment on the distribution of large-bank rankings based on the modified scorecard. The rating adjustment results in an increase in the percentage of large banks placed in the risk category 1A1, though this percentage remains below the percentage of small banks in the 1A1 category. The percentage gap between large and small 1A1 institutions may reflect the relatively stronger asset-quality measurements for smaller institutions.

Table 8

Options for Pricing Large Institutions Using CAMELS Ratings with Credit Ratings (Year-End 2002)

	Subcategories		
	1A1	**1A2**	**1A3**
Composite 1 Rated	15 32.6%		
Composite 2 Rated *and* Credit Rating A– or better		24 52.2%	
Composite 2 Rated *and* Credit Rating Worse than A–			7 15.2%

Note: The figures in the cells refer to the number and percentage of the 46 largest institutions for which S&P ratings are available.

Table 9

Distribution of Well-Capitalized and Highly-Rated Institutions by Size Based on the Scorecard (Year-End 2002)

	Subcategories		
	1A1	**1A2**	**1A3**
Small Banks	43.5%	38.5%	18.0%
Large Banks[a] with Noncore Funding Adjustment	36.7	57.1	6.1
Large Banks[a] without Noncore Funding Adjustment	32.7	59.2	8.2

Note: The scorecard-derived scores (see table 6) produce the distribution shown here. In the scorecard, the adjustment for noncore funding rewards institutions rated by S&P as AA– or better with a 3-point upward adjustment, and institutions rated A– to A+ with a 1-point upward adjustment.

[a] Large banks are the top 50 banks by asset size.

Conclusion

All the options discussed in this article involve trade-offs among the desirable attributes of a deposit insurance pricing system. As applied to historical data, the statistical approaches tend to provide greater risk differentiation than the supervisory ratings approach but also tend to be more complex, more difficult to implement, and more likely to create unintended perverse incentives. The scorecard has an advantage over pure statistical models in terms of simplicity, flexibility, and incentives, but it is less accurate.

The combined statistical and supervisory approach was presented as an option that can ensure that CAMELS 1-rated institutions never pay more than CAMELS 2-rated institutions. Also, the combined approach supplements the informational content of the CAMELS ratings with the more recent information reported in Call Reports. However, the combined approach does not eliminate all the disadvantages of either of the two pure approaches. For example, if a combined methodology breaks the well-capitalized and highly-rated group of institutions into three or four subcategories, there is still the potential for cliff effects—small changes in a measured variable that produce large changes in the deposit insurance premium. In addition, a combined system is more complex than a system based on CAMELS ratings alone.

Nonetheless, combining the statistical and supervisory approaches can mitigate several of the concerns relating to either approach in isolation. The combined approaches and perhaps the scorecard approach provide the opportunity to make practical trade-offs and achieve the right balance among desirable attributes and policy objectives.

Separate deposit insurance pricing options were presented for new banks to address their special characteristics. Additional options also were presented for large banks that incorporate market data, which may better identify risk in larger, more complex institutions. Ultimately, the selection of one or another approach will reflect a particular weighting of the desirable attributes and a judgment regarding the approach that achieves the best balance.