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Using Market Information to Help Identify Distressed Institutions

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Using Market Information to Help Identify Distressed Institutions: A Regulatory Perspective

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In recent years the call for incorporating market signals into bank supervision has spread from academic circles to U.S. bank regulators, Congress, and international regulatory bodies.[1] Donna Tanoue, Chairman of the Federal Deposit Insurance Corporation (FDIC) from 1998 to 2001, Alan Greenspan, Chairman of the Federal Reserve System, and other Federal Reserve Governors have commented on the importance of harnessing market forces to help with supervisory monitoring and to encourage market discipline.[2] The Basel Committee on Bank Supervision, which establishes capital standards for international banks, recently proposed using market forces as one of its "three key pillars" of comprehensive capital-adequacy regulations.[3]

Interest in the use of market information arises from the ability of financial markets to interpret public information very quickly. Even though bank supervisors have an advantage over the market owing to their access to extensive private information from on-site bank examinations, these examinations occur only after relatively long intervals, usually every 12 to 18 months, and

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[1] This note focuses on the academic literature. Flannery (1998) summarizes this literature through the late 1990s. More recently, Berger and Davies (1998) use event-study methodology to find that the equity market anticipates upgrades in regulatory ratings but follows downgrades. Berger, Davies, and Flannery (2000) find that regulators acquire information sooner than the equity markets and bond rating agencies do, but the regulatory assessments are generally less accurate than either stock or bond market indicators in predicting the future performance of bank holding companies. Elmer and Fissel (2000) find that equity market variables can be used to augment accounting-related information to predict bank failure. Krainer and Lopez (2001) find that equity market variables such as stock returns and equity-based default frequencies are useful to bank regulators for assessing the condition of bank holding companies. Gunther, Levonian, and Moore (2001) find that a measure of financial viability based on stock prices (expected default frequency) helps predict the financial condition of bank holding companies as reflected in their supervisory ratings. Curry, Elmer, and Fissel (2001) find that incorporating market data into traditional off-site monitoring models helps identify downgraded and upgraded banks and thrifts that were not affiliated with multibank holding companies. Curry, Fissel and Hanweck (2003) find that market-indicator variables add value to models in predicting bank holding company supervisory ratings.

[2] Tanoue (2001); Greenspan (1998); Meyer (1998). The term *market discipline* generally refers to the ability of the market to price or impose costs on institutions based on their risk. The costs, for example, might take the form of higher issuance costs in the bond markets and/or lower equity prices.

[3] The three pillars include minimum capital requirements, supervisory review and market discipline.

may quickly become outdated.[4] As for off-site reviews, they depend on quarterly accounting data that may not be audited or may not reflect the changing risk profile of the institution. However, these same quarterly accounting data are widely available to the public and therefore are used by financial markets as well as regulators to assess risk. If financial markets can process and interpret this public information more efficiently than bank regulators, market prices might either complement or supplement the off-site and/or on-site monitoring systems used by the regulators.

Studies that have examined the potential use of market signals in bank supervision have focused primarily on the debt market for signs of changing risk patterns in insured institutions. This focus has been popular because the concerns of investors in these markets, particularly subordinated-debt investors, are closely aligned with the concerns of bank supervisors. Equity markets, however, should provide as much information as debt markets because equity investors are the first to lose if a bank experiences problems.[5] Moreover, the number of banking institutions with publicly traded equity is much larger than the number of institutions with publicly traded subordinated debt, and trading volume tends to be much higher for equities than for subordinated debt.

The purpose of this article is to assess the relationship, in timing and magnitude, between equity market valuations of commercial banks and thrift institutions and changes in the supervisory ratings for these organizations. In particular, we ask two questions: to what extent do market variables such as stock prices, returns, and trading volume (among others) provide timely market signals? And if they do provide timely signals, can they add incremental value to off-site monitoring systems that attempt to predict changes in the CAMEL ratings assigned by regulators?[6] We begin to address these questions by discussing the institutional setting for the downgrading of a bank's CAMEL rating. We then evaluate problems associated with interpreting market data before examination ratings are changed. Finally, we perform statistical tests to test the incremental predictive content of market-related variables compared with accounting data from bank financial reports.

The Institutional Setting

Modern bank supervision uses information gathered from on- and off-site supervisory tools as the starting point for its analysis. The larger banks and bank holding companies are monitored by on- and off-site inspectors (examiners), who keep abreast of any information that can be found, including news reports, Wall Street analyses, and traditional quarterly financial data.[7] Most smaller and midsized banks are initially monitored with automated analysis of quarterly financial statements and then, if risk is identified, are reviewed by analysts in addition to regular on-site examinations.

Periodic on-site safety-and-soundness examinations begin with off-site pre-exam reviews of quarterly and other pertinent data. This information is then checked in on-site reviews, which also explore issues that might not be revealed in the quarterly reports. In fact, on-site examinations provide extensive financial information that is not generally available to the public, such as the current status of performing and nonperforming

[4] Federal law mandates that all federally insured banking institutions be examined at least every 12 to 18 months, depending on the size and condition of the institution. Weaker institutions are often subject to more frequent scrutiny. For evidence that bank examinations may age quickly, see Cole and Gunther (1998).

[5] Levonian (2001) has shown that equity market information and debt market information should produce similar results.

[6] The acronym "CAMEL" stands for **C**apital, **A**ssets, **M**anagement, **E**arnings, and **L**iquidity, five components of a bank's financial operation that are examined by the regulators. In the late 1990s a sixth component was added to the CAMEL rating system, recognizing bank and thrift Sensitivity to interest-rate or market risk (CAMELS). CAMELS ratings are assigned on a scale of 1 to 5 with 1 being the highest and 5 the lowest. Because the empirical portions of our analysis relate to ratings assigned before the late 1990s, we reference the five-component rating system in effect at that time.

[7] It should be noted that for the largest U.S. banks, in recent years the Comptroller of the Currency and other regulators (including the FDIC) have established supervisory programs with continuous on-site presence.

loans, loan classifications and the adequacy of loan-loss provisions, and bank capital; on-site examinations also provide a close-up view of managerial abilities and expertise.

At the end of on-site examinations, bank inspectors assign an overall, or composite, CAMEL rating (see note 6); these ratings range from 1 to 5. Ratings of 1 or 2 are assigned to institutions in fundamentally sound financial condition. When a previously 1- or 2-rated bank is downgraded to 3, an important signal of supervisory concern is sent and is normally accompanied by an understanding between the bank's primary regulator and senior bank management specifying the nature of the bank's weakness and procedures for changing bank policies to rectify the perceived problems. These understandings are classified by regulators as "informal" enforcement actions because they are not administratively or judicially enforceable in a court of law in the event of noncompliance.[8] Nevertheless, such actions represent a loud "shot across the bow" signaling significant regulatory concern and the need for change. Institutions downgraded to a 3 will typically retain that rating for periods ranging from six months to several years before being assigned a higher or lower rating.

Downgrading a bank's CAMEL rating to 4 or 5 indicates the existence of serious problems that, if not resolved, present a distinct possibility of insolvency. In practice, the term "problem" bank is often reserved for institutions with a composite rating of 4 or 5, and regulatory "problem-bank lists" tend to specify institutions with these ratings, although practices vary. Banks downgraded to 4 typically require immediate remedial actions and intensive monitoring by regulatory officials. In some cases, bank supervisory officials may opt not to choose the more serious "formal" enforcement actions for 4-rated banks as long as bank management addresses regulatory concerns.

However, consistent with supervisory policy, most banks downgraded to a 4 or 5 are subject to formal enforcement actions, and these actions have been made public since 1989.[9] Institutions with a CAMEL rating of 4 can continue in business for as long as several years before either returning to an improved rating, moving to a worse rating, or being declared insolvent by their primary regulator. A rating of 5 indicates a high probability of failure, usually within the next 12 months.

Interpreting Market Signals

If information embedded in market prices is to be integrated into the off-site monitoring process, the message contained in the information must be clear and timely and must add incremental predictive value to other sources of information commonly used by off-site monitoring, such as the quarterly financial data. If these characteristics are lacking, the value of the information declines either because its interpretation is vague or because it fails to improve existing supervisory practices.

The interpretability and practical usefulness of market information are keys to integrating it into off-site monitoring. (Here we discuss interpretation; in the remaining sections of the article we discuss usefulness.) Market prices are notorious for their wide fluctuations over short periods of time, and interpreting the information contained in prices that repeatedly jump upward and downward may be difficult. Although short-term fluctuations would be reduced if the focus were on longer-term price and return trends, the choice of a time period to use for these types of analyses is subjective, and smoothing trends over longer periods reduces the timeliness of the information.

Interpretation issues aside, the use of market data would open the door to a substantial list of variables that might be helpful in bank analysis. Two such variables are return volatility and trading

[8] Informal enforcement actions may require institutions to make changes, such as raising new equity capital, limiting the origination of certain types of loans, or increasing loan-loss reserves. Although regulators vary in their practices, the most common type of informal action accompanying a downgrade to 3 is a "memorandum of understanding" (MOU), which is written by bank supervisors and signed by bank officials and supervisors.

[9] The Financial Institutions Reform, Recovery, and Enforcement Act of 1989 (FIRREA) mandated that formal enforcement actions become part of the public record.

volume. For example, Merton's (1973) option model expects a rise in return volatility as an institution approaches insolvency. Wang (1994) ties trading volume to the flow of information about a firm's financial health, suggesting that trading volume should rise as information about financial distress is released. Although a comprehensive analysis of market-related variables goes beyond the scope of this article, return volatility and trading volume represent two that are easily observed and that are expected by financial theory to contain predictive content.

In summary, although the interpretability of price and other market changes remains an issue, there are nevertheless compelling arguments for finding ways to integrate market data into the off-site monitoring process, and there are also a variety of market variables that might be used to this end. Therefore, debate about regulatory use of market-related information in prudential bank supervision should focus on empirical, not conceptual, issues. One particular empirical issue is whether market-related variables add incremental predictive value to quarterly accounting data or other information that is easily available to regulators in off-site monitoring systems. Unless market signals increase predictive value, they may be viewed as redundant information with little supervisory value.

The Sample

Our empirical analysis begins with a sample of publicly traded banks and thrifts whose ratings were downgraded to problematic levels between the first quarter of 1988 and the last quarter of 1995.[10] Since a CAMEL rating of 3 signifies significant regulatory concern but ratings of 4 and 5 signify more severe financial distress that is often followed by failure, we separate institutions downgraded to 3 from those downgraded to 4 or 5. Combining the 4s and 5s into a single group appeared reasonable inasmuch as institutions pass to failure from these two ratings fairly commonly, but do so from a rating of 3 or better only occasionally.

To improve the integrity of the analysis, we imposed several additional restrictions. The sample was limited to institutions that had a lengthy period of superior ratings before being downgraded. We implemented this condition by requiring that institutions have CAMEL ratings in the 1–2 range for at least two years before being downgraded to 3. Similarly, institutions downgraded to a 4 or 5 were required to have had ratings in the 1, 2, or 3 range for at least two years preceding downgrade to 4 or 5. The sample was also limited to banks and thrifts that either were not affiliated with bank holding companies or were members of bank holding companies that held only a single institution. Restricting the sample in this fashion ensured that the extensive financial data reported on bank quarterly reports corresponded closely to the institution that issued the stock. This restriction also reduced contamination from activities of nonbank subsidiaries of bank holding companies.[11] Since the empirical analysis combines quarterly financial data with stock market information reported by the Center for Research in

[10] The sample population was drawn from a universe of all banks and thrifts from 1988 to 1995 that were publicly traded, as reflected in the availability of stock price information from the Center for Research in Security Prices (CRSP). To obtain stock price information for individual commercial banks and thrifts, we matched CRSP data against bank quarterly reports going back to 1986. We then matched the firms against bank examination ratings to obtain the historical CAMEL ratings. Within the group for which all this information was available, we identified all institutions that were downgraded to a 3, 4, or 5 during our period. To form the sample in our study, we reduced this group by the additional restrictions discussed in the next paragraph of the text. The sample of CAMEL 1- or 2-rated, or "healthy," banks against which the downgraded groups were matched was also taken from this universe of publicly traded institutions (see note 14).

[11] Analysis of multibank holding company equity securities carries disadvantages (as well as advantages) compared with analysis of non-affiliated banks and thrifts and one-bank holding companies. For example, multibank holding companies tend to be large institutions that are widely traded and rated by nationally recognized rating agencies. Although one-bank holding companies and banks not affiliated with holding companies tend to have the opposite characteristics, their quarterly financial data nevertheless correspond directly to the institution that is publicly traded, and the quarterly financial data are far more extensive than financial data released at the holding-company level. Moreover, the many activities of holding company subsidiaries cannot be separated from the aggregated data reported at the holding-company level, and this lack of separability obscures the extensive information released by individual banks. Market signals at the holding-company level may or may not correspond to the performance of the bank subsidiary. The potential disconnect between the performance of individual banks and the market signals of their holding companies may widen as holding companies respond to passage of the Gramm-Leach-Bliley Act of 1999 by diversifying into additional nonbank activities.

Security Prices (CRSP), both sources of data were required for an institution to be included in the sample; in addition, historical CAMEL ratings over the period had to be available. For the logistic regressions, the downgraded banks in each of the two groups are paired against a sample of healthy banks (those rated a 1 or 2).

Table 1 provides summary statistics for the two groups of downgraded institutions. The sample size is relatively large for both groups, with 83 institutions downgraded to 3 and 107 downgraded to 4 or 5. Considerable diversity is apparent in the sample. For example, both groups of downgraded institutions include thrifts as well as banks, and both groups had a wide range of asset sizes, encompassing institutions with total assets under $100 million as well as institutions with assets over $5 billion. More than 75 percent of the institutions had assets under $1 billion, while slightly less than 20 percent had assets in the $1–5 billion range and about 5 percent were in the over-$5 billion range. The relatively healthier condition of institutions downgraded to 3 is reflected in their higher book equity-to-assets and return-on-assets ratios compared with the ratios reported for institutions downgraded to 4 or 5. Stronger financial health appears to be recognized by the market, as reflected in a more favorable book-to-market equity ratio for institutions downgraded to 3, compared with the ratio for those downgraded to 4 or 5.

Univariate Trends Preceding Downgrades

Table 2 displays univariate characteristics of stock prices, returns, and other market-related variables for banks and thrifts during the eight quarters preceding the institutions' downgrades to CAMEL rating 3, 4, or 5.[12] The sample varies slightly from quarter to quarter because the delisting rules of various exchanges (rules such as minimums for capital requirements and trading activity) reduce the availability of stock price information for individual firms.

[12] Examinations that lead to rating downgrades can last from several weeks to a month or more, depending on the severity of the case. They conclude with a notification to management that the institution's rating will be downgraded. Thus, the zero quarter can be regarded as contemporaneous with the notification quarter or the quarter of the rating change.

Table 1

Summary Statistics for Sample of Downgraded Institutions

	A. At Time of Downgrade to 3				B. At Time of Downgrade to 4 or 5			
	No.	**Minimum**	**Median**	**Maximum**	**No.**	**Minimum**	**Median**	**Maximum**
Call Report Financial Data								
Total Assets ($000s)	83	36,647	40,381	9,375,411	107	20,316	381,583	15,469,836
Book Equity/Asset Ratio (%)	83	4.82	7.37	96.98	107	0.00	6.02	16.50
Return on Assets (%)	83	–7.71	0.40	2.27	107	–16.75	–1.03	1.20
CRSP Market Data								
Market Price ($ per share)	83	0.74	7.96	36.25	107	0.53	5.23	16.87
Market Capitalization ($000s)	83	2,523	21,434	656,355	107	444	14,700	453,148
Book/Market Equity Ratio	83	0.09	1.45	10.60	107	0.02	1.58	9.04
Total Sample	83				107			
Number with Assets <$1 Billion	64				79			
Number with Assets $1–5 Billion	16				19			
Number with Assets >$5 Billion	3				9			
Number of Banks	77				99			
Number of Thrifts	6				8			

Note: The data are from quarterly financial data reported to regulators or are derived from CRSP during the quarter in which the CAMEL rating of the institution was downgraded. Market capitalization equals equity price times number of shares at the end of the quarter of the downgrade.

Table 2

Characteristics of Stock Price, Return, and Other Market Variables by Quarter Preceding Downgrade in CAMEL Rating

Qtrs to Rating Change	Sample	Avg. Stock Price (dollars)	Change in Stock Price (dollars)	Cum. Qtrly. Return (percent)	CRSP Equal Wt. Excess Return (percent)	CRSP Value Wt. Excess Return (percent)	Industry Value Wt. Excess Return (percent)	Std. Dev. Daily Return (percent)	Change in Std. Dev. Daily Return (percent)	Avg. Daily Trading Volume (shares)	Avg. Qtrly Turnover Ratio (percent)
A. Trends Preceding Downgrade to 3											
–8	79	15.42	0.16	2.95	–4.10	–1.55	–1.55	2.63	–0.02	10,449	13.52
			0.53	1.51	–2.47**	–0.96	–0.91		9.93***		
–7	83	14.66	–0.78	–0.83	–6.08	–4.58	–4.58	2.59	–0.07	10,077	13.29
			–1.88*	–0.50	–3.81***	–2.89***	–2.85***		–0.70		
–6	83	13.64	–1.04	–2.40	–7.01	–5.98	–5.49	2.55	0.00	9,595	13.65
			–2.76***	–1.42	–4.62***	–3.98***	–3.54***		–0.08		
–5	84	12.98	–0.77	–0.88	–4.79	–3.86	–2.61	2.79	0.25	10,660	13.39
			–1.37	–0.44	–3.04***	–2.30**	–1.65*		2.23***		
–4	84	12.32	–0.66	0.45	–6.88	–3.68	–4.24	2.82	0.00	10,646	12.50
			–2.99***	0.24	–4.51***	–2.02**	–2.23**		0.26		
–3	84	11.78	–0.54	–0.04	–8.74	–7.08	–6.06	2.97	0.15	11,991	13.89
			–2.92***	–1.94*	–5.63***	–4.23***	–3.73***		1.20		
–2	83	11.34	–0.50	–3.77	–7.05	–5.02	–3.57	3.54	0.55	12,372	14.87
			–2.82***	–1.47	–3.33***	–2.20**	–1.68*		4.75***		
–1	83	10.52	–0.82	–2.73	–9.08	–6.15	–6.71	4.05	0.51	12,023	15.12
			–3.55***	–1.15	–4.84***	–2.91***	–3.59***		2.88***		
0	83	9.91	–0.56	–1.69	–11.16	–5.43	–7.37	4.01	–0.06	12,625	15.52
			–2.36**	–0.65	–5.24***	–2.19**	–2.99		–0.32		
B. Trends Preceding Downgrade to 4 or 5											
–8	105	12.20	0.15	0.46	–3.60	–2.74	–1.51	2.92	–0.14	14,908	15.19
			0.30	0.25	–2.40**	–1.71*	–1.00		–0.81		
–7	107	11.76	–0.32	–4.87	–7.66	–7.41	–5.58	3.06	0.20	13,620	14.06
			–1.68*	–2.90***	–5.05***	–4.76***	–3.48***		1.68*		
–6	107	11.09	–0.66	–3.32	–8.50	–7.44	–6.84	3.08	–0.03	13,196	13.75
			–2.02**	–1.72*	–5.39***	–4.33***	–4.32***		–0.23		
–5	109	10.26	–0.69	–5.89	–11.17	–9.60	–8.79	3.45	0.23	12,130	12.94
			–5.39***	–3.59***	–7.32***	–6.57***	–5.73***		1.72*		
–4	110	9.83	–0.34	–6.52	–11.87	–10.51	–10.42	3.53	0.36	12,400	13.35
			–1.87*	–3.05***	–6.41***	–5.39***	–5.59***		2.52***		
–3	108	9.19	–0.75	–5.32	–9.98	–8.49	–7.02	4.08	–0.10	14,619	13.94
			–3.07***	–1.97**	–4.32***	–3.40***	–3.00***		–0.15		
–2	107	8.14	–1.03	–9.89	–15.72	–12.59	–12.83	4.89	0.58	13,424	12.67
			–5.80***	–4.53***	–8.39***	–5.90***	–6.14***		3.23***		
–1	107	6.94	–1.20	–5.89	–12.80	–9.04	–9.48	5.79	0.48	14,739	13.45
			–6.28***	–1.59	–4.06***	–2.56**	–2.90**		2.05**		
0	107	5.97	–0.97	–9.68	–15.52	–11.42	–12.42	5.87	0.61	15,506	13.61
			–5.48***	–2.63***	–4.85***	–3.28***	–3.83***		2.43**		

Note: The data reported on each of the quarter-to-quarter rating change lines (–8 to 0) are calculated as simple averages for all trading days in each quarter. If the data required for any quarterly calculation are missing, they are omitted from the calculation. Excess returns are calculated as the difference between the cumulative quarterly return of each stock and the cumulative quarterly return of the various indices. T-statistics testing the hypothesis that the mean equals zero are shown below many of the quarterly average return and change-in-return statistics. A single, double, or triple "*" indicates significance at the 10 percent, 5 percent, or 1 percent level, respectively.

The data show quarterly average stock prices falling continually throughout the eight quarters before the downgrades. As expected, the decline in stock prices is more precipitous for the more distressed group—the 4- and 5-rated institutions. To examine the consistency of changes in stock prices across the sample, we used a t-test to test the hypothesis that the mean change of each quarterly sample equals zero. For the 3-rated group, this test shows that the decline in stock price is consistently statistically significant beginning in the fourth quarter preceding the downgrade. For the 4- or 5-rated group, the change is significant seven quarters before the downgrade, reflecting the more distressed nature of this group. The t-test results suggest that a simple test can be used to identify declining stock prices that might precede a drop in an institution's CAMEL rating.

The steady decline in quarterly prices preceding a downgrade causes persistent patterns of negative cumulative quarterly returns as well.[13] Quarterly returns are negative preceding downgrades for both groups under consideration, although the t-tests are not as conclusive as they are for declining prices. For institutions downgraded to CAMEL 3, the negative returns are not significantly distinguishable from zero preceding the downgrade, although institutions downgraded to 4 or 5 have significant negative returns in most quarters preceding their rating change.

Patterns of negative returns are more easily seen if one calculates the differences between quarterly stock returns and the quarterly returns for either of several indices of market performance. Using three indices of market returns (the CRSP equal-weighted and value-weighted indices and an industry value-weighted index constructed from bank and thrift institutions), table 2 shows that market excess returns are generally negative and statistically significant during the eight quarters preceding a downgrade, regardless of the market index used as a benchmark. These results hold for the 3-rated group as well as the 4- or 5-rated group. The consistency of the t-test results again supports the notion that simple tests might be used to identify problematic institutions, while reaffirming Pettway's (1980) finding of negative excess returns for lengthy periods preceding financial distress.

Consistent with financial theory, a measure of return volatility—the standard deviation of daily returns—tends to rise as the time of downgrade approaches. That is, the volatility variable rises steadily for both groups as the downgrades approach, especially during the four quarters immediately preceding the downgrades. Volatility is noticeably higher for the most distressed institutions (CAMEL 4 or 5) than for the moderately distressed institutions (CAMEL 3). The statistical significance of the rising volatilities is confirmed with significant t-statistics for two quarters preceding a downgrade, but these patterns are not consistently found in earlier periods preceding a downgrade.

Two measures of trading activity are used to examine the hypothesis that trading increases as distress approaches. These variables, however, generally fail to follow the rising trend preceding downgrade (financial theory expected otherwise). The most direct measure of trading activity—average daily trading volume for the quarter—increases slightly before the downgrades for the 3-rated group but fails to follow a consistent trend for the 4- or 5-rated group. A second measure of trading activity, known as *turnover*, divides the shares traded in any quarter by total shares outstanding at the end of each quarter. The turnover variable also increases slightly before downgrades to 3 but not before downgrades to 4 or 5. Therefore, the trading activity variables appear to contain very little informational content before CAMEL rating downgrades.

[13] The cumulative quarterly return is calculated by multiplying unity plus the daily return for each stock i on day $t(1+r_{it})$ across all trading days in each quarter, then subtracting unity.

Incorporating Market Information into Supervisory Models

Testing the incremental importance of stock price, return, and other market variables against the traditional financial variables contained in the quarterly reports allows us to formally distinguish the marginal predictive value of the two types of explanatory variables. This approach proceeds by initially specifying a traditional, or ratio-based, CAMEL rating prediction model, then extending the model to include market-related variables. Although the market variables need not dominate the traditional ratio-based model, a minimum level of competency is required to justify a conclusion that market-related information provides a meaningful addition to the traditional analysis. For example, if the market has a unique ability to interpret quarterly financial data, then market variables should provide statistically significant explanatory power to models that predict rating downgrades on the basis of traditional financial ratios.

In this section, a binomial logistic model is estimated to explain changes in financial institution supervisory (CAMEL) ratings. The binary dependent variable (CAMELCAT) in the equation takes a value of "1" if the institution is downgraded to the 3, 4, or 5 level over the 1988–1995 period, and a "0" if the institution remains a healthy 1- or 2-rated institution.[14] The logistic regression estimates the likelihood that a bank or thrift will be downgraded. Table 3 defines the variables used in the regression model for the downgraded and control groups, along with their means and standard deviations. The regressions are run four quarters (one year) before the quarter of the downgrade. Since bank regulators generally release financial data one to two months after the end of each quarter, the quarterly financial data in the regressions are measured five quarters before the downgrade quarter, whereas the data from the market variables are measured four quarters before the downgrade quarter.

Several control variables are used to account for factors that might influence the likelihood of a downgrade. The first variable (BK_SIZE) controls for differences in institution size and is measured as a dummy variable, with a value of "1" for institutions greater than $1 billion and "0" otherwise. To the extent that firm size provides greater opportunities for diversification and access to capital markets, a negative relationship between the probability of a downgrade and institution size is expected. A second control variable (STATE) accounts for differences in economic conditions over the period of this study among the states and regions from which the sample was drawn. The STATE variable is defined as measuring the quarterly percentage change in requests for housing permits. A negative sign is expected between the STATE variable and the probability of being downgraded.

A regulatory variable is specified in the model to account for differences in the amount of private as opposed to public information available at the time of the downgrades. Bank supervisory officials have access to considerable amounts of private information about the financial condition of their regulated institutions: confidential financial data, previously assigned confidential CAMEL ratings, information gathered during discussions with management, and so forth. Since much of this information is considered in the assignment of the management component of the CAMEL rating, this variable (MGT_RAT) makes a convenient summary measure of regulatory interpretations of private information. We include the variable in our test by measuring it from the bank examination on record as of four quarters before the institutions were downgraded.

[14] As mentioned above, the control sample of healthy banks was also selected from the universe of CAMEL-rated banks and thrifts that were publicly traded over the 1988–1995 period. To be eligible for inclusion in the control sample, these institutions had to have a 1 or 2 CAMEL rating for two consecutive years and had to maintain that rating at their first on-site examination after the two consecutive years were completed. When these criteria were satisfied, the control sample selected contained 151 institutions.

Table 3

Definition of Variables, Means, and Standard Deviations

		CAMEL 3-Rated		CAMEL 4/5-Rated		Control Sample	
		Mean	**Standard Deviation**	**Mean**	**Standard Deviation**	**Mean**	**Standard Deviation**
Dependent Variable							
CAMELCAT	Dummy variable equal to "1" if the institution experienced a CAMEL rating downgrade to a 3 or a 4 or 5, and "0" otherwise.	1.00	0.00	1.00	0.00	0.00	0.00
Control Variables							
BK_SIZE	Dummy variable equal to "1" if the institution was over $1 billion, and "0" otherwise.	0.21	0.41	0.24	0.43	0.13	0.33
STATE	Percentage change in quarterly residential housing permits by state	–19.52	20.86	–25.57	15.59	–2.76	18.22
Regulatory Variable							
MGT_RAT	Component rating for quality of bank management.	2.02	0.38	2.43	0.67	1.73	0.52
Financial Variables							
EQ_ASSET	Equity capital divided by total assets (%).	10.11	10.06	8.09	2.78	10.71	4.40
NC_ASSET	Noncurrent (delinquent) assets less loan-loss reserves, divided by total assets (%).	1.79	1.27	2.77	2.03	0.59	0.93
RES_ASSET	Reserves for loan losses divided by total assets.	0.76	0.49	1.04	0.70	0.61	0.46
LPROV_ASSET	Loan-loss provisions divided by total assets.	0.31	0.40	0.59	0.80	0.10	0.21
ROA	Quarterly annualized earnings divided by total assets (%).	0.52	1.33	0.03	1.69	1.02	0.56
SEC_ASSET	Securities divided by total assets (%).	17.04	13.80	14.59	12.71	26.52	14.14
VOL_ASSET	Volatile liabilities divided by total assets (%).	21.47	10.73	21.46	11.00	13.42	11.23
Market Variables							
EXPRC	Log of the ratio of the stock price divided by the S&P bank-stock industry index.	–2.76	0.68	–3.02	0.82	–2.35	0.83
EXRET	Market excess or abnormal return, calculated as the difference between the cumulative quarterly return of each stock and the cumulative quarterly return of the CRSP value-weighted index.	–0.04	0.17	–0.11	0.20	–0.02	0.20
COEFVAR	Coefficient of variation is equal to the standard deviation of the stock price for the quarter divided by the average quarterly stock price (%).	6.09	4.18	8.50	8.35	6.08	4.36
BKEQ_MEQ	Book equity divided by market capitalization.	1.41	0.89	1.91	2.45	0.91	1.12
TURNOVER	Number of shares traded in a quarter divided by the number of shares outstanding at the end of the quarter (%).	12.50	11.58	13.35	12.64	11.98	16.43
Number of observations		84		110		151	

The first accounting-related variable in the model, the equity-to-assets ratio (EQ_ASSET), measures the ability of a firm to absorb loan losses before bankruptcy and is expected to be negatively related to the likelihood of future distress. The credit quality of the loan portfolio is captured by three variables: the level of delinquent or noncurrent assets less loan-loss reserves relative to total assets (NC_ASSET), the level of loan-loss reserves to total assets (RES_ASSET), and the quarterly amount of loan provisions to total assets (LPROV_ASSET). The bank reserve variable is expected to be negatively related to the likelihood of a rating downgrade, whereas the noncurrent asset and quarterly loan provision variables are expected to be positively related. Profitability is measured by the return-on-assets variable (ROA), which is expected to be negatively related to future downgrades. Two measures of liquidity are the securities-to-assets ratio (SEC_ASSET) and the volatile-liabilities to assets ratio (VOL_ASSET). The SEC_ASSET variable is expected to be negatively related to future distress, reflecting the fact that higher levels of securities to assets provide sources of additional liquidity in troubled times. A positive sign is expected for the volatile-liabilities ratio (VOL_ASSET), reflecting the notion that higher levels of volatile liabilities reflect expensive and/or potentially risky funding strategies.

Market prices and returns are our primary market variables. Stock price (EXPRC), measured as the natural logarithm of the ratio of the average quarterly price divided by the S&P bank-stock industry index, is expected to be negatively related to rating downgrades. Market excess returns are captured by EXRET, which measures the CRSP value-weighted excess quarterly returns for each observation (and is discussed above in the univariate analysis). Given the high degree of negative excess-return persistence observed above, we expect EXRET to have at least some predictive content and be negatively related to the future downgrades.

Several market variables reflect risk, as in the market model of Fama and French (1993) or the option model of Merton (1974). Price volatility is captured by the coefficient of variation in equity prices (COEFVAR) and is expected to be positively related to downgrades. The book-equity to market-equity ratio (BKEQ_MEQ) provides a second measure of the market's valuation of the firm and is expected to have a positive coefficient because the ratio moves inversely with changes in an institution's stock prices. A trading activity variable, TURNOVER, which measures stock turnover on a quarterly basis, is expected to be positively related to rating downgrades.

The following equation shows the basic logit estimation equation:

$$
\begin{aligned}
Camel_{it} &= \alpha_i + \sum_{j=1}^{2} \beta_j \left(Control\ Variables_{ijt} \right) \\
&+ \sum_{j=3}^{3} \beta_j \left(Regulatory\ Variables_{ijt} \right) \\
&+ \sum_{j=4}^{10} \beta_j \left(Financial\ Variables\ s_{ijt} \right) \\
&+ \sum_{j=11}^{15} \beta_j \left(Market\ Variables\ s_{ijt} \right) + \varepsilon_{it}
\end{aligned}
$$

The regression results are presented in table 4. Panel A shows the results for firms that were downgraded to 3, and panel B shows the results for firms that were downgraded to 4 or 5. Five models are specified to test the downgrade-predictive value of publicly available as opposed to confidential supervisory information. In particular, specifications 1–3 focus on publicly available information in bank quarterly reports and stock market data, whereas specifications 4–5 add confidential supervisory management ratings to the publicly available information used in models 1–3.

Specification 1 displays a traditional model of bank financial distress, based on publicly available financial data. The model contains two control variables, bank size (BK_SIZE) and geographic location (STATE), although the size variable is generally not statistically significant. Following the two control variables are seven financial ratios, most of which perform as expected. The

Table 4

Logit Regression Results: Four Quarters before Downgrade

Independent Variable	Anticipated Sign	A. CAMEL 3-Rated Group Specification 1	2	3	4	5	B. CAMEL 4/5-Rated Group Specification 1	2	3	4	5
Intercept		–0.86	–3.39	–2.13	–3.76	–4.46	0.90	–5.63	–1.09	–5.82	–7.58
		(1.23)	(5.00)***	(2.07)**	(2.71) ***	2.95 ***	(0.83)	(5.98)***	(0.69)	(2.96)***	(3.12)***
Control Variables											
BK_SIZE	–	0.09	0.82	0.21	0.12	0.21	–0.46	1.38	–0.52	0.34	0.12
		(0.16)	(1.83)	(0.36)	(0.21)	(0.34)	(0.69)	(2.86)***	(0.66)	(0.43)	(0.13)
STATE	–	–0.03	–0.05	–0.03	–0.03	–0.03	–0.07	–0.09	–0.07	–0.11	–0.13
		(2.97)***	(5.06)***	(2.72)***	(3.05)***	(2.80)***	(4.50)***	(6.93)***	(4.17) ***	(4.29)***	(3.91)***
Regulatory Variable											
MGT_RAT	+				1.33	1.23				3.26	3.41
					(2.46)**	(2.18) **				(4.34)***	(3.96)***
Financial Variables											
EQ_ASSET	–	–0.02		–0.04	–0.01	–0.02	–0.42		–0.51	–0.48	–0.61
		(1.04)		(1.54)	(0.25)	(0.68)	(3.30)***		(3.26)***	(3.08)***	(–3.04)***
NC_ASSET	+	0.88		0.83	0.82	0.77	1.22		1.17	1.13	1.11
		(3.99)***		(3.63)***	(3.70)***	(3.34)***	(4.44)***		(4.17) ***	(3.87)***	(3.52)***
RES_ASSET	–	–1.19		–1.24	–0.91	–0.94	–0.71		–0.95	–1.08	–1.31
		(1.81)*		(1.80)*	(1.36)	(1.35)	(1.23)		(1.56)	(2.01)**	(2.18) **
LPROV_ASSET	+	2.78		2.89	2.67	2.78	4.29		4.63	5.87	6.61
		(2.37)**		(2.34)**	(2.28)**	(2.29)**	(3.48)***		(3.43)***	(3.79)***	(3.63)***
ROA	–	–0.83		–0.65	–0.75	–0.61	–1.29		–0.86	–1.09	–0.68
		(2.40)**		(1.96)**	(2.20)**	(1.84)*	(2.59)***		(1.43)	(1.76)*	(0.92)
SEC_ASSET	–	–0.04		–0.05	–0.04	–0.05	–0.05		–0.05	–0.09	–0.09
		(2.82)***		(2.89)***	(2.83)***	(2.92)***	(2.14) **		(2.07)**	(3.08)***	(2.82)***
VOL_ASSET	+	0.07		0.07	0.07	0.07	0.08		0.08	0.09	0.09
		(4.08)***		(4.05)***	(4.00)***	(4.01) ***	(3.38)***		(3.08)***	(2.84)***	(2.66)***
Market Variables											
EXPRC	–		–0.94	–0.52		–0.41		–1.34	–0.95		–0.78
			(3.38)***	(1.56)		(1.23)		(3.88)***	(2.38)**		(1.66)*
EXRET	–		0.25	–0.07		–0.10		–1.17	0.60		0.06
			(0.28)	(0.06)		(0.09)		(1.31)	(0.45)		(0.04)
COEFVAR	+		–0.07	–0.04		–0.05		–0.01	–0.05		–0.11
			(1.50)	(0.59)		(0.86)		(0.22)	(1.27)		(1.89)*
BKEQ_MEQ	+		0.12	0.25		0.26		0.03	0.39		0.45
			(0.72)	(1.29)		(1.28)		(0.18)	(0.98)		(0.87)
TURNOVER	+		0.00	0.01		–0.01		0.01	0.00		0.02
			(0.11)	(0.43)		(0.35)		(0.54)	(0.18)		(0.73)
AIC		194.50	261.36	197.50	189.50	194.07	128.11	224.75	126.32	95.03	97.86
R^2		0.43	0.23	0.45	0.45	0.46	0.61	0.43	0.63	0.66	0.67
χ^2 (relative to specification 1)				7.00	7.00 ***				11.79 **	35.08 ***	
χ^2 (relative to specification 4)						5.43					7.16
degrees of freedom				5	1	5			5	1	5

Note: This table performs logit regression analysis on the sample of commercial banks and thrift institutions. All independent variables are defined in table 3. T-statistics are shown in parentheses below their corresponding regression coefficients. A single, double, or triple "*" indicates significance at the 10%, 5%, or 1% level, respectively.

equity-to-asset ratio (EQ_ASSET) has a negative sign as expected for both groups, thereby confirming the importance of equity levels in models predicting distressed CAMEL ratings. The first asset-quality variable, NC_ASSET, is highly significant at the 1 percent level for all specifications for both groups, showing a direct link between the level of loan delinquency and the likelihood of obtaining a rating downgrade as expected. Another asset-quality variable, RES_ASSET, has the expected negative sign, but it is significant in only four of the eight specifications that use this variable. A third asset-quality variable, LPROV_ASSET, has its expected sign and is significant at the 1 percent level for all relevant specifications. The return-on-asset variable (ROA) also exhibits a negative sign as expected and is generally significant for both groups. The two liquidity measures (SEC_ASSET and VOL_ASSET) also perform as expected. Since almost all the coefficients in specification 1 have their expected signs and are significant at the 1 percent level, this specification provides a good benchmark for assessing the marginal or incremental value of information in market-based variables or in confidential supervisory data.

Specification 2 displays a model with only publicly available market variables. Five market variables are specified: the excess price (EXPRC), a measure of abnormal returns (EXRET), price volatility (COEFVAR), the book-equity to market-equity ratio (BKEQ_MEQ), and the turnover ratio (TURNOVER). The results show that of the five market variables for the two downgraded groups, only the EXPRC variable is statistically significant at the 1 percent level for both the 3-rated group and the 4/5-rated group. None of the other market variables appears to be a good predictor of the downgrades. The comparison of the first two models shows that the model using only market variables, specification 2, performs poorly in comparison with the basic CAMEL prediction model using only quarterly accounting data, specification 1.

The analysis proceeds with specification 3, where market variables are added to the benchmark regression of specification 1 to form a combined model to determine if the market data add significantly to the predictive ability of the model. In addition to identifying the significance of variable coefficients and t-tests, we are able to compare the models through the Akaike information criterion (AIC) and the likelihood-ratio-test statistic. If the AIC variable is lower and the likelihood-ratio-test statistic is positive and statistically significant from a comparison of 3 to 1, we may conclude that a model based on public information combining quarterly and market-based data has higher explanatory power than the benchmark model in specification 1. The results for the combined model show that although only one of the market variables in the regression is significant, the overall model reveals a marginal improvement over specification 1 for the 4- and 5-rated group but no higher explanatory power for the 3-rated group. For the 4- and 5-rated group only, the AIC variable is lower, and its log likelihood test is significant at the 5 percent level. This result highlights the fact the 4/5-rated group presents a more extreme case of financial distress when compared with the 1- and 2-rated control group than does the relatively healthier 3-rated group.

Specification 4 contains financial variables similar to those of the other specifications as well as an additional confidential supervisory variable that captures the past component management rating (MGT_RAT) of the institution. Thus the model reflects a mixture of both public and private information. The supervisory variable (MGT_RAT) is highly significant for both groups, and this significance reveals that private information held by bank supervisors is important in predicting future downgrades. Furthermore, for specification 4, the AIC variable is lower and the log-likelihood-test ratio is significant at the 1 percent level for both the 3- and 4/5-rated groups, a result that demonstrates improvement over specification 1.

Finally, the last model specification (5) adds market information to the model in specification 4. The results show no significant improvement over specification 4, as reflected in a higher AIC variable and an insignificant likelihood-ratio test.

Table 5 contains in-sample tests of the model for both the 3- and 4/5-rated groups for all five specifications. The critical cutoff probability is 50 percent, which is used to determine how the model performs in identifying which banks or thrifts in the two groups are properly classified as likely to experience future CAMEL rating downgrades.[15] Within the in-sample classification for the 3-rated institutions, the correct downgrade prediction of distressed banks and thrifts is about 73 percent for the combined model with public data (specification 3), which is the same level as specification 1. Specification 2, with only stock market data, falls off to only 54 percent in correct downgrade predictions.

Generally the classifications for the 4/5-rated group improve over those for the 3-rated group; and for the 4/5-rated group, specification 3 improves over specification 1. When specification 4 is compared with specification 1, the addition of confidential supervisory information increases the correct downgrade prediction to 95 percent or at the same level as specification 3. Adding stock market data in specification 5 yields the largest correct downgrade classifications, at 96 percent.[16] In terms of absolute numbers, the net change in forecast accuracy increases from 61 to

[15] The "critical probability" refers to the cutoff level, which determines which institutions fall into the predicted downgrade group and which do not. The logistic regression equation calculates a probability for each observation. The institutions whose calculated probability is 50 percent or more are considered likely to be downgraded and are placed into the "predicted downgrade" category.

[16] An out-of-sample test was not conducted because of the limited number of observations for the sample groups. An out-of-sample test requires a "holdout" sample of 20 to 30 percent of the original observations. Holding out that many observations would have significantly reduced the size of the sample available for the analysis.

Table 5

CAMEL Prediction Accuracy and Error Analysis: Four Quarters before Downgrade

Model Specification In-Sample Classification	D–Pred (D) (Correct D)		D–Pred (ND) (Type 1 Error)		ND–Pred (ND) (Correct ND)		ND–Pred (D) (Type 2 Error)	
	Percent	Number	Percent	Number	Percent	Number	Percent	Number
A. CAMEL 3-Rated Group								
1	72.62	61	27.38	23	90.73	137	9.27	14
2	53.57	45	46.43	39	89.40	135	10.60	16
3	72.62	61	27.38	23	91.39	138	8.61	13
4	71.43	60	28.57	24	90.73	137	9.27	14
5	73.81	62	26.19	22	91.39	138	8.61	13
B. CAMEL 4/5-Rated Group								
1	92.73	102	7.27	8	94.04	142	5.96	9
2	73.64	81	26.36	29	88.74	134	11.26	17
3	95.45	105	4.55	5	94.04	142	5.96	9
4	95.45	105	4.55	5	94.70	143	5.30	8
5	96.36	106	3.64	4	95.36	144	4.64	7

Note: The critical value for classification of downgrades is 50 percent.

only 62 institutions in the 3-rated group, an increase that is not significant. However, for the 4/5-rated group the change goes from 102 to 106 institutions as we move from specification 1 to specification 5. Thus, the in-sample classifications for the more distressed group show some incremental increase in correct downgrade predictions when stock market variables are added to the model.

Conclusion

This article explores the notion that publicly available stock price, return, and other market-related variables can provide timely information about bank and thrift financial condition; the article also determines whether such information can be used to improve the predictive accuracy of traditional off-site monitoring models for the purpose of anticipating changes in the CAMEL ratings assigned by regulators. A sample of banks and thrifts that were downgraded to the CAMEL 3, 4, or 5 level between the years 1988 and 1995 was used in the analysis and was compared with a sample of 1- or 2-rated healthy institutions. The first part of the analysis—extensive univariate analysis—confirms the existence of timely information: relatively simple measures of stock price and returns exhibit downward trends as much as two years before banks and thrifts experience rating downgrades, while overall return volatility increases. However, no simple relationship appears in univariate comparisons of several other market variables, including average trading volume and average quarterly turnover of shares.

The second part of the analysis tests whether adding market information to models containing quarterly financial data incrementally improves the ability of the model to predict commercial bank and thrift CAMEL rating downgrades. Specifically, equity market variables such as stock price, returns, price volatility, market valuation, trading volume, and share turnover are combined in a binomial logistic model containing traditional default-prediction variables for the purpose of identifying distressed institutions. The results show that even though for the univariate analysis the market variables appeared to provide timely information before bank and thrift downgrades, in the regression model market information provided only marginal improvements when combined with quarterly financial data. Specifically, the stock market variables improved the fit of the regression model as well as the in-sample predictive content of traditional accounting-based models only for the most distressed institutions—the CAMEL 4- and 5-rated banks and thrifts. No similar evidence was found for the healthier 3-rated firms.

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The SCOR System of Off-Site Monitoring: Its Objectives, Functioning, and Performance

*by Charles Collier, Sean Forbush, Daniel A. Nuxoll, and John O'Keefe**

The Federal Deposit Insurance Corporation (FDIC) and other bank supervisors have developed a number of tools with which to monitor the health of individual banks as well as the health of the industry as a whole.[1] One tool is on-site examinations: each bank is examined every 12 to 18 months and is assigned a CAMELS rating.[2] These examinations provide the most complete and reliable information about banks' financial health, and supervisors regard CAMELS ratings as the best single indicator of banks' condition. However, between examinations a bank's financial condition may change so that the CAMELS rating is no longer accurate. Therefore, the FDIC and other bank supervisors have developed other tools: off-site systems to monitor insured institutions between examinations.

The FDIC's major off-site monitoring tool is the **S**tatistical **C**AMELS **O**ff-site **R**ating (SCOR) system. The system was designed to help the FDIC identify institutions that have experienced noticeable financial deterioration. This article discusses that objective and the data and method used to meet it. The article then discusses the performance of SCOR in terms of that objective, as well as some auxiliary features that make the system more useful. Two appendices address key technical issues that arose during the development of SCOR.

Objectives of the Project

The SCOR system was developed in the late 1990s to detect banks whose financial condition had substantially deteriorated since their last on-site examination. As its name indicates, the model is an off-site system that is meant to supplement the current system of on-site examinations.

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The opinions expressed here are the authors' and do not necessarily reflect the views of the FDIC.

[1] Throughout this article, the term *banks* includes all insured financial institutions–commercial banks, savings banks, and thrifts.

[2] CAMELS is an acronym for **C**apital, **A**sset quality, **M**anagement, **E**arnings, **L**iquidity, and market **S**ensitivity. Examiners have rated sensitivity only since 1998. Strictly speaking, examination ratings before that year are CAMEL ratings, but we ignore this distinction and use "CAMELS" throughout, except in Appendix 1.

After an examination, examiners assign the bank a composite CAMELS rating—a rating that reflects the bank's overall financial condition. The ratings range from 1 to 5, with 1 the best and 5 the worst (the meanings of the ratings are summarized in table 1). Banks with a rating of 4 or 5 are considered problem banks. Examiners also rate each of the six CAMELS components, again on a scale of 1 to 5. The meanings of the component ratings parallel those of the composite rating.

Table 1

Definitions of the CAMELS Ratings

Rating	Characteristic
1	"sound in every respect"
2	"fundamentally sound"
3	"exhibit some degree of supervisory concern"
4	"generally exhibit unsafe or unsound practices or condition"
5	"exhibit extremely unsafe or unsound practices or condition"

Source: FDIC Manual of Examination Policies.

Off-site monitoring at the FDIC attempts to identify institutions that received a rating of 1 or 2 on the last examination but might well receive a rating of 3 or worse at the next examination. According to the definitions in table 1, institutions with a rating of 1 or 2 are sound, whereas those with a rating of 3 or worse have some significant problems; once an institution is rated 3 or worse, it has been identified as a concern, and the FDIC monitors it intensively. Consequently, only the likely passage from 1 or 2 to 3 or worse is of interest in off-site monitoring. Identifying 3- or 4-rated institutions that are likely to receive a worse rating at the next examination is not particularly useful from the supervisory perspective.

The difference between a rating of 2 and a rating of 3 has a number of practical implications. Institutions with a rating of 3 or worse are examined more frequently, generally receive closer supervision, pay higher deposit insurance premiums, and may face some legal restrictions on their activities. (Supervisors often take either formal or informal enforcement actions against these banks, and enforcement actions generally restrict an institution's activities or commit it to remedying an identified problem in its operations.)[3]

Consequently, the major objective of the SCOR project was to identify correctly the 1- and 2-rated institutions that were in danger of being downgraded to 3 or worse. The accuracy of the proposed system was analyzed in terms of two types of error, conventionally called Type I and Type II errors. Type I errors consist of false negatives or, more colloquially, "freeing the guilty." In our context, a false negative is failing to detect a downgrade before it occurs, so the level of Type I errors is the percentage of downgraded banks that the model did not identify as problems. Conversely, Type II errors consist of false positives, or "convicting the innocent." The level of Type II errors is the percentage of banks that are identified by the model, yet are found to be sound by a subsequent examination.[4]

There is a trade-off between Type I and Type II errors. Anyone can achieve 0 percent Type I error without a model simply by identifying all banks as likely to be downgraded. By identifying all banks, one has certainly identified all banks that will actually be downgraded. However, one has also identified as problems all of the banks not actually downgraded, so Type II error is 100 percent. Conversely, one can easily attain 0 percent Type II error by identifying no banks; however, this results in 100 percent Type I error. Generally, the more banks identified by a model, the lower the Type I error and the higher the Type II error.

Ideally, the users of a model determine the acceptable trade-off of Type I and Type II errors in terms of the relative costs of the two types of error. At

[3] See Curry et al. (1999) for a discussion of the effectiveness of enforcement actions.

[4] Actually, the relevant Type I and Type II errors are not those discussed in the text. For the FDIC's purposes, the critical question is whether the regional office is aware that a bank might present a supervisory concern, but because that awareness cannot be established retrospectively, all backtesting uses examination ratings. Because case managers have information besides examination ratings, the regional office is often aware of potential downgrades before they occur, but the backtests assume that the regional office is not aware of problems until an examination has begun. Thus, the backtests overstate the model's ability to identify banks that present a concern.

the FDIC, each bank is assigned a case manager at the appropriate regional office. After a bank has been identified by SCOR as likely to be downgraded, the bank's case manager reviews the information available about the bank and determines whether further action is warranted. If the review causes sufficient concern, the FDIC manager can schedule an examination and can allocate resources to supervise the bank more closely. In the context of off-site monitoring, therefore, the cost of Type I error is slow reaction to problems at a bank—that is, a delay in increasing the supervision of the bank. On the other hand, the cost of Type II error is the waste of staff time spent conducting unnecessary reviews. In addition, Type II error undermines the credibility of the system, so case managers have little reason to be conscientious about reviews.

For ease of presentation, this article discusses Type I and Type II accuracy instead of error. Type I accuracy is the percentage of actual downgrades that were identified in advance by the model. Type II accuracy is defined analogously as the percentage of identified banks that are in fact subsequently downgraded.

For the designers of SCOR, accuracy was the major objective, and the benchmark for accuracy was CAEL, the off-site monitoring system developed at the FDIC during the mid-1980s. CAEL was an expert system that used basic ratios from the Call Reports (the quarterly financial reports filed by banks) to rate **C**apital, **A**sset quality, **E**arnings, and **L**iquidity (hence the name **CAEL**);[5] CAEL did not produce management ratings because the quality of management cannot readily be identified with any financial ratio. The ratings of the four components were combined by means of a complicated system of weights to produce a composite rating, which was used to identify institutions for off-site review.

CAEL rated institutions on a scale of 0.5 to 5.5. Conceptually, CAEL ratings are easily mapped to CAMELS ratings: a CAEL rating between 0.5 and 1.5 corresponds to a CAMELS ratings of 1, a CAEL rating of 1.5 to 2.5 corresponds to a CAMELS rating of 2, and so forth.[6]

SCOR was intended to produce ratings comparable to CAEL's while also being easier to analyze. CAEL's use of a complicated system of weights to derive a final composite rating made it difficult for examiners to understand which financial ratios were responsible for the poor ratings an institution received. Thus, although CAEL informed examiners which institutions had problems, it was not always informative about the nature of the problems. Consequently, a secondary objective for the designers of SCOR was to develop a method of analyzing ratings in terms of the underlying ratios.

Development and Functioning of SCOR

In contrast to the expert-system approach of CAEL, SCOR uses a statistical model. It compares examination ratings with the financial ratios of a year earlier. SCOR identifies which financial ratios were most closely related to examination ratings and uses that relationship to forecast future ratings.[7] For example, to predict ratings on the basis of the June 2003 Call Report, SCOR compares data from the Call Report of June 2002 with actual examination ratings from the period July

[5] This expert system was designed by a group of experienced examiners, who decided which ratios were the best precursors of future problems. Updating the system would involve convoking another group of experienced examiners to deliberate about the model. For more information on CAEL, see FDIC (1997), 507ff.

[6] Actually, the mapping is not quite that simple because CAEL was built with a bias toward downgrading institutions. Without any bias, an institution receiving a CAEL rating of 2.5 would be as likely to receive a 2 at the next examination as a 3. The bias, however, means that an institution with a rating of 2.5 will in fact be more likely to receive a 2 than a 3. Because of the bias, CAEL identifies more banks as possible problems, thus increasing the Type II errors while decreasing the Type I errors.

[7] The SCOR model is very similar to the SEER rating model, originally called FIMS, developed by the Federal Reserve System. Both SEER and SCOR draw on a long history of models of bank failure and distress. Demirgüç-Kunt (1989) reviews pre-FIMS developments, and Gilbert, Meyer, and Vaughn (1999) explain the rationale behind such models. For a discussion of the SEER system, see Cole, Cornyn, and Gunther (1995). SEER and SCOR differ in one important respect: SCOR does not use past CAMELS ratings to forecast future ratings. For a discussion of the issue of using past ratings to forecast future ratings, see Appendix 1.

2002 to June 2003. This procedure identifies the Call Report data that were the best indicators of ratings over the past year and uses that relationship to forecast ratings based on June 2003 data. The assumption is that the data that were the best indicators of ratings over the year just past will also be the best indicator over the year to come. The SCOR method, by identifying which ratios are consistently related to examination ratings, attempts to identify which ratios examiners consider the most significant and therefore could be interpreted as an attempt to read examiners' minds.

If the relationship between examination ratings and financial ratios changes, that change will be reflected in the model, generally through a change in coefficients, but only after a delay. For example, if examiners find that intangible factors (such as underwriting) have on average deteriorated and if they therefore assign poorer ratings, then the average SCOR rating will also worsen, even if the deterioration will not yet have affected the basic financial ratios. But because the model is estimated with examination ratings from the past year, the changes in the relationship between ratings and ratios will not be incorporated into the model until the next year.[8]

It is also important to note that SCOR is estimated every quarter and that therefore the ratings for June 2003 (for example) do not depend on any data before June 2002. The estimated relationship between ratings and ratios depends only on very recent data and changes slightly from quarter to quarter. Consequently, even if the Call Report ratios were identical, the ratings for June 2003 could be very different from those for June 1993—in principle. In practice, however, banks similar to those that had poor ratings in 1993 would also have poor ratings in 2003.

SCOR uses a stepwise estimation procedure that eliminates ratios whose relationship with examination ratings is not consistent (that is, ratios that are not statistically significant). In general, the stepwise procedure drops relatively few variables.

SCOR uses only two peer groups: banks and thrifts. Experimentation has indicated that additional peer groups do not improve the model's forecasting power.[9]

The model was developed with a somewhat conservative bias to avoid the problem of excessive data mining. This problem occurs because one can always find a complete coincidence that is statistically significant if one looks at enough data. For example, one might find that banks with a disproportionate number of left-handed tellers had poor CAMELS ratings. Clearly, one would be foolish to use this information to forecast ratings because there is no plausible connection between these two phenomena.[10]

One can avoid this pitfall by choosing variables that actually do cause problems in banks. Choosing such variables necessarily involves using informed judgment. The original specification for SCOR was chosen after both a review of the literature on bank failures and discussions with bank examiners.[11] Discussions with examiners were particularly germane because examiners actually assign the ratings that the model is attempting to forecast. Alternative specifications were tested, and if testing demonstrated that a specification clearly improved the model's ability to detect downgrades of 1- and 2-rated institutions to 3 or worse, changes were made.

8 With regard to underwriting, at the conclusion of each exam FDIC examiners evaluate separately the quality of the institution's underwriting practices. The FDIC is currently researching whether these ratings can be used to forecast future examination ratings.

9 In two different experiments, credit card banks and large banks were eliminated from the model. In both cases, the model's forecasting power was worse. Homogeneity is the enemy of statistical models.

10 The FDIC does not collect data on left-handed tellers, but it does collect a vast amount of data on banks. It would be truly remarkable if some of these data were not correlated with CAMELS ratings. Statisticians are well aware that statistics can demonstrate correlation but not causation.

11 The variables discussed in Cole, Cornyn, and Gunther (1995) are typical of those used in failure models. See also Hooks (1995) and Demirgüç-Kunt (1989).

The final SCOR model uses 12 variables; all are financial data from the Call Report, expressed as a percentage of assets. Table 2 lists the variables and some ratios for a completely hypothetical bank.[12]

Table 2

SCOR Variables and Ratios for a Hypothetical Bank

SCOR Variable	Percentage of Total Assets
Equity	13.59
Loan-Loss Reserves	1.31
Loans Past Due 30–89 Days	2.23
Loans Past Due 90+ Days	0.89
Nonaccrual Loans	1.51
Other Real Estate	0.45
Charge-offs*	1.18
Provisions for Loan Losses and Transfer Risk*	1.28
Income before Taxes and Extraordinary Charges*	0.10
Volatile Liabilities	25.31
Liquid Assets	28.16
Loans and Long-Term Securities	68.79

*Flow variables. These variables are lagging 12-month totals and have been adjusted for mergers.

Tests of statistical significance show that all the variables are closely related to CAMELS ratings. In addition to the variables in table 2, we experimented with other variables, such as loan growth and average employee salaries. We also experimented with the definitions of some of the variables. For example, we experimented with using Tier-1 capital instead of simple equity, and with using average total assets instead of total assets in the denominators of the ratios. We did not find any other specification that produced consistently better forecasts than the model currently embodied in SCOR.

In table 2, the variables marked with asterisks are items from the income statement (flows), in contrast to the unmarked variables, which are from the balance sheet (stocks). Stocks are measured at a point in time; SCOR uses the end-of-quarter figures from the Call Report. Flows are measured over a period of time; SCOR uses trailing four-quarter totals, instead of the year-to-date numbers found on Call Reports.

Four-quarter totals can be significantly affected by mergers. To eliminate these effects, SCOR uses merger-adjusted data. If banks merge, SCOR does a pro forma merger of the data from pre-merger quarters. Although certainly not ideal, this method eliminates a major distortion due to mergers.[13]

The model forecasts the probability that a bank will receive a specific rating. An example of ratings for a completely hypothetical bank can be found in table 3. According to SCOR, this completely hypothetical bank has approximately a 3 percent chance of receiving a rating of 1, a 55 percent chance of receiving a rating of 2, and so forth.

Table 3

Sample SCOR Output for a Hypothetical Bank

Rating	Probability
1	3.2
2	55.0
3	36.5
4	4.9
5	0.4
Probability of Downgrade	41.8
SCOR Rating	2.44

[12] An earlier specification of SCOR used 13 variables. Dividends were included, and net income was used instead of income before taxes. Pretax income is now used because of the increasing number of banks that are sub-chapter S corporations and do not pay corporate income tax, and dividends were dropped because supervisors commonly restrict dividends at troubled institutions. Thus, dividends are necessarily low at an institution after supervisors have identified it as troubled (it is important to remember, however, that low dividends do not necessarily signal that a sound institution is having trouble). Both changes–dropping dividends, and replacing pretax income with net income–demonstrate the importance of using informed judgment when selecting variables. The current version of SCOR is at least as accurate as the older version.

[13] However, this method might introduce another distortion. Suppose major portions of the disappearing bank (for example, branches or a credit card portfolio) were sold within 12 months of the merger. SCOR's method of adjusting for mergers would include income from operations that were not part of the merged entity. Although examples of this sort of distortion can be found, they are relatively uncommon.

The SCOR model also estimates the probability of receiving a downgrade. If our hypothetical bank is currently rated 2 or better, that probability is defined as its chance of receiving a rating of 3 or worse (36.5% + 4.9% + 0.4% = 41.8%).[14] Associated with these probabilities is a SCOR rating that equals the expected rating [(1 x 3.2%) + (2 x 55.0%) + (3 x 36.5%) + (4 x 4.9%) + (5 x 0.4%)].[15]

The FDIC flags any bank with a downgrade probability of 35 percent or greater. Flagging means a bank must be reviewed by its case manager, and 35 percent was chosen because case managers have only a limited amount of time for reviewing banks. SCOR flags approximately as many banks as CAEL, but during the 1991–1992 recession the SCOR system would have flagged many more banks than CAEL. If SCOR flags so many banks that the review process overwhelms regional analysts—which could happen, for example, during a recession—the flag can be easily changed.[16]

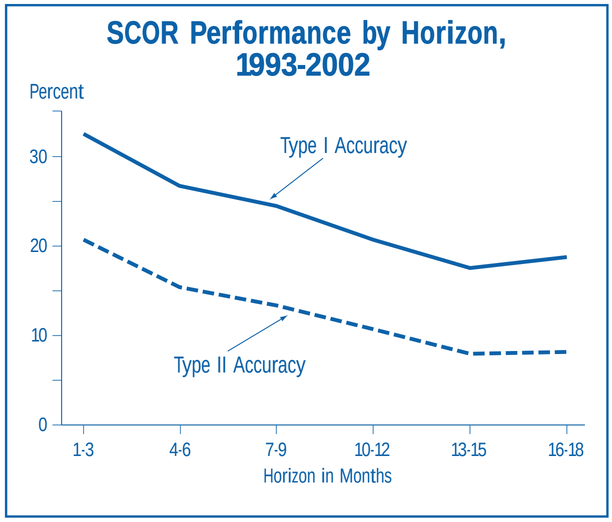
Results

The previous section refers to various experiments that were done while SCOR was being developed. The success of these experiments was evaluated in terms of the objective of the model: whether the modifications produced a model able to correctly identify banks that were subsequently downgraded. This section reports on the results of the final model and demonstrates the type of testing that was repeatedly done during the course of this project, and the type of testing that demonstrated SCOR's superiority to its predecessor, CAEL.

Although the forecasts were evaluated at a variety of time horizons, testing focused on downgrades that occurred four to six months after a given Call Report date. The rationale for this emphasis is that the Call Report data are finalized 60 days after the Call Report date. Consequently, forecasts are not available to bank supervisors until 60 days after the Call Report date.[17]

Figure 1 shows the accuracy of the model at various time horizons. These results include only the first examination after the Call Report was filed. Clearly, accuracy decreases as the forecast horizon lengthens. However, SCOR has some success even at horizons of 16–18 months. Even at this time horizon, SCOR is at least seven times better than a random guess.[18]

Figure 1



[14] If the bank had a rating of 3, the probability of a downgrade would equal 5.3 percent (4.9% + 0.4%). If it had a rating of 4, the probability of a downgrade would equal 0.4 percent. By definition, the downgrade probability for 5-rated banks is zero.

[15] In practice, most banks have a high probability of receiving one or two specific ratings and almost no probability of receiving the other three ratings. The example shown in table 3 is typical. In these cases, we can closely approximate the downgrade probability by dropping the integer part of the SCOR rating. For the hypothetical bank in table 3, the approximate probability of being downgraded to a 3 is 42 percent. This approximation is exact if three of the five probabilities are zero.

[16] When SCOR was adopted in 1999, a 30 percent downgrade probability was used to flag banks for review. By 2001, when the weakening economy undoubtedly affected the financials at banks and caused more poor SCOR ratings and more reviews, that flag was resulting in too many reviews. Accordingly, the higher probability was adopted.

[17] Another reason for focusing on the four- to six-month horizon is that after an examination, the Call Reports filed immediately before the examination almost always (but not absolutely always) are revised. Revisions to the Call Report that immediately precede the exam will bias the backtest because the SCOR model will have access to the corrected data instead of the data that were actually available to supervisors before the examination. This bias is minimized by the use of forecasts based on the Call Report filed four to six months before the examination–a Call Report less likely to be revised.

[18] Banks that have problems are more likely to be examined, and the reported results include only the first examination after the Call Report that provided the data for the SCOR rating. Consequently, the results for a 16- to 18-month horizon include only the strongest banks, and only 2.6 percent of these were downgraded. In contrast, 18.8 percent of the banks identified by SCOR are downgraded 16 to 18 months later.

Figure 2 shows, by Call Report year, the Type I and Type II accuracy achieved under the SCOR system. (The data for figure 2 are found in table 4.) Accuracy is assessed at a four- to six-month horizon, which corresponds closely to the period when the forecasts would be available to supervisors.

Figure 2

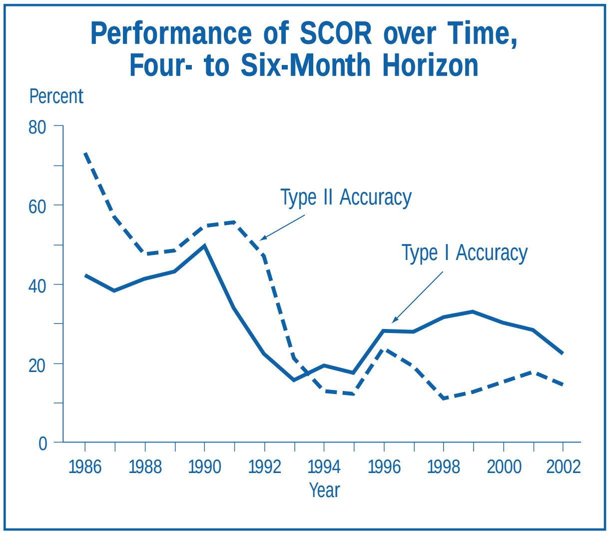


Table 4

Performance of SCOR at Four- to Six-Month Horizon

	Examined	Downgraded	Flagged	Correct
1986	6,465	1,038	1,800	760
1987	6,990	691	1,027	394
1988	6,655	669	767	318
1989	7,236	691	776	335
1990	7,098	894	988	490
1991	7,740	714	1,170	397
1992	9,403	348	727	164
1993	9,911	187	253	40
1994	9,444	191	129	25
1995	8,961	153	108	19
1996	8,279	167	142	40
1997	7,321	156	107	30
1998	6,805	232	82	26
1999	7,020	302	118	39
2000	6,676	274	139	42
2001	6,623	312	196	56
2002	3,878	143	93	21
Total	126,505	7,162	8,622	3,196

Note: This table reports on the results of examinations conducted four to six months after the Call Report that is the basis for a SCOR rating. Downgrades are from ratings of 1 or 2 to 3 or worse.

Clearly the accuracy of the model has declined substantially, and performance has been especially weak since 1993. Since 1993, SCOR has identified approximately 16 percent of the banks that were subsequently downgraded (Type I accuracy), and approximately 27 percent of the banks identified by SCOR were downgraded (Type II accuracy). It must be noted, however, that although the SCOR model is not extremely accurate, it is informative. While Type II accuracy of 27 percent is low, it is approximately nine times better than a random guess. The model does produce valuable information, distinguishing banks that are likely to be downgraded from those that are not.[19] SCOR was adopted to replace CAEL because it had higher levels of Type I and Type II accuracy for almost all time periods.

The low level of accuracy might be expected inasmuch as SCOR relies completely on financial ratios. Any such model will probably be more accurate when the reasons for downgrades are financial, and less accurate when the reasons have to do with some aspect of bank operations that does not affect the bank's financial ratios. For example, examiners may downgrade a bank because they discover that it has significantly weakened its underwriting standards or has weak internal controls—but as long as the more risky loans have not become past due, problems might not have made their way to the financial statements. Consequently, one might reasonably expect that SCOR would be less accurate over the last decade.[20]

The reliance on financial data has several other effects on SCOR's performance. For one thing, it means that SCOR is completely dependent on the accurate reporting of financial information. But in two of the more spectacular bank failures of the last few years—BestBank and the First National Bank of Keystone—the bank's condition had been substantially misstated; consequently, SCOR gave extremely good ratings to both banks.

[19] The reviews done by case managers almost inevitably indicate that banks flagged by SCOR have noticeable weaknesses, even though the weaknesses might not warrant an examination or closer supervision.

[20] The recession of 2001 affected mostly the larger banks and had minimal effects on the rest of the industry.

These problems with SCOR demonstrate that it can never be a substitute for full-scope examinations. Examinations can detect unsafe practices before they affect the bank's financial condition; examinations can also detect misstated financial reports.[21] As we have said before and will say again, SCOR is a complement to bank examinations, not a substitute for them.

Additional Features

A secondary objective of the SCOR project was to produce ratings that were easier to understand and analyze than CAEL ratings. Several features were added to the model to help users of the ratings understand the reasons SCOR identifies a particular institution. First, the SCOR system produces component ratings that help identify specific areas of weakness in a bank. The most controversial of the component ratings has been the management rating because the conventional wisdom is that a model that uses financial ratios cannot identify weaknesses in management. Nonetheless, the SCOR management rating does indicate which banks are at risk of being downgraded.

The second auxiliary tool is a system of weights that indicate which variables are causing poor ratings. The operation of these weights is discussed in this section, while the more technical explanation is relegated to an appendix.

In addition to producing ratings that are more easily analyzed than CAEL ratings, SCOR has also proved useful for tracking trends in the industry. This ability is an extension of the more traditional off-site monitoring.

The Component Ratings

The SCOR model produces a forecasted rating not only for the CAMELS composite but also for each of the six CAMELS components. Case managers and examiners find these ratings useful for identifying the weaknesses in banks.[22]

The component ratings are produced by exactly the same method that is used to produce the composite rating. Most notably, the same variables are used for all the component ratings. But although all the variables in table 2 are relevant to the composite rating, some are more relevant to one or another of the six components. For example, the equity-asset ratio is obviously relevant to the capital component of CAMELS but is less important to the earnings component. SCOR, however, uses all the variables to forecast all the components and, by means of the stepwise procedure mentioned above, selects the variables that are more relevant to explaining the observed component.

The results indicate that examiners do not rate the components in isolation. Consider the capital component. Although the equity-asset ratio is critical for the rating of this component, other variables, too, are used to forecast it. For example, high levels of loans past due 30–89 days are consistently related to poor capital ratings. The reason SCOR uses this variable for this component may not be obvious, but the capital rating is determined by the adequacy of the bank's capital in relationship to its need for capital, and banks with high levels of past-due loans are likely to experience more losses in the future and are therefore likely to need more capital to absorb those losses. Consequently, if two banks have the same equity-asset ratio but one of them has a very high level of past-due loans, that one would receive a worse capital rating.[23]

Although the component ratings are widely used, several financial analysts have raised questions about using SCOR to forecast the management rating. In contrast to the other components, this one is not obviously directly related to any finan-

[21] The FDIC's Division of Supervision and Consumer Protection rightly insists that bank examiners are not a substitute for adequate internal and external auditing. However, it was examinations that uncovered the fraud at both BestBank and First National Bank of Keystone. See Berger and Davies (1998) for a discussion of the auditing function of examinations.

[22] As mentioned above, CAEL produced ratings for capital, asset quality, earnings, and liquidity, which were then combined into a composite rating.

[23] CAEL captured this type of relationship by treating some ratios as primary causes of ratings and others as secondary causes.

cial ratios;[24] internal controls and underwriting standards, for example, cannot be readily reduced to such ratios. In other words, many of the factors behind management ratings are intangible, and a statistical model cannot consider factors that cannot be reduced to accounting.

However, all the data in the Call Report can be viewed as indicators of the quality of a bank's management. Obviously factors such as economic conditions affect a bank's financial health, but the quality of management is always a critical factor as well. In the case of loans past due 30–89 days, for example, a high level of such loans implies that the bank has a problem with the quality of its assets and is more likely to have a poor asset rating at the next examination. However, that same level of loans past due 30–89 days might also mean that the bank's management has done a poor job underwriting the loan portfolio and that the bank is more likely to have a poor management rating. Other factors besides underwriting standards affect past-due ratios, so management ratings and past-due ratios do not move in lockstep.

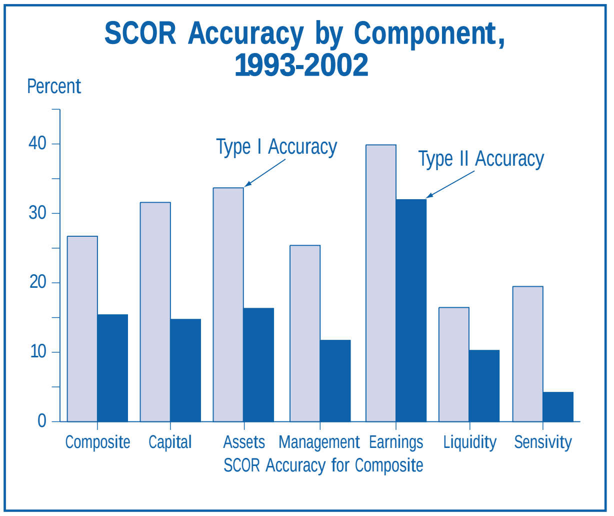
Moreover, the management rating is not alone in involving factors that do not appear on the Call Report. All the other components also involve such factors. For example, the asset rating depends on the level of classified loans, but no data on loan classifications are available until after the examination is actually complete. Thus, asset ratings cannot be assigned only on the basis of information from the Call Report. Similarly, capital ratings depend on the level of classifications as well as on qualitative assessments of the risk because the fundamental question is whether the available capital is adequate for the level of risk.

In short, the management rating is much like the other ratings. SCOR forecasts management ratings by using the same technique it uses for the other ratings: it examines the characteristics of banks to which examiners have recently assigned poor management ratings. SCOR has found that examiners give poor management ratings to banks with low earnings, low reserves for loan losses, and high levels of past-due and problem loans.

[24] Recall that this is the reason CAEL excluded the management component.

Most importantly, SCOR can produce reasonably accurate forecasts of management ratings. Figure 3 shows the accuracy of the component (and composite) forecasts. Although management forecasts are less accurate than some others, SCOR can still use relevant Call Report data to identify institutions likely to have management problems.[25]

Figure 3



Weights of the Call Report Data

Besides producing forecasted composite (and component) ratings, SCOR produces a system of weights that highlights which aspects of a bank's data are responsible for poor ratings.[26] Each ratio is assigned a weight that indicates the contribution that that ratio made to the poor SCOR rating. By indicating which aspects of a bank's operations account for the subpar rating, these weights give case managers and others a starting point for analyzing ratings.

[25] Some other aspects of the forecasted management rating are worth noticing. First, the accuracy of the forecasted management rating deteriorates less over time, so at long horizons it is among the more accurate of the component forecasts. Second, the forecasted management rating does help signal downgrades in the composite rating.

[26] The mathematics behind the "weighting" system can be found in Appendix 2.

In order to define a poor rating, SCOR needs some standard for a good rating. SCOR uses the typical 2-rated bank as the benchmark because, by definition, 2-rated banks are sound institutions with some minor weaknesses.[27] In contrast, 1-rated banks are very strong institutions, and banks with 3, 4, and 5 ratings have weaknesses severe enough that the institutions warrant close supervision. SCOR was designed to identify those banks that are in danger of receiving examination ratings worse than 2, so the 2-rated banks are the obvious standard of comparison.

SCOR considers the "median-2" bank to be the typical 2-rated bank. The median-2 bank is constructed from the median financial data for all the banks that were rated 2 in on-site examinations over the previous year. Thus, the capital-asset ratio is the median ratio for all the banks that received a 2-rating in the previous year. The median-2 bank does not actually exist; it is a statistical construct.[28]

The median-2 bank does not necessarily have a SCOR rating of exactly 2. If the typical 2-rated bank is a strong 2 (more like a 1-rated bank than a 3-rated bank), then the median 2 would probably have a SCOR rating of better than 2. In fact, at present the industry is very healthy. As a result, the median-2 bank has a SCOR rating of approximately 1.6.

Table 5 reports a hypothetical example of the SCOR weighting system. The weights indicate that the problems in the hypothetical bank are due primarily to poor-quality assets and low earnings. Income has a weight of approximately 29 percent, and nonaccrual loans have a weight of 28 percent. This means that the difference in income ratios accounts for approximately 29 percent of the difference between the SCOR rating of the median-2 bank and the rating of the hypothetical bank.

Table 5

SCOR Weights for a Hypothetical Bank

	Median-2 Bank	Hypothetical Bank	
Variable	Ratio	Ratio	Weight
Equity	9.31	13.59	–7.16
Loan-Loss Reserves	0.80	1.31	0.00
Loans Past Due 30–89 Days	0.75	2.23	18.56
Loans Past Due 90+ Days	0.10	0.89	10.27
Nonaccrual Loans	0.23	1.51	28.05
Other Real Estate	0.00	0.45	9.31
Charge-offs	0.13	1.18	4.66
Provisions for Loan Losses and Transfer Risk	0.18	1.28	0.00
Income before Taxes and Extraordinary Charges	1.38	0.10	29.13
Volatile Liabilities	14.13	25.31	5.24
Liquid Assets	32.34	28.16	1.95
Loans and Long-Term Securities	71.29	68.79	0.00
SCOR Rating	1.60	2.44	

Loans past due 30–89 days and loans past due 90+ days also have high weights.

Weights can be negative or zero. Weights are used to explain poor ratings, and those variables that would actually contribute to a better rating receive negative weights. For example, in table 5 the bank actually has more capital than the median-2 bank, so equity has a negative weight. This ratio is better, not worse, than that of the median 2, so it would tend to be a reason for a better, not a worse, rating.

Zero weights occur when there is no consistent relationship between a ratio and the examination ratings. For example, in table 5 loan-loss reserves have a zero weight. This could occur if some banks with high loan-loss reserves were being conservative and providing for any possible losses whereas other banks with high loan-loss reserves had asset-quality problems. In such a case, some banks with high reserves would have good ratings and some would have poor ratings, and SCOR would not find a consistent relationship.[29] The

[27] See table 1. Peer groups could easily be used for this analysis but currently are not.

[28] The median-2 bank is used as the basis of comparison instead of the "mean 2" because outliers tend to increase mean financial ratios. A simple example illustrates the point. If 99 banks have capital-asset ratios of 9 percent and 1 has a capital-asset ratio of 90 percent, the mean capital-asset ratio is 9.81 percent. The median is 9 percent, which is more representative.

[29] There are other possible reasons that a stepwise procedure might eliminate a variable. For example, if two of the explanatory variables were highly correlated, the stepwise procedure would choose the one most closely related to CAMELS ratings and would ignore the other.

In practice, the coefficients used by SCOR are very stable from one period to the next, and the stepwise procedure adds or drops only marginally important variables. In historical tests, SCOR uses almost all the variables each quarter to forecast either a composite or a component rating.

stepwise procedure assigned that variable a zero coefficient.[30]

The weights in table 5 are typical of the banks that are identified as potential concerns. In general, these banks have either asset problems (high levels of loans past due, of nonaccrual loans, or of other real estate) or poor earnings. High levels of non-core funding or lack of liquid assets are also occasional contributing factors.

The weights are a starting point for analysis. They do not diagnose the problem, but they do indicate which factors are of special concern and which are not particularly important.

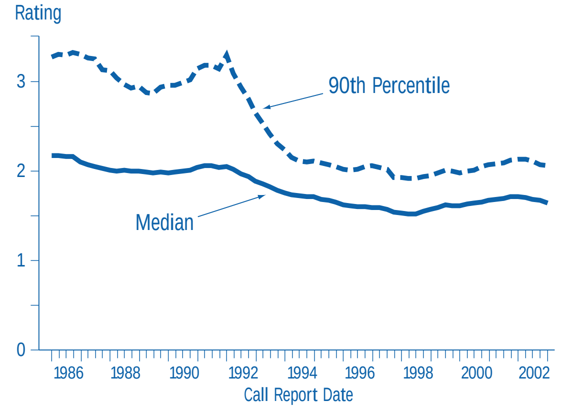
Trends in the Industry

Although SCOR was developed to identify specific institutions, trends in SCOR ratings can also be used to identify changes in the overall health of the banking industry. Figure 4 shows the trends in the median SCOR composite rating and in the 90th percentile. By definition, 50 percent of the banks have ratings better than the median, while 90 percent have ratings better than the 90th percentile and 10 percent have worse ratings. The median can be interpreted as the rating of the typical bank, whereas the 90th percentile indicates trends among the 10 percent of the banks that have the worst ratings. These banks, of course, are the ones of particular concern to supervisors.

The banking problems of the late 1980s and early 1990s are apparent in the data presented by figure 4. The figure also indicates that the banking industry's health peaked in 1998, when the median SCOR rating was 1.52. By the end of 2001, the median rating was 1.71. During 2002, ratings improved.[31]

Figure 4

Trends in SCOR Ratings,1985-2002



Concluding Comments

SCOR permits the FDIC to track industry trends and helps identify the institutions that are especially weak. The SCOR output also helps the FDIC identify which financial ratios contribute to poor ratings. However, in periods of economic prosperity, SCOR forecasts are wrong more often than they are right, and since 1993 the model has missed approximately 80 percent of the downgrades, and its forecasts of a downgrade have been incorrect about 75 percent of the time. In contrast, when data are used from the early 1990s—a period when recession was causing financial problems for many banks—SCOR produces more accurate forecasts. Although this single piece of evidence is not conclusive, it does suggest that SCOR will become even more useful if economic troubles again begin affecting the banking industry. SCOR could then help the FDIC focus its limited resources on the institutions that need closer supervision.

[30] Because these weights are calculated with a Taylor first-order approximation, they necessarily sum to 100 percent.

[31] As discussed above, SCOR is reestimated each quarter, so the coefficients change slightly over time. As also discussed above, changes in coefficients would occur if, for example, examiners found that underwriting standards had changed. However, by using the 1998 coefficients to rate banks in 2001 and using 2001 coefficients to rate banks in 1998, one can determine whether the change in SCOR ratings is driven by the underlying financial ratios or by the change in coefficients. This exercise indicates that the change in coefficients accounts for approximately half the trend between 1998 and 2001, while changes in the ratios account for the other half. The change in the model could be interpreted as reflecting examiners' growing concern about aspects of bank operation (for example, underwriting) that are not measured by the ratios.

The model identifies systematic financial strength or weakness but does not consider intangible factors. However, intangibles are too important to ignore because during periods of economic prosperity, poor ratings are more likely to be the result of poor policies and procedures—that is, intangible factors—than of financial weakness. Consequently, the accuracy of SCOR will be lower during periods of prosperity, as it is during the current period. Thus off-site monitoring, with its dependence on financial ratios, cannot replace on-site monitoring. The SCOR model and other systems of off-site monitoring are an aid to examiners but should never be allowed to replace regular examinations.

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APPENDIX 1

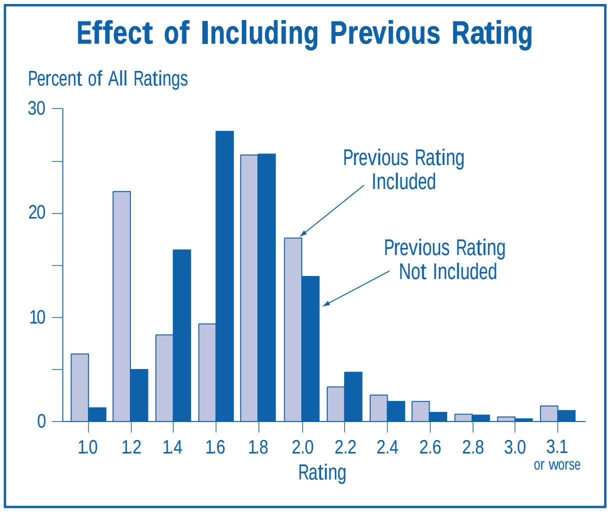
Exclusion of Current CAMELS Ratings

The SCOR model does not use current CAMELS ratings as an explanatory variable, for several reasons. First, the models that use current ratings produce forecasts that tend to cluster around the integers of 1, 2, 3, 4, or 5. For example, ratings near 2 (say, 2.05) are common, but ratings further from 2 (say, 2.40) are rare. This clustering suggests that most banks are really one of five identifiable types. If 2-rated banks are in fact substantially different from other banks, most 2-rated banks will have actual ratings close to 2 (say, 2.05), and only the odd institution that does not really fit one of the established types will have an intermediate rating (say, 2.40).

However, CAMELS ratings are undoubtedly approximate measures of financial strength, and 2-rated banks are not an identifiable type as much as they are a group of banks whose "true" financial strength might be rated somewhere between 1.5 and 2.5. The category of 2-rated banks includes both "strong 2s" (with "true" ratings of 1.6) and "weak 2s" (with "true" ratings of 2.4).

SCOR ratings tend to be more uniformly distributed than ratings produced by models that incorporate prior examination ratings; the distribution of SCOR ratings probably reflects the actual distribution of financial strength among banks. Figure A.1 illustrates the difference in the distributions of the two types of rating systems. The screened bars show the distribution of SCOR ratings based on December 1996 data. The solid bars show the distribution of ratings from an otherwise identical model that includes the CAMEL rating as of December 1996. The forecasts that use the CAMEL ratings are clearly clustered, whereas the distribution of SCOR ratings is smoother.[32]

Figure A-1



The second reason the SCOR model does not use current CAMELS ratings is that examiners wanted a system that used only financial data: they were suspicious of any model that forecasted future ratings in terms of current ratings, especially when the model said that ratings tend not to change. A model that exhibits inertia might miss changes in a bank's condition. There is some evidence that information in CAMELS ratings does become dated, so older CAMELS ratings might well be misleading.[33]

Finally and most importantly, the historical data did produce some evidence confirming examiners' concerns. Models that use CAMELS ratings are marginally worse than SCOR at forecasting the ratings of those banks of most interest to the FDIC—formerly sound banks that are currently experiencing difficulties. Over the past couple of years, the SCOR model has produced better (albeit only slightly better) forecasts of downgrades than models that use prior examination ratings.[34] Consequently, the SCOR model uses only financial data.

[32] The distribution of SCOR ratings also resembles the distribution of the average of the six component ratings. It should be noted that this average is not meaningful because examiners would almost certainly assign higher weights to some components than to others. Moreover, SCOR ratings are distributed much like CAEL ratings, though CAEL ratings tend to be lower. (As explained above, CAEL was intended to be "biased" toward downgrading banks, and SCOR is not biased.)

[33] See Cole and Gunther (1998).

[34] The differences are not statistically significant.

On the other hand, including current ratings would have some advantages, and some prototypes of SCOR did use this approach.[35] First, CAMELS ratings include information not available on the balance sheet. When examiners rate banks, they consider many intangible factors, such as the quality of internal controls, and these intangible factors tend to persist over time. A model that uses only financial data ignores this extra information.

Second, models that include current ratings are more accurate in distinguishing between 1- and 2-rated banks.[36] SCOR cannot differentiate between these banks, apparently because 1-rated banks are financially very similar to 2-rated banks. Conventional wisdom holds that most of the difference between 1-rated and 2-rated banks lies in intangible factors.

Third, models that use current CAMELS ratings tend to produce forecasted ratings that differ only slightly from the current examination ratings, and in fact the best single predictor of future ratings is the current rating. Almost all banks that have a 2 rating before an examination receive a 2 rating after it.

[35] The Federal Reserve Board's contemporaneous SEER model includes management ratings.
[36] As discussed in the main body of the text, however, bank supervisors are relatively unconcerned about distinguishing between 1- and 2-rated banks.

APPENDIX 2

Calculation of the SCOR Weights

The method used to calculate the SCOR weights takes advantage of the linear portion of the logit model. Ignoring the intercept terms, the linear portion is a weighted sum of the bank's financial data, which can be denoted βx which equals $\beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_{12} x_{12}$.

If the weights are computed for the composite CAMELS rating, this sum can be considered a measure of the bank's general financial strength. If the weights are computed for the capital rating, βx can be considered the measure of the bank's capital adequacy.

The ratings of two banks can be readily compared. Consider two institutions: Bank A (with financial data $x^A = x_1{}^A, x_2{}^A, \ldots, x_{12}{}^A$) and Bank B (with financial data $x^B = x_1{}^B, x_2{}^B, \ldots, x_{12}{}^B$). The difference in the measure of financial strength of the two banks is $\beta x^A - \beta x^B = \beta\,(x^A - x^B)$. The first variable accounts for $\beta_1\,(x_1{}^A - x_1{}^B)$ of this difference, or, in percentage terms:

$$100 * \frac{\beta_1\left(x_1^A - x_1^B\right)}{\beta\left(x^A - x^B\right)}$$

This percentage would indicate the importance of the capital-asset ratio, for example, in explaining the difference in financial strength of the two banks. These percentages (for variables x_1, x_2, and so forth) necessarily sum to 100. The percentages can be negative; a negative percentage could occur if Bank A were stronger, on the whole, than Bank B but had a lower (weaker) capital-asset ratio.

It might be noted that this method is closely related to a Taylor expansion of the logit model. The first derivative of the logistic function equals K β_i where K is a number that depends on the point at which the derivative is evaluated. However, K is the same for all variables. Thus, the first term in a Taylor expansion about the point x^B is $K\,\beta_1\,(x_1{}^A - x_1{}^B)$, and the total is $K\,\beta\,(x^A - x^B)$. Of course, the intercept terms will not enter the Taylor expansion because they are constants. If the individual terms are expressed as percentages of the total, then K cancels from both numerator and denominator, and the result is identical to the formula above.

Recent Developments Affecting Depository Institutions

*by Lynne Montgomery**

CONDITION OF THE BANKING INDUSTRY

First-Quarter 2003 Financial Results for Commercial Banks and Savings Institutions

In its *Quarterly Banking Profile* for the first quarter of 2003, the Federal Deposit Insurance Corporation (FDIC) reported that FDIC-insured commercial banks and savings institutions earned a record $29.4 billion, an increase of $4.1 billion from earnings in the first quarter of 2002. Key factors in the higher earnings were gains on sales of securities and lower expenses for delinquent loans. The average return on assets was 1.38 percent, up from 1.29 percent one year earlier. The number of commercial banks and savings institutions on the FDIC's "Problem List" declined from 136 in the fourth quarter of 2002 to 129 in the first quarter of 2003, and assets of "problem" banks fell from $39 billion to $35 billion. The *Quarterly Banking Profile* can be accessed at **http://www2.fdic.gov/qbp**. *FDIC Quarterly Banking Profile, First Quarter 2003.*

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Reference sources: *American Banker* (AB), *BNA's Banking Report* (BBR), and *Federal Register* (FR).

First-Quarter 2003 Financial Results for the Insurance Funds

The FDIC reported that for the first quarter of 2003 the Bank Insurance Fund (BIF) had comprehensive income (net income plus/minus current-period unrealized gains/losses on available-for-sale securities) of $332 million, compared with income of $258 million for the same period in 2002. Although net income was actually $7 million lower than in the first quarter of 2002, unrealized gains on available-for-sale securities increased by $81 million. As of March 31, 2003, the BIF balance was approximately $32.4 billion, up from $32.1 billion at year-end 2002. The BIF reserve ratio rose from 1.27 percent at December 31, 2002, to 1.28 percent at March 31, 2003.

The Savings Association Insurance Fund (SAIF) reported comprehensive income of $159 million for the first quarter of 2003, compared with $114 million for the same period in 2002. The increase in comprehensive income was due primarily to lower estimated losses for future failures and higher unrealized gains on available-for-sale securities. The SAIF balance as of March 31, 2003, was $11.9 billion, up from $11.7 billion at year-end

2002. The SAIF reserve ratio held steady at 1.37 percent between December 31, 2002, and March 31, 2003. *PR-45-2003, FDIC, 5/7/03; FDIC Quarterly Banking Profile, First Quarter 2003.*

Bank Failure

On May 9, 2003, the First National Bank of Blanchardville, Blanchardville, Wisconsin, was closed by the Office of the Comptroller of the Currency (OCC), and the FDIC was named receiver. First National had total assets of approximately $35 million and total deposits of approximately $29 million. The Park Bank, Madison, Wisconsin, acquired First National's insured deposits and purchased the failed bank's cash and cash-equivalent assets. The remaining assets have been retained by the FDIC for later disposition. First National was the second failure of a BIF-insured institution in 2003. *PR-47-2003, FDIC, 5/9/03; PR-48-2003, FDIC, 5/10/03.*

Emerging Risks to the Banking Industry

The summer 2003 edition of the *FDIC Outlook* reports that even as the banking and thrift industries' earnings set new records, U.S. banks and savings institutions continue to face risk-management challenges in several key areas. The report discusses how banks have been addressing their credit, market, and operational risks. The report also discusses potential bank problem areas that FDIC analysts and examiners continue to monitor, including commercial real estate portfolios; subprime consumer lending; net interest margin compressions; interest rate and funding risks related to the unusually low interest-rate environment; exposure to market-sensitive, non-interest income sources; and the adequacy of internal audit and other fraud controls. The *FDIC Outlook* also addresses developments in each of the FDIC's six regions (Atlanta, Chicago, Dallas, Kansas City, New York, and San Francisco). The summer 2003 *FDIC Outlook* can be accessed at **http://www.fdic.gov/bank/analytical/regional/ro20032q/na/index.html**. (Past editions of the FDIC Outlook can be accessed at **http://www.fdic.gov/bank/analytical/regional/index.html**.) *PR-66-2003, FDIC, 6/18/03.*

REGULATORY AGENCY ACTIONS

Interagency Actions

Guidance on Sound Practices for Resilience of the Financial System

On April 8, 2003, the Board of Governors of the Federal Reserve System (FRB), the OCC, and the Securities and Exchange Commission (SEC) issued a paper entitled *Interagency Paper on Sound Practices to Strengthen the Resilience of the U.S. Financial System*, which identifies sound practices to strengthen the resilience of U.S. financial markets and minimize the immediate systemic effects of wide-scale disruptions. The paper identifies four sound practices for clearing and settlement organizations and firms that play significant roles in critical financial markets. Specifically, the sound practices consist of (1) identifying clearing and settlement activities in support of critical financial markets, (2) determining appropriate recovery and resumption objectives for clearing and settlement activities in support of critical markets, (3) maintaining sufficient geographically dispersed resources to meet recovery and resumption objectives, and (4) routinely using or testing recovery and resumption arrangements. These sound practices are intended to supplement the agencies' own policies and other guidance on business continuity planning by financial institutions. The agencies expect organizations that fall within the scope of the paper to adopt the sound practices within the specified implementation time frames. *PR-FRB, 4/8/03; BBR, 4/14/03, p. 602.*

Guidance on Use of the Discount Window

On July 23, 2003, the FDIC, the FRB, the OCC, the Office of Thrift Supervision (OTS), and the National Credit Union Administration issued guidance on the appropriate use of the Federal Reserve's new discount window program, which was introduced in January 2003. The guidance provides information on the new primary and secondary credit programs. It also reiterates well-established supervisory policies on sound liquidity contingency planning, and discusses sound practices in using primary-credit-program borrowings in liquidity contingency plans. *PR-73-2003, FDIC, 7/23/03.*

New Electronic Filing System for Beneficial Ownership Reports

On July 30, 2003, the FDIC, the FRB, and the OCC unveiled a new interagency electronic filing system that allows faster and easier submission and public retrieval of beneficial ownership reports filed by directors, officers, and principal shareholders ("insiders") of institutions whose equity securities are registered with the FDIC, the FRB, or the OCC. The new electronic system is part of the agencies' ongoing efforts to streamline the submission and retrieval of reports filed with the agencies under the Securities Exchange Act of 1934. The new system will also reduce the burden on insiders, who are required to file these reports within two business days of completing a transaction in equity securities of the institutions. Initially, filing under the new system will be voluntary, although the agencies encourage insiders to use the system as soon as practicable. *PR-74-2003, FDIC, 7/28/03.*

Federal Deposit Insurance Corporation

New Approach to Compliance Exams

The FDIC adopted a new examination process for measuring an institution's compliance with consumer protection laws and regulations. Under the new approach, compliance examinations will combine the risk-based examination process with an in-depth evaluation of an institution's compliance-management system. The new approach was developed to keep pace with the banking industry's compliance responsibilities, which have become more numerous and complex. Past examinations placed too much emphasis on checklists, and on-site examinations often involved reviewing every bank regulation and determining whether a bank was in compliance with each one. The new approach emerges from regulators' belief that bank officials have a common-sense understanding of their compliance responsibilities and therefore do not require the checklist approach during examinations. The new process will be used for on-site examinations occurring after June 30, 2003. *BBR, 6/23/03, p. 1006.*

Exam Guidance for Payday Lending

On July 2, 2003, the FDIC issued examination guidance for FDIC-supervised institutions that engage in payday lending, which typically involves issuing small-dollar, unsecured, short-term advances at high annual percentage rates. Payday lenders will now be subject to special examination procedures to verify and monitor their performance. In addition, the FDIC will hold an institution's board of directors and management responsible for ensuring that all facets of the payday lending operation—including those handled by a third party—are conducted in a safe and sound manner and in compliance with all applicable consumer protection laws, regulations, and policies. Failure to meet the standards will result in enforcement actions, which could require an institution to exit the payday lending business. *PR-70-2003, FDIC, 7/2/03.*

Federal Reserve Board

Home Mortgage Disclosure Act (HMDA) Transition Rules

On May 23, 2003, the FRB released transitional rules that provide lenders with guidance on how to comply with revisions to the Home Mortgage Disclosure Act that become effective January 1, 2004, in cases in which a mortgage application is submitted before the effective date but final action is not taken until after it. The transitional rules provide that (1) lenders will not have to indicate whether an application or loan involved a request for preapproval or was related to a manufactured home; (2) lenders may, at their option, continue to apply the current (instead of the revised) definitions for home improvement loans and for refinancings; and (3) lenders need not report the rate spread for loans in which the rate lock occurs before January 1, 2004. Lenders must report certain information available at the time of final action, such as the purchaser type and whether a loan is subject to the Home Ownership and Equity Protection Act. *PR-FRB, 5/23/03.*

Regulation Y

On June 30, 2003, the FRB adopted a final rule amending Regulation Y, which outlines permissible derivative activities of bank holding companies. The amendment permits bank holding companies to (1) take and make delivery of title to commodities underlying commodity derivative contracts on an instantaneous, pass-through basis; and (2) enter into certain commodity derivative contracts that do not require cash settlement or do not specifically provide for assignment, termination, or offset before delivery. The final rule became effective August 4, 2003. *PR-FRB, 6/30/03.*

Survey on Bank Lending Practices

In its April 2003 issue of the quarterly Senior Loan Officer Opinion Survey on Bank Lending Practices, the FRB reported that since the January 2003 survey, both domestic and foreign banks had continued to tighten business lending practices. However, the percentage of domestic banks that reported tightened lending standards for commercial and industrial (C&I) loans to large and middle-market firms during the period dropped significantly—from 20 percent in the January 2003 survey to 9 percent. The percentage of domestic banks that tightened their standards for business loans to small firms during the period dropped from 20 percent in the January survey to 13 percent. Both foreign and domestic institutions indicated that the most important reason for tightening standards and terms on C&I loans was a less-favorable economic outlook: the institutions reported that the demand for C&I and commercial real estate loans weakened between the January and April surveys. Domestic banks attributed the reduced demand to a decline in customers' needs for bank loans to finance capital expenditures, reduced needs to finance inventories and account receivables, and reduced merger and acquisition business. Foreign institutions attributed the reduced demand to a decline in merger and acquisition activity and reduced customer investment in plant and equipment. For the report, the Federal Reserve surveyed loan officers from 56 large domestic banks and 18 foreign banking institutions. The survey focused on changes during the preceding three months in the supply of and demand for bank loans to households and businesses. A copy of the survey can be obtained at **http://www.federalreserve.gov/boarddocs/SnLoanSurvey/**. *Senior Loan Officer Opinion Survey on Bank Lending Practices, FRB, April 2003.*

STATE LEGISLATION AND REGULATION

New Jersey

On July 23, 2003, the OTS announced that federal law preempts provisions of New Jersey's recently enacted anti-predatory-lending law, the New Jersey Home Ownership Security Act of 2002, preventing these state provisions from applying to federal savings associations and their operating subsidiaries. Federal preemption of the New Jersey law is based on the Home Owners' Loan Act and the OTS regulations that comprehensively and exclusively regulate lending by federal savings associations. The OTS says that federal law authorizes the OTS to provide federal savings associations with a uniform national regulatory environment for their lending operations, and requiring federal savings associations to treat customers in New Jersey differently would impose increased costs and an undue regulatory burden. *OTS 03-22, 7/23/03.*

Texas

The Texas Finance Commission adopted a rule, 7 Texas Administrative Code Section 12.33, that authorizes state-chartered banks to offer and sell debt cancellation contracts (DCC) and debt suspension agreements (DSA) to consumer-loan borrowers. DCCs and DSAs are offered to borrowers to cancel or suspend payments in the event of death, medical disability, or unemployment. The new rule establishes standards for state banks when they issue DCCs and DSAs, and it addresses consumer protections, fees, disclosures, and affirmative elections the customer must make to purchase the products. Because the sale of DCCs and DSAs transfers to the bank a risk that formerly was assumed by third parties, Texas Department of Banking managers advise banks to give priority to establishing a methodology to calculate reserve adequacy for potential losses. The new rule became effective on May 1, 2003. *BBR, 5/5/03, pp. 723–24.*

RECENT ARTICLES AND STUDIES

In a paper released on April 21, 2003, the FDIC reported that new capital rules being considered by the Basel Committee on Banking Supervision are expected to reduce the risk-based capital requirements for syndicated loans held by the largest U.S. banks. The risk characteristics of rated syndicated bank loans suggest a reduction in risk-based capital requirements for such loans on the order of 10 percent to 40 percent, with the magnitude of the decrease largely dependent on the approach used to estimate one of the key risk parameters: loss given default (LGD). A number of factors would limit the extent to which overall capital might decline under the new capital rules (known as "Basel II"), including the continued existence of Prompt Corrective Action capital tripwires, pressures from market participants, and Basel II's new capital charge for operational risk. However, meaningful changes in risk-based capital requirements for selected portfolios at the largest U.S. banks still remain possible. The report, entitled "Risk-Based Capital Requirements for Commercial Lending: The Impact of Basel II," was released through the FDIC's FYI series, which addresses emerging issues in banking. A copy of the paper can be obtained at **http://www.fdic.gov/bank/analytical/fyi/2003/042103fyi.html**.

A Federal Reserve study released in May 2003 suggests that mortgage lenders are more risk averse in states where tough foreclosure laws require lengthy court proceedings to evict a delinquent homeowner. The study, conducted by Federal Reserve economist Karen Pence, looked at Home Mortgage Disclosure Act data from 55 communities that cross state lines, such as the New York City, Washington, D.C., and Kansas City metropolitan areas. The study reports that consumers have a more difficult time getting credit in states with a more time-consuming foreclosure process. Consumers may appreciate the extra protection against foreclosure, but they should be aware that they are paying for the protection. Laws that benefit consumers in foreclosure also lead to higher interest rates, which make mortgages more expensive for consumers who do repay their loans. *Dow Jones Newswires, 5/14/03.*

On June 23, 2003, the FDIC released a report entitled "How Long Can Bank Portfolios Withstand Problems in Commercial Real Estate?" which states that bank loans secured by commercial real estate and construction projects continue to perform well, despite declining fundamentals in most commercial property types. The report discusses factors that have helped buffer banks' commercial real estate portfolios against the effects of declining market fundamentals, including historically low interest rates, more-conservative underwriting practices, and greater financial market involvement in the industry. Although these factors offer significant reassurance that the present downturn will not lead to credit problems on the same scale as those experienced in the real estate cycle of the late 1980s and early 1990s, in coming quarters bank commercial real estate loan losses seem likely to rise from their current low levels, as more borrowers experience problems servicing their debt. The report was released as part of the FDIC's FYI series. A copy of the full report may be viewed at **http://www.fdic.gov/bank/analytical/fyi/2003/062303fyi.html**.

INTERNATIONAL DEVELOPMENTS

Argentina

On May 8, 2003, Argentina's Congress passed a law forcing foreign banks to inform the public whether their headquarters would use their homeland assets to honor their commitments in Argentina in the event of a new financial crisis. The legislation is in response to the behavior of foreign banks during the December 2001 banking disaster, when some foreign banks lacked the funds to pay off depositors. The new legislation seeks to ensure that customers are not misled into thinking that money deposited at a major foreign institution will be protected during a crisis. Argentina's Superintendent of Financial and Exchange Institutions will monitor enforcement of the new law. *BBR, 5/19/03, pp. 834–35.*

Basel Committee

On July 17, 2003, the Basel Committee on Banking Supervision issued two papers setting international guidelines on risk-management principles, one for electronic banking and the other for the management and supervision of cross-border electronic banking activities. The first paper, "Risk Management Principles for Electronic Banking," lays out 14 principles aimed at helping banking institutions expand their existing risk oversight policies and processes to cover their electronic banking activities. The principles focus on the oversight responsibilities of the board of directors and management, the need for appropriate security controls, and the management of legal and reputational risk associated with electronic banking activities. The second paper, "Management and Supervision of Cross-Border Electronic Banking Activities," identifies additional risk-management principles specific to cross-border electronic banking activities. *BBR, 7/21/03, p. 120.*

Japan

The Industrial Revitalization Corporation (IRC), the Japanese governmental company responsible for the reconstruction of troubled borrowers, announced on May 12, 2003, that it had reached an agreement with the National Tax Administration to extend tax privileges to banks that assist corporate reconstruction. The agreement provides that a bank that writes off part of its loans to borrowers in cooperation with the IRC can treat the write-off as a loss and deduct it from taxable income. Previously such losses and deductions were allowed only with National Tax Administration approval. The tax measure is expected to encourage distressed companies and banks to take advantage of this opportunity for prompt turnaround and a return to healthy operations. *BBR, 5/19/03, p. 835.*