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Abstract

Since 1990, the banking sector has experienced enormous legislative, technological, and financial change, yet research into the causes of bank distress has slowed. One consequence is that current supervisory surveillance models may no longer accurately represent the banking environment. After reviewing the history of these models, we provide empirical evidence that the characteristics of failing banks have changed in the last ten years and argue that the time is ripe for new research using new empirical techniques. In particular, dynamic models that use forward-looking variables and address various types of bank risk individually are promising lines of inquiry. Supervisory agencies have begun to move in these directions, and we describe several examples of this new generation of early-warning models that are not yet widely known among academic banking economists.

Key words: off-site models, risk measurement, bank examination, bank supervision, bank failure

JEL Classification: C51, C53, G21

CFR research programs: risk measurement

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In the early 1970s financial economists both in academia and in government began rigorously assessing the extent to which accounting data could predict distress at U.S. banking organizations. Several studies along these lines were published in top finance journals.[1] Since the late 1980s, however, research on the characteristics of banks headed for trouble has slowed considerably. The work that has been done has been confined largely to the in-house publications of the supervisory agencies. Judging by the research record, economists appear to believe that the causes of banking problems are unchanging and well understood. Yet such complacency may be unwarranted. A consistent pattern across troubled banks is a prerequisite for reliable models of bank distress because predictive power hinges on the ability to identify and quantify these patterns. Models that are updated infrequently or that ignore the changing environment may lose their predictive abilities over time.

In fact, significant legislative, technological, and financial changes that have transformed the banking industry since the majority of the bank-distress studies were conducted. Since 1990, Congress has enacted several major pieces of banking legislation, including the FDIC Improvement Act (FDICIA), National Depositor Preference (NDP), the Riegle-Neal Interstate Banking and Branching Efficiency Act, and the Gramm-Leach-Bliley (Financial Modernization) Act. These changes, among others, allowed banking organizations to exploit scale and scope economies, and they altered the incentives that depositors, shareholders, and regulators have to respond to bank risk taking. Technological innovations such as credit-scoring and risk-management models, the improvement in computing power, the spread of ATMs, and the development of on-line banking have further enhanced scale economies and diminished the importance of relationship banking. Finally, the substantial increases in the depth, breadth, and sophistication of financial markets—including the explosion in derivatives markets, the development of retail sweep accounts, and the growth of secondary markets for bank assets—introduced new competitors and products, which provided banks with new possibilities for both risk taking and risk management. For all of these reasons, we might suspect that banks' behavior as they approach distress is substantially different from what it was before 1990.

Are the current predictive models of bank distress still relevant? The answer to this question is important because such models help supervisory agencies identify and contain banking crises. Although on-site examination is widely regarded by bank regulators as the most effective method of ensuring satisfactory risk levels at banking institutions, it is a costly procedure for both banks and taxpayers. Consequently, supervisors would like to perform such exams only when necessary and to target them as specifically as possible. In relatively calm financial periods, off-site monitoring can help supervisors make decisions about the timing and scope of routine examinations. Although FDICIA, passed in 1991, stipulates that all banks and thrifts must be examined at least once every twelve to eighteen months, the scheduling, focus, and intensity of these exams can be altered. In periods of widespread bank distress, supervisory resources are stretched to their limits, and off-site monitoring devices can assist in the rationing of those resources (Pantalone and Platt, 1987). Each of the three federal bank regulators—the Office of the Comptroller of the Currency (OCC), the Federal Deposit Insurance Corporation (FDIC), and the Federal Reserve (Fed)—uses early-warning models on a quarterly basis to monitor banks' conditions. However, if the nature of banking has indeed shifted dramatically since these models were developed, they may no longer be accurate. Waiting until the next banking crisis to test these models could prove a costly strategy.

In this article, we make three contributions to the literature. First, we provide a survey of the bank-distress literature since its inception in the 1970s through the development of the models in place today. Second, we provide theoretical reasons and empirical evidence that the models that continue to dominate in both academic and supervisory circles may no longer accurately represent the nature of bank distress. These observations argue for renewed research into the topic. Finally, we describe some efforts that are currently underway to develop new early-warning models at the Fed and the FDIC. These models do not simply update previous findings; rather, they use new techniques to make them more adaptable to future alterations in the structural environment of banking. One strand of the new monitoring devices attempts to complement traditional early-warning models by adopting a more dynamic approach using forward-looking variables. Another strand isolates and models unique banking risks to facilitate the risk-focused approach to bank supervision. Because regulatory banking economists often work on projects with confidential data and because many ongoing projects are not formally disclosed to the public, it is difficult for outside economists to benefit from supervisory work. We attempt to bridge that gap here in the hope of stimulating more research in this area outside of government agencies.

1. A Review of the Progress to Date

1.1. Early Studies

Although predictive studies of bank performance and the actual supervisory models based on those studies have used a wide variety of specific approaches over the years, the fundamental technique has always been the same. By comparing a set of banks that can be identified, ex post, as having faced financial distress against a sample of banks that did not face such problems, the goal has been to identify a common set of variables that differ in systematic ways between the two groups. Because banks—particularly those prone to failure—rarely issue publicly traded securities, this research has relied almost exclusively on accounting data, mostly from the Consolidated Reports of Condition and Income ("call reports") that banks file quarterly with their lead supervisory agency.[2]

Of course, the broad, qualitative differences between risky and safe banks have been known to both regulators and academics for many years. Banks on the verge of failure have rapidly falling equity ratios; negative profitability; low levels of liquid assets; heavy reliance on noncore and non-risk-priced funds; and poor credit quality as reflected by the levels of delinquent loans, other real estate owned, and commercial and industrial loans. Moreover, many of the differences between banks that remain safe and banks that fail are evident several quarters before failure. Although some of these differences are not individually significant until failure is imminent, jointly the differences between banks that fail and their peer group are significant several quarters before bankruptcy and are the basis for all multivariate early-warning models.[3]

During the 1960s, several studies of nonbank firms attempted to determine the usefulness of various financial ratios in predicting bankruptcy. In his seminal article, Altman (1968) used discriminant analysis over five variables to determine the characteristics of manufacturing firms headed for bankruptcy. His paper ushered in a wave of research applying similar methodology specifically to depository institutions (see especially Stuhr and van Wicklen, 1974; Sinkey, 1975; Altman, 1977; Rose and Scott, 1978; and Sinkey, 1978). One drawback to the use of discriminant analysis is that, although it permits model assessment based on classification, it does not readily allow for testing the relative importance—statistical or economic—of different independent variables. Regression analysis was used as early as Meyer and Pifer (1970) but, perhaps because of its relatively high computational demands, did not achieve widespread use until the mid-1980s.

The development of discrete-response regression techniques, together with the increased availability of the computing power necessary to apply them to large datasets, aided the advancement of bank-distress models beginning in the late 1970s (Hanweck, 1977; Korobow et al., 1977; and Martin, 1977). Because of its analytical simplicity, the logistic specification has been the favorite model of this type, although arctangent and probit models have also appeared occasionally. As pointed out by Martin (1977), discriminant analysis can be viewed as a special case of logistic regression in the sense that the existence of a unique linear discriminant function implies the existence of a unique logit equation, but the converse is not true. However, the existence of a linear discriminant function is commonly rejected when the number of observations is substantially smaller for one class than the other. For this reason, early discriminant studies typically used sub-samples of the population of safe banks (which have always far outnumbered risky banks by any measure), either matching them according to certain nonrisk characteristics or randomly selecting the control sample. The use of a logit model obviates the need for these restrictive sampling assumptions. In addition, logit models are useful for modeling ordered responses with more than two classes. The most common application of this technique in the early-warning literature is the modeling of supervisory ratings, which, in the current regulatory regime, take integer values from 1 to 5.

Martin's (1977) study set the standard for discrete-response models of bank-failure prediction. Whereas most other research focused on a small sample of banks over two or three years, Martin used all Fed-supervised institutions during a seven-year period in the 1970s, yielding over 33,000 observations. In what would become a standard approach, he confronted the data agnostically with 25 financial ratios and ran several different specifications in search of the best fit. He found that capital ratios, liquidity measures, and profitability were the most significant determinants of failure over his sample period. Although Martin did not use direct measures of asset quality, his indirect measures—provision expense and loan concentration—also turned out to be significant.

A host of other studies around the same time, using both logit and discriminant analysis, confirmed these basic results. (Table 1 summarizes a selection of these papers.) Poor asset quality and low capital ratios are the two characteristics of banks that have most consistently been associated with banking problems over time (Sinkey, 1978). Indeed, as described in Putnam (1983), early-warning research in the 1970s and 1980s displayed a remarkable consistency in the variables that emerged as important predictors of banking problems: profitability, capital, asset quality, and liquidity appeared as statistically significant in almost every study, although they were often measured differently.

Table 1. Comparison of Selected Early Studies Predicting Bank Condition

Model Number	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Dependent variable	Failure	Rating	Failure	Failure	Failure	Rating	Failure	Rating
Technique	OLS	Discrim. An.	Logit	Probit	Probit	Factor + Logit	Logit	Factor + Logit
# Obs.	60	214	33627	221	820	~5,700	339	70
Sample period	1948-65	1967-68	1969-76	1971-76	1980-83	1980-82	1983-84	1983-86
Loans vs. securities mix		X	X	X	X	X	X	
Efficiency, net operating expense, or overhead	X	X	X	X	X	X		X
ROA or ROE	X	X	X			X	X	X
Capital / assets		X	X	X		X	X	X
Classified loans	X	X			X	X		
Loan mix	X		X			X	X	
Size		X		X		X		
Charge-offs			X		X			
Deposit mix	X					X		
Past-due or nonperforming loans					X			X
Liquid Assets			X			X		
Volatile liabilities or jumbo CDs						X		X
Dividend payout ratio		X						
Interest income, expense, or margin						X		
Interest-rate sensitivity					X			
Provision expense			X					X
Insider activity	X							
Income volatility	X							
Balance-sheet volatility	X							
Asset or loan growth	X							
Income growth				X				
Loan-loss reserves								X
Other	X						X	X

Notes: Variables listed in the table are those included in each study. In most cases, variables were selected because of their significance, and so the table also largely reflects variables that were significant in predicting bank problems. In some studies, some additional variables were considered, but they do not receive an "X" in the table because they were found to be statistically insignificant. The studies referenced are: (1) Meyer and Pifer, 1970; (2) Stuhr and van Wicklen, 1974; (3) Martin, 1977; (4) Hanweck, 1977; (5) Bovenzi et al., 1983; (6) West , 1985; (7) Pantalone and Platt, 1987; (8) Whalen and Thomson, 1988.

Much of the early research on bank distress was conducted by economists within supervisory agencies was specifically directed toward the establishment of an off-site early-warning model for use in everyday supervision. The work of David Stuhr and his colleagues[4], produced the first formal statistical model adopted by a supervisory body, the Fed.[5] Much of the research of the era used data gathered by on-site examinations—particularly loans classified by examiners as “substandard,” “doubtful,” or “loss”—to supplement the accounting data. This direction was problematic, however, as data collected on-site could hardly be useful in an off-site model. Moreover, although early work with these variables led to some success (Sinkey, 1978), later studies showed the marginal contribution of these variables to be small. This became especially true after the call report was modified in 1982 to include information on past-due and nonaccruing loans. Since that time, the importance of examination data collected on site has waned in comparison with the use of call-report data.

1.2. Screen-Based Supervisory Models

Although off-site analysis and monitoring of financial institutions have always been an integral part of banking supervision, formal algorithmic and statistical systems for this purpose did not arise until the OCC adopted the National Bank Surveillance System (NBSS) in 1975. Table 2 describes the evolution of various off-site surveillance systems, and Table 3 lists the key components of these models. Before the NBSS, off-site monitoring had consisted largely of informal rules of thumb based on individual financial ratios. According to White (1992), the impetus for the shift toward a more systematic approach was the OCC’s failure to detect the financial difficulties at two large institutions—United States National Bank and Franklin National Bank—that became insolvent in the early 1970s. The OCC’s response to these shortcomings in off-site surveillance was, in part, to avail itself of new computing technology to condense the call-report data into key financial ratios for each bank under its supervision. One component of the NBSS, the Anomaly Severity Ranking System (ASRS), ranked selected bank ratios within peer groups to detect outliers.[6]

Table 2. Evolution of Key Off-Site Surveillance Systems

Screen-Based Systems				
National Bank Surveillance System (NBSS)	*Agency:*	*OCC*	*Period used:*	*1975 to ?*
Condensed the call report data into key financial ratios and compared them to peer ratios. One output of the NBSS, the Anomaly Severity Ranking System (ASRS), ranked bank ratios by peer group to detect outliers. Another output was the Bank Performance Report (BPR). In cooperation with the FED and FDIC, the OCC transformed the Bank Performance Report into the Uniform Bank Performance Report (UBPR). Although the OCC no longer uses the NBSS, the UBPR is used presently by all federal and state supervisory agencies for both on-site and off-site analysis.				
Minimum Bank Surveillance Screen (MBSS)	*Agency:*	*Fed*	*Period used:*	*late 1970s to mid-80s*
Employed a set of ratios as offsite screens, and added institutions that lay outside a critical range to an "exception list" that received extra scrutiny. A composite score was also constructed by summing the normalized values of seven of these ratios.				
Integrated Monitoring System (IMS)	*Agency:*	*FDIC*	*Period used:*	*1977 to 1985*
A screening device within IMS called "Just A Warning System" (JAWS) compared 12 key financial ratios to critical values as determined by examiner expertise. JAWS did not compute composite scores or make direct comparisons to peer levels.				
Uniform Bank Surveillance Screen (UBSS)	*Agency:*	*Fed*	*Period used:*	*mid-1980s to 1993*
Improvement upon the MBSS. Computed peer group percentiles of six financial ratios and summed them to derive the composite score. Banks in the highest percentiles of the composite score were placed on a watch list.				
Hybrid Systems				
CAEL	*Agency:*	*FDIC*	*Period used:*	*1985 to late 1998*
Replaced IMS. An "expert system," designed to replicate the financial analysis that an examiner would perform to assign an examination rating. Ratios were chosen to evaluate capital (C), asset quality (A), earnings (E), and liquidity (L). Analysts subjectively determined the weights for each of the ratios that fed into the four CAEL components. The CAEL components were multiplied by their respective weights and summed to yield a composite CAEL score.				
Canary	*Agency:*	*OCC*	*Period used:*	*2000 to present*
Canary consists of a package of tools organized into four components--Benchmarks, Credit Scope, Market Barometers, and Predictive Models. Benchmarks are screen-based ratios that indicate risky thresholds. The Peer Group Risk Model (PGRM) is a predictive model that projects a bank's return on assets over the next three years under various economic scenarios.				
Multinomial Limited Dependent Variable Systems				
System to Estimate Examination Ratings (SEER)	*Agency:*	*Fed*	*Period used:*	*1993 to present*
Replaced the UBSS. First named the Financial Institutions Monitoring System (FIMS), SEER is a logit model that consists of two components, a "risk-rank" model that forecasts bank-failure probabilities, and a "rating" model that estimates current CAMELS scores.				
Statistical CAMELS Offsite Rating (SCOR)	*Agency:*	*FDIC*	*Period used:*	*1998 to present*
Replaced CAEL. Like SEER, the model consists of two components: a CAMELS downgrade forecast and a rating forecast. The downgrade forecast computes the probability that a 1- or 2-rated bank will receive a 3, 4 or 5 rating at the next examination. The OCC also uses output from the SCOR model in offsite surveillance.				
CAMELS Downgrade Probability (CDP)	*Agency:*	*St. Louis Fed*	*Period used:*	*1999 to present*
Similar to the downgrade forecast of SCOR, the CDP estimates the probability that a 1- or 2-rated bank will be downgraded to a 3, 4 or 5 rating over the next two years.				

The FDIC and the Fed quickly followed the OCC with similar screen-based models of their own. In 1977 the FDIC introduced the Integrated Monitoring System (IMS). One component of this system was the modestly titled “Just A Warning System” (JAWS), which consisted of twelve financial ratios. The system compared each ratio with a benchmark ratio determined by examiner judgment. Banks with ratios that “failed” various screens were flagged for additional follow-up. About the same time, the Fed adopted the Minimum Bank Surveillance System (later, the Uniform Bank Surveillance Screen), which examined seven bank ratios. These ratios were weighted by their Z-scores, which were then summed to yield a composite score for each bank.

Because the logistic-regression technique was still too new and too computationally intensive to be practical, the initial systems adopted by all three federal agencies relied on a variant of discriminant analysis. Although none of these systems used a formally estimated discriminant function, the techniques of all of them were in this spirit, comparing selected ratios with predetermined cutoff points and classifying banks accordingly. Thus, the heavy reliance on univariate screens in this period was both a reflection of the technology of the era and a consequence of thinking in terms of low-order linear discrimination.

The consistent pattern of relevant variables contributing to bank distress motivated the Uniform Financial Rating System (UFRS), which was established in November 1979. Under this system, capital, asset quality, liquidity, and earnings constitute four of the six major risk factors emphasized by examiners.[7] Together with two other factors—management and (beginning in 1997) market sensitivity—these categories make up the CAMELS rating, which is the summary measure of bank condition used by all bank regulatory agencies.[8]

1.3. Subsequent Improvements

The FDIC's CAEL model, introduced in 1985, represented a significant breakthrough in off-site monitoring devices. This hybrid system—a mixture of statistical methods and examiner input—used examiner judgment to assign coefficients to a ratings estimation equation. CAEL examined four separate ratios for each of the capital (C), asset quality (A), earnings (E), and liquidity (L) components of the CAMELS score and relied on experienced examiners to weight the ratios subjectively. CAEL then weighted the four components to yield a composite rating, which was mapped into a CAMELS rating table. The rating table was updated each quarter to mirror the actual distribution of CAMELS ratings in the previous year. In essence, the model was a calibrated limited dependent-variable model, with examiner guidance replacing the computationally intensive econometric procedure.

Meanwhile, academic work continued to push in new directions. One innovation was a shift toward modeling supervisory behavior. This research stemmed from two key events: the adoption of the UFRS, which created consistent data on supervisory assessments of every financial institution in the country, and the regulatory forbearance that many blamed for the S&L crisis. Accordingly, an important area of new research asked what determined CAMELS ratings.[9]

Using supervisory ratings rather than failure events as the measure of overall risk in multinomial logit models provides the econometrician with more heterogeneity in the dependent variable because the number of poorly rated institutions always exceeds the number of failures.[10] From a supervisory perspective, it allows examiners to observe quarterly estimates of CAMELS ratings based on current call-report data. Cole and Gunther (1998) demonstrate that actual CAMELS scores can become obsolete within as little as six months after being assigned.

Similarly, Hirtle and Lopez (1999) find that the private supervisory information contained in CAMELS ratings decays as the ratings age. These studies suggest that early-warning models that estimate current CAMELS ratings are useful tools enabling supervisors to keep up with bank fundamentals without incurring the cost of an examination. Indeed, such models have subsequently become important components of official surveillance systems.

1.4. The Current Regime

Since 1990, nearly all research into the idiosyncratic causes of banking problems has been undertaken by supervisory agencies for the purpose of either verifying or expanding existing early-warning systems. Most of this research has relied on the copious bank-failure observations that became available between 1985 and 1991. Thanks to these data, to the development of discrete-response modeling, and to the falling cost of computing power, more sophisticated, multivariate devices relying on the new data have begun to replace the older systems.

In 1993, the Fed adopted as its in-house early-warning model the Financial Institutions Monitoring System, which was modified slightly and renamed the System to Estimate Examination Ratings (SEER). This model, which remains in place today, consists of two components, a "risk-rank" (failure) model that forecasts bank-failure probabilities, and a "rating" model that estimates current CAMELS scores. In 1998, the FDIC developed a model similar to SEER, known as the Statistical CAMELS Offsite Rating (SCOR). The SCOR model also consists of two components: a CAMELS downgrade forecast and a rating forecast. The variables included in the SEER and SCOR models, too, are listed in Table 3.[11]

Table 3. Comparison of Early-Warning Systems

Model Acronym	JAWS	UBSS	CAEL	SEER	SCOR	Downgrade	GMS	LAGS
Agency	FDIC	FRB	FDIC	FRB	FDIC	FRB	FDIC	FRB
Model type	Screens	Screens	Hybrid	logit	logit	logit	logit	VAR
Teir-1 or tangible capital	X	X	X	X	X	X		X
Total or risk-weighted assets				X		X		X
Past due 30			X	X	X	X		
Past due 90		X	X	X	X	X		
Nonaccruals			X	X	X	X		
OREO			X	X	X	X		
Residential real-estate loans	X			X		X		
C&I loans				X		X		
Securities	X			X		X		
Jumbo CDs	X			X		X		
Net income (ROA)	X	X	X	X	X	X		
Charge-offs			X		X			
Provision expense	X		X		X			
Liquid assets	X	X			X			
Loan growth	X						X	
Total or Risk-Weighted Asset growth		X					X	X
Volatile liability expense		X						
Volatile liabilities			X		X		X	
Loan-loss reserve			X		X			
Loan / deposit ratio	X		X					
Interest expense	X							
Loans & long-term securities					X		X	
NCNRP funding								X
Operating expenses or revenues	X		X					
Change in capital	X		X				X	
Change in deposits	X							
Dividends	X							
Region								
Prior composite supervisory rating							X	
Prior supervisory management rating								

Notes: Merged cells indicate that the model employs a composite variable that combines the indicated categories in some way. For purposes of comparison, some liberties have been taken with variable definitions, e.g., such categories as liquid assets and tangible capital have been defined in slightly different ways in the various models, and the construction of certain ratios differs slightly.

Each of the two models in the SEER framework serves a separate, specific purpose. The SEER *failure* model is designed to detect deficiencies in balance-sheet and income-statement ratios that are severe enough to cause an outright failure or a critical shortfall in capital. Because these events have been rare since the inception of SEER, the variables and coefficient estimates have remained frozen since they were first estimated on late 1980s and early 1990s failures. Although this model does not have the flexibility to detect sources of risk that were not present in the earlier estimation period, it does have the advantage that analysts can trace changes in estimated risk to changes in the underlying core set of risk factors.[12] The SEER *rating* model, in contrast, is reestimated on a quarterly basis, allowing for different coefficient estimates—and, indeed, different independent variables—in each quarter. This model has the advantage of allowing for new sources of bank risk, but interpreting changes in risk can be difficult when the main driver of the change is the inclusion of a variable that was not present in the model in the previous quarter. The two models are used together to achieve a balance between flexibility and consistency. As Cole et al. (1995), Cole and Gunther (1998), and Gilbert et al. (1999) demonstrate, SEER's performance is superior to that of a variety of other early-warning systems (including actual CAMELS scores assigned by examiners) in terms of the trade-off between SEER's Type-I and Type-II errors.

The rating component of the FDIC's SCOR model is quite similar to the SEER rating model. SCOR uses a multinomial logit to estimate a composite CAMELS rating as well as ratings for all six of the CAMELS components, in keeping with the formulation of the preceding CAEL system. In contrast to SEER's risk-rank model, SCOR was developed to detect downgrades of banks that are currently rated safe and sound (ratings of 1 or 2) but that will receive a rating of 3, 4, or 5 at the next examination. This emphasis resulted in a model that excludes prior examination ratings as an explanatory variable, so the forecasts of SCOR are based only on financial ratios and are more sensitive to changes in financial condition.

The Fed, too, has conducted research on downgrade probabilities. The downgrade model of Gilbert et al. (2002), included in Tables 2 and 3, uses a logistic model to estimate downgrade probabilities for CAMELS composites. After extensive testing, the authors concluded that the variables included in SEER were the most appropriate for their purposes as well, but one advantage of the downgrade model relative to the SEER failure model is the ability to update the coefficients on a periodic basis. Although failures were quite rare in the 1990s, downgrades were common.

2. New Directions in Bank-Distress Research

2.1. The Need for New Work

Off-site early-warning systems have certainly become more sophisticated since 1970, but given the dramatic changes in the banking sector over the past decade, we may expect that the current systems—like the screen-based mechanisms that preceded them—have already fallen behind the pace of financial evolution.[13] The prevailing early-warning techniques face two main criticisms: they are not well suited to the risk-focused approach to bank supervision, and they are backward looking.

Although the prevailing models of bank distress are quite effective at identifying overall risk, the risk-focused approach to supervision adopted by regulators in 1997 needs information about specific risks. The key elements of this approach are explained in the Supervision and Regulation Letter 97-25 of the Board of Governors titled "Risk-Focused Framework for the Supervision of Community Banks." The document, dated October 1, 1997, states:

> The objective of a risk-focused examination is to effectively evaluate the safety and soundness of the bank... focusing resources on the bank's highest risks. The exercise of examiner judgment to determine the scope of the examination during the planning process is crucial to the implementation of the risk-focused supervision framework, which provides obvious benefits such as higher quality examinations, increased efficiency, and reduced on-site examiner time. . . . [E]ach Reserve Bank maintains various surveillance reports that identify outliers when a bank is compared to its peer group. The review of this information assists examiners in identifying both the strengths and vulnerabilities of the bank and

> provides a foundation from which to determine the examination activities to be conducted.

Rather than identifying high-risk banks in the aggregate, risk-focused off-site monitoring devices attempt to assess the particular risks of banking organizations, allowing examiners to better scope an upcoming exam. The focus of these models is not when or whether to examine a given bank, but what aspects of the bank to emphasize during an exam. Because the variables in the current early-warning models are backward looking (as we explain below), their focus is primarily on credit risk and earnings. They do not include, for example, an analysis of interest rate risk and operational risk, and they only superficially analyze liquidity risk. Therefore, current early-warning models can be supplemented with more targeted off-site models.

In addition to not directly addressing a risk-focused approach, the prevailing bank-failure models are backward looking in the sense that they were estimated using models and data from the late 1980s and early 1990s. Bank failures have been such rare events since that time that neither the SEER risk-rank variables nor the coefficients have been updated in a decade. If the banking environment had remained more or less stable since 1990, we might not view the models from that period with much suspicion. Instability, however, has been a more apt description of the banking environment. Indeed, arguably banks have faced greater regulatory, financial, and technological innovations over the past decade than at any other time in recent history.

First, a number of key legislative changes have occurred—including some of the most sweeping banking legislation since the Great Depression. Table 4 summarizes these changes. The general intent of the legislation has been both to shift more of the burden of bank failure from taxpayers to uninsured creditors and to remove constraints that previously kept banks from expanding into new geographic areas and product lines. With regard to the former, the most important regulatory changes were contained in FDICIA and the National Depositor Preference Act. Both acts contained provisions moving away from protection of uninsured depositors and other junior debtholders, giving these claimants greater incentives to monitor distressed institutions and discipline them by either withdrawing funds or demanding higher yields. Several studies have documented the changes in market discipline that appear to have been caused by this legislation (Flannery and Sorescu, 1996; Marino and Bennett, 1999; Hall et al., 2002; Goldberg and Hudgins, 2002; King, 2003; and Flannery and Rangan, 2003). In addition, the 1990s saw the introduction of risk-based deposit-insurance premia, which Cornett et al. (1998) suggest imposed substantial costs on risky institutions.

Table 4. Key Legislative Changes in the 1990s
Financial Institutions Reform, Recovery, and Enforcement Act of 1989 (FIRREA)
Opened Federal Home Loan Bank (FHLB) membership to commercial banks. Previously membership had been available only to thrifts and certain insurance companies. Advances from the FHLB are a ready source of non-risk-priced funding. Over two-thirds of all banks are now FHLB members, and over half of them routinely utilize advances. As Stojanovic et al. (2001) show, risky banks are more likely to rely on advances than safer banks.
Federal Deposit Insurance Corporation Improvement Act of 1991 (FDICIA)
Restricted regulatory forbearance and creditor protection through Prompt Corrective Action and least-cost-resolution provisions. This legislation may have induced greater discipline in uninsured credit markets (see Goldberg and Hudgins, 2002; and Hall et al., 2002), resulting in higher funding costs and different liability structures for troubled institutions. Mandatory closure rules potentially increased the mean and reduced the variance of the capital levels of failing banks.
Reigle-Neal Interstate Banking and Branching Efficiency Act of 1994
Allowed bank branching across state lines. Although this Act allowed for greater geographic diversification, it also exposed banks to increased competition.
National Depositor Preference (1993)
Enacted as part of the Omnibus Budget Reconciliation Act of 1993, this legislation changed the failure-resolution hierarchy to make domestic depositors more senior claimants than foreign depositors. Like FDICIA, this legislation may have changed funding costs for risky banks and caused them to rearrange their liability structures. See Marino and Bennet (1999).
The Gramm-Leach-Bliley Act of 1999 (Financial Modernization Act)
Repealed the Glass-Steagal Act, and allowed financial holding companies to engage in insurance, securities underwriting and brokerage services, and merchant banking. This Act introduced new potential sources of risk in banking, although it facilitated the diversification of some traditional sources of risk.

The second major regulatory change of the 1990s was the relaxation of restrictions that had previously prohibited geographic and product diversification. State banking laws governing branching and multibank holding companies grew increasingly lax during the 1980s and early 1990s. Consequently, competition intensified, interest margins were squeezed, banks turned to new product lines and alternative sources of funding, and portfolios became more geographically diversified (Hannan and Prager, 1998). This trend culminated in the Riegle-Neal Act of 1994, which was partially responsible for the unprecedented merger wave of the last ten years. Expansion of a different sort was permitted by the Financial Modernization Act (FMA) of 1999, which rolled back the Depression-era prohibitions of certain financial activities at depository institutions. As a consequence of this legislation, many banks have expanded into investment banking, insurance, and other financial services, and an increasing fraction of bank revenue derives from fee income generated by these operations.

Beyond the challenges posed by new lines of business, risk managers at banks have also had to cope with new asset-liability management issues. Some of these are legislative, and others have to do with the organic evolution of financial markets. For example, the Federal Home Loan Bank (FHLB) opened its doors to commercial banks in 1989 and, as we show below, quickly grew into one of banks' most important nondeposit sources of funding. In 1999 the FMA increased the potential pervasiveness of the FHLB by permitting the use of small-business loans as collateral (Stojanovic et al., 2001; Craig and Thomson, 2003). On the other side of the balance sheet, bank loans have become more liquid, as secondary markets have developed and Government Sponsored Enterprises such as Fannie Mae and Freddie Mac have facilitated the growth of the mortgage market.

Finally, as in many other industries, technological innovations revolutionized the business of banking in the 1990s. Electronic payments, online banking, and credit scoring are now common and quickly growing activities. As Claessens et al. (2002) argue, these developments have the potential to change the competitive landscape dramatically. The presence of automatic teller machines has also exploded over the past decade—just one prominent example of technology that has allowed banks to substitute capital for labor, reduce operating costs, and improve efficiency.

Although none of these observations necessarily implies any fundamental change in the process through which banks deteriorate, together they constitute a prima facie case that, at the very least, older models of bank distress should be validated on recent data. Furthermore, some simple empirical analysis indicates that the above changes have indeed had an effect on the typical pattern of bank distress. Figure 1 plots separately nine key ratio averages for failed and nonfailed banks in the twelve quarters leading to failure between 1984 and 1994 and again between 1995 and 2003. The patterns that emerge, which are verified by difference-in-means tests in Table 5, suggest that many characteristics of banks in the quarters before failure changed significantly between the two time periods. (The table reports the tests for one and six quarters before failure. The choice of the six-quarter horizon reflects the average time between bank exams.)

Failing banks in the 1995–2003 period had lower relative levels of liquidity risk compared with banks in the 1984–1994 period. Specifically, reliance on jumbo CDs and fed funds purchased was substantially lower for failing banks between 1995 and 2003, both in absolute terms and relative to safe banks. Although the ratio of demand deposits to total assets was lower for all banks in the later period compared with the earlier period, in the later period the ratios for failing banks were nearly identical to those at nonfailing banks, whereas in the earlier period failing banks on average had significantly fewer demand deposits than nonfailing banks. These interperiod differences in liquidity risk could reflect the increased depositor discipline imposed by the 1990s legislative changes, for risky banks in the 1995–2003 period may have had a more difficult time attracting uninsured funds.

Table 5. Trends at Failed Banks, before and after 1995

		Comparison of Ratios at Failed Banks				*Comparison of Ratios at Failed Banks Less Peer Values*			
Variable	Time prior to failure	1995 - 2003	1984 – 1994	Difference of Means (t statistic)	Statistical Significance	1995 - 2003	1984 - 1994	Difference of Means (t statistic)	Statistical Significance
Jumbo CDs	1 Qtr	14.70%	18.80%	-4.10% (-2.06)	**	4.10%	9.30%	-5.2% (-2.65)	***
	6 Qtrs	13.40%	21.30%	-7.90% (-5.04)	***	3.60%	12.10%	-8.5% (-5.46)	***
Fed Funds Purchased	1 Qtr	0.37%	0.99%	-0.62% (-3.30)	***	-1.15%	-0.20%	-0.95% (-5.07)	***
	6 Qtrs	0.77%	1.29%	-0.52% -1.64		-0.69%	0.17%	-0.86% (-2.72)	***
Demand Deposits	1 Qtr	12.70%	14.90%	-2.20% (-1.23)		0.70%	-4.80%	5.5% -3.12	***
	6 Qtrs	11.70%	15.20%	-3.5% (-1.99)	**	-0.40%	-6.30%	5.8% -3.29	***
Loan-Loss Reserves / Loans	1 Qtr	4.04%	3.14%	0.90% -2.15	**	2.51%	1.90%	0.61% -1.46	
	6 Qtrs	2.63%	1.87%	0.76% -3.7	***	1.06%	0.67%	0.38%* -1.86	*
Cash & Due	1 Qtr	7.11%	8.20%	-1.08% (-1.28)		1.81%	-0.45%	2.26% -2.67	***
	6 Qtrs	6.14%	9.03%	-2.89% -3.7	***	0.85%	0.17%	0.68% -0.87	
Commercial RE Loans	1 Qtr	15.80%	11.60%	4.1%** -2.16	**	-0.10%	3.10%	-3.3% (-1.70)	*
	6 Qtrs	15.80%	11.60%	4.2%** -2.36	**	1.10%	3.50%	-2.50% (-1.40)	
Fee Income	1 Qtr	2.57%	1.11%	1.46% -2.44	**	1.58%	0.34%	1.24% -2.07	**
	6 Qtrs	2.87%	1.00%	1.86% -1.59		1.91%	0.29%	1.62% -1.38	
Other Real Estate Owned	1 Qtr	1.70%	3.48%	-1.78% (-3.78)	***	1.54%	3.11%	-1.57% (-3.33)	***
	6 Qtrs	1.49%	1.70%	-0.22% (-0.55)		1.30%	1.40%	-0.10% (-.25)	
Total Assets	1 Qtr	$133 mil	$161 mil	-$28 mil (-0.57)		-$88 mil	$47 mil	-$135 mil (-2.72)	***
	6 Qtrs	$137 mil	$192 mil	-$55 mil (-0.88)		-$51 mil	$88 mil	-$139 mil (-2.23)	**

Note: This table shows differences in means for selected risk variables between failing banks in the period 1995-2003 compared with those in 1984-94. Both the differences in levels and the differences in levels less the peer values for the corresponding periods are given, at both one- and six-quarter horizons. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) levels. All of the nine variables reported here have exhibited significant changes since 1995 (by at least one of these difference-of-means tests) in their patterns as failure approaches.

In the earlier period, credit-risk ratios also reflect significant differences between the two periods. Commercial real estate lending was significantly higher (about 4 percentage points, as scaled by assets) at failing banks relative to nonfailing banks. In the later period the ratio was about the same both at failing and at nonfailing banks. Other real estate owned, previously one of the best predictors of failure, did not change substantially in the 1995–2003 period during the quarters leading up to failure. Although it continues to be somewhat higher at failing banks, this gap has shrunk, and the upward trend has nearly vanished. The diminished importance of credit-risk ratios could reflect the improved risk-management at banks, facilitated by the deepening of financial markets. Indeed, Schuermann (2004) argues that most banks came through the 2001 recession in excellent shape in part because of more effective risk management. Advances in credit scoring allowed banks to better risk-price their syndicated, retail, and small-business loans.

Other ratios, too, reflect the changing characteristics of failed banks. Loan-loss reserves to total loans were higher in the later period relative to the earlier period, although in both time periods the ratio increased before failure. Cash to assets increased at failing banks in the quarters leading up to failure in the later period, but that ratio was relatively unchanged in the earlier period. Fee income as a percentage of assets, which was previously about the same at safe and at failing banks, is now substantially higher for failing banks. Finally, failing banks were larger on average than nonfailing banks in the earlier period but smaller in the later period, potentially reflecting the diversification benefits that banks receive from expanding in size and product offerings.

Despite the differences, we should be cautious about drawing strong conclusions from Figure 1. The 1995–2003 sample contains only 44 bank-failure observations, so that, although most of our statistical tests yield statistically significant differences, the small degrees of freedom raises doubts about the reliability of the failed-bank comparisons. In addition, it is not clear how bank-failure patterns will evolve over the *next* ten years relative to failure patterns today. Moreover, some series that we have not emphasized have remained fairly constant. For example, failing banks continue to hold fewer mortgages and securities, and the pattern of capital deterioration looks similar in the two periods. Finally, we do not explain *why* the empirical changes that we have noted resulted from the institutional changes of the 1990s. Our point is simply that the fundamental shifts that have occurred in the banking environment make it possible that the path to bank distress has changed, and the recent data are consistent with this possibility.

Because much of the academic research and most of the prevailing early-warning systems are based on data from the 1984–1994 period, the above comparison gives us cause for concern. Indeed, an examination of pre-1984 bank failures shows that the pre-1984 failure patterns are much closer to those in the 1980s than to those in the 1990s. In sum, something fundamental seems to have changed in the 1990s. This conclusion is motivating supervisors to consider new approaches to off-site monitoring.

Figure 1. Trends at Failed Banks, before and after 1995

This figure presents the information in Table 3 in graphical form. In each case, the pink line indicates the path of a failing bank as the failure date approaches, and the blue line indicates the average values for nonfailing banks. Values on the horizontal axis indicate the number of quarters before failure. Again, for every variable reported here, there is an obvious change in the pattern between the two periods.

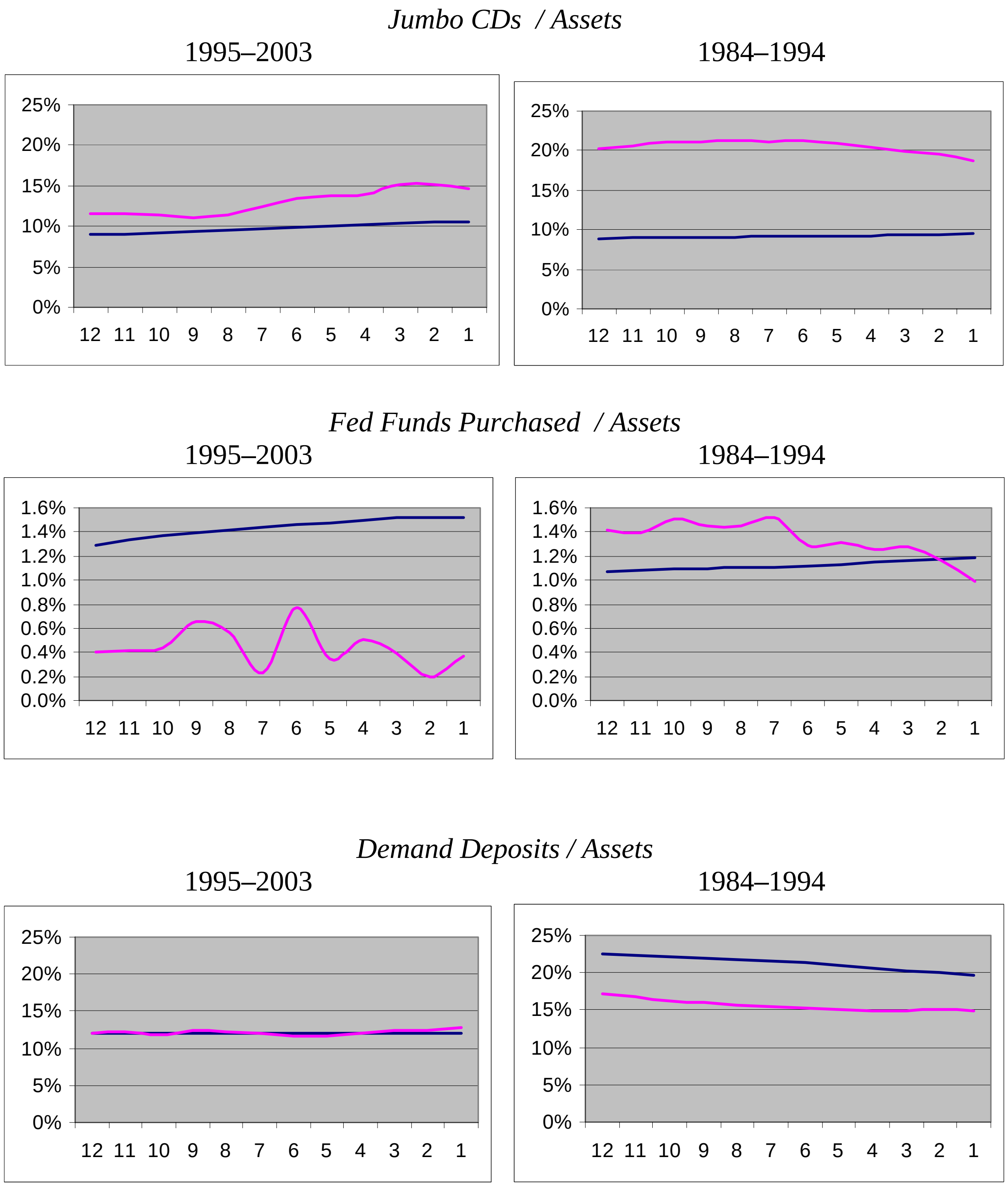
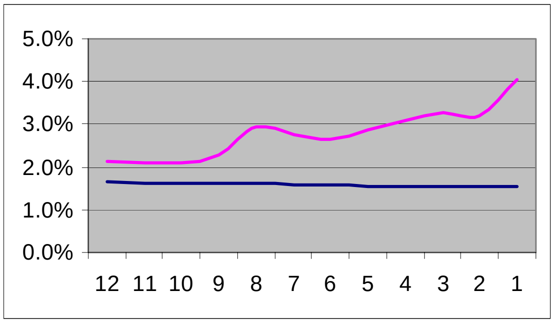


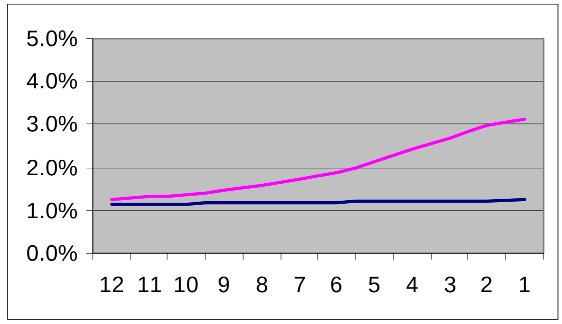
Figure 1 (continued). Trends at Failed Banks, before and after 1995

Loan-Loss Reserves / Loans

1995–2003

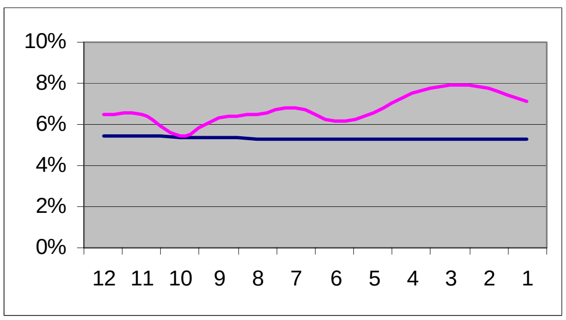


1984–1994

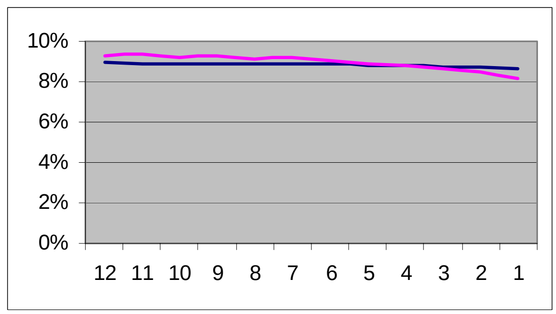


Cash/Assets

1995–2003

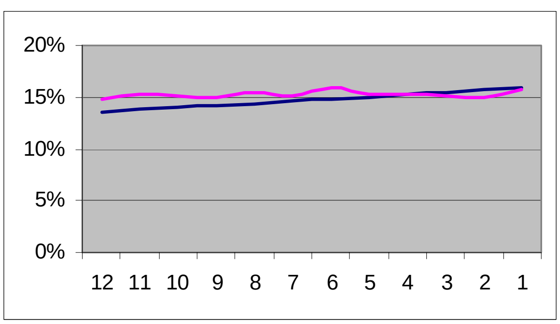


1984–1994



Commercial RE Loans / Assets

1995–2003



1984–1994

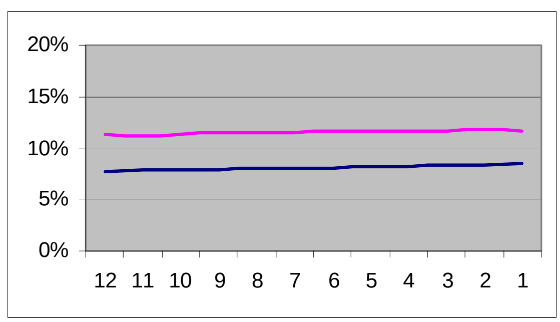
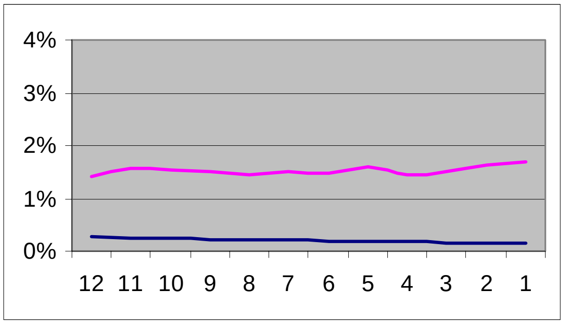


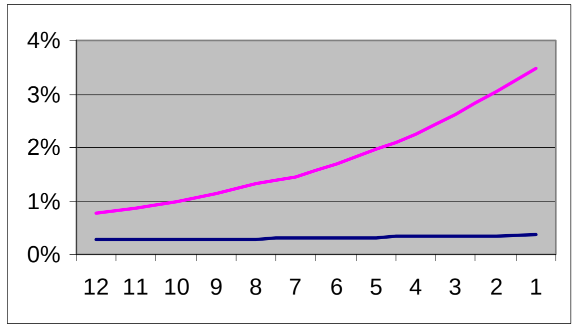
Figure 1 (continued). Trends at Failed Banks, before and after 1995

Other Real Estate Owned / Assets

1995–2003

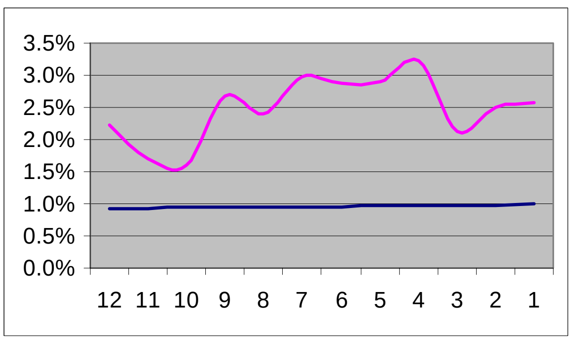


1984–1994

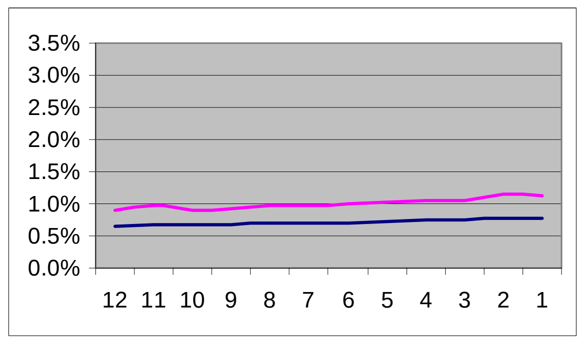


Fee Income / Assets

1995–2003

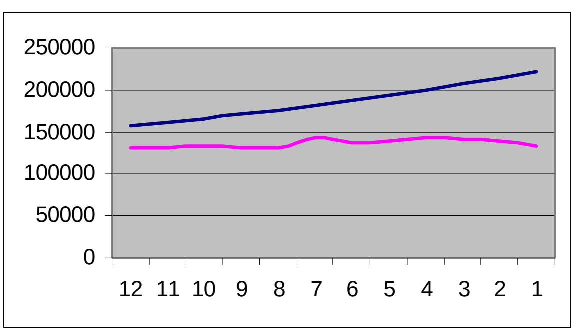


1984–1994

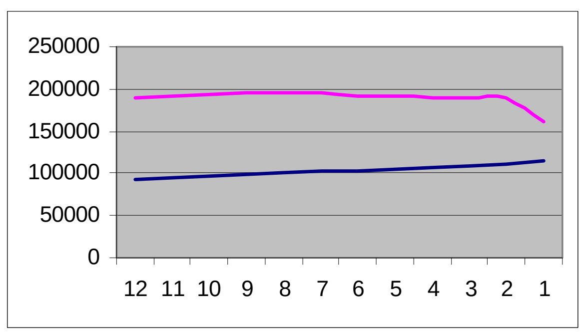


Total Assets

1995–2003



1984–1994



2.2. New Directions in Bank-Distress Models

In this section we describe some recent attempts by supervisory economists to build bank-distress models that adjust to the new banking environment and conform to the risk-focused approach. These goals are not mutually exclusive. Indeed, the risk-focused system was, in part, a response to be more agile and to focus resources more efficiently in a world of rapid change, growing complexity, and potentially volatile risks. We group the new models into two types: (1) forward-looking early-warning models that detect the conditions in which theory suggests that bank problems are likely to occur, and (2) risk-focused models that attempt to isolate specific sources of bank risk before the problems become big enough to threaten the solvency of the entire institution. Both of these new approaches permit real-time updating, without analysts having to wait until large numbers of failures provide heterogeneous data sufficient for adding new variables to traditional early-warning models.

Another innovation that applies to many of the models in both categories is the use of a dynamic econometric framework in which the first differences (rather than just the levels) of the relevant variables are used, and variables are allowed to feed into one another intertemporally. These techniques, which have their roots in early work by Santomero and Vinso (1977) and Avery and Hanweck (1984), allow one to capture information similar to that contained in Figure 1 by looking at effects beyond the first order.

2.2.1. Forward-Looking Models

Some recent early-warning models differ from earlier models in that they do not focus on the current condition of the bank. Rather, they emphasize the circumstances that theoretically may lead banks to increase their risk taking. In addition to focusing on traditional variables like capital ratios, these models have tended to focus on asset growth and liquidity. The importance of these two characteristics stems from two complementary theories.

One theory views banks as having well-established relationships with a core set of customers. On the liability side of the balance sheet, these customers provide stable low-cost funding, while on the asset side the bank has information about the creditworthiness of these customers that is generally not available to other lenders. Banks that pursue a rapid growth strategy must move into new markets or offer new products, finding both a new set of borrowers and the funds to finance the growth. Although growth is not a problem per se, a bank suffers from adverse selection as its pool of prospective new borrowers is composed disproportionately of those who have been rejected by other banks. The question is whether the bank has sufficient expertise and devotes sufficient resources to address the credit problems inherent in rapid growth. These problems are not observable immediately because new credits are unseasoned.

The second theory reflects standard moral-hazard incentives. Deposit insurance and other sources of collateralized funding allow banks to take risks, keeping the profits should the risks pay off, and putting the losses to the FDIC in the event of failure. Managers of banks with relatively high capital ratios have incentives to manage their banks prudently because the owners of the bank have their own funds at stake, but if capital ratios begin to slip, those incentives erode. When bank performance begins to deteriorate for whatever reason, managers and owners increasingly face the prospect of losing their jobs and wealth should regulators close the bank. Rather than watch the bank fail, banks might gamble for resurrection by booking high-risk loans funded with insured or collateralized funding.

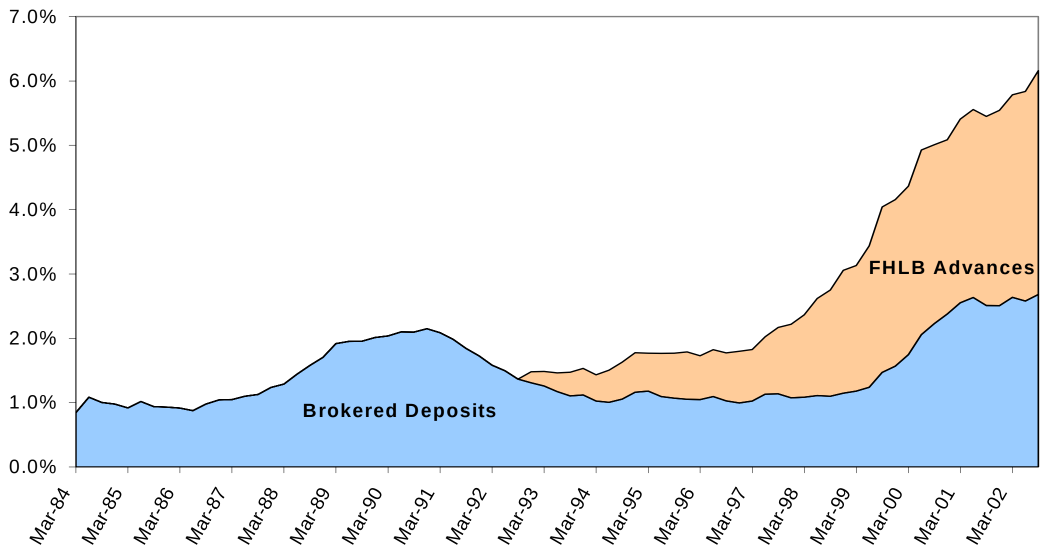
Banks have traditionally tried to avoid market discipline by relying on core deposits, and some evidence suggests that riskier banks shift to core funding for exactly this reason.[14]

Managers adopting this strategy, however, run up against two constraints. First, banks that deliberately try to sidestep market discipline with FDIC-insured deposits may invite greater regulatory scrutiny. Second, the limited supply of core funding imposes a natural ceiling on asset growth. Since the early 1990s, competition for insured deposits has intensified. Faced with less insured funding and greater demand for bank assets, managers have sought new funding sources. Banks that want to grow quickly but are unwilling or unable to pay the risk premia demanded by uninsured liability-holders may turn to noncore, non-risk-priced sources of funding, such as brokered deposits and FHLB advances. Brokered deposits funded much of the risky growth at thrifts during the savings and loan crisis of the late 1980s. FHLB advances, which were historically available only to thrifts but, as noted above, became available to commercial banks in 1989, have many of the same properties as brokered deposits.[15] Both types of funding are easily accessible in large quantities, and neither is priced according to the failure risk of the borrower. Brokered deposits are insured by the FDIC, while FHLB advances are fully collateralized. The lenders therefore have little incentive to monitor a borrowing bank's condition.

As Figure 2 illustrates, bank reliance on brokered deposits and FHLB advances is at a historically high level, both in absolute terms and as a percentage of total bank assets. Advances in particular have grown from essentially zero to 3.5 percent of banks' balance sheets in less than ten years. Furthermore, rapid loan growth has accompanied the growth in noncore funding at many institutions. Between 1992 and 2002, bank lending increased 54 percent faster than total national income. Although aggregate capital levels and asset quality remain relatively sound, banks might be assuming high levels of risk. The FDIC and the Federal Reserve Bank of St. Louis have independently developed alternative early-warning models called the Growth

Monitoring System (GMS) and the Liquidity and Asset Growth Screen (LAGS), respectively, to address the concerns about rapid growth and moral hazard. We briefly describe each in turn.

Figure 2. Noncore, non-risk-priced funding at U.S. Banks
(as a percentage of total assets)



2.2.1.1 Growth Monitoring System

The FDIC has used GMS as part of the off-site review process since the mid-1980s.[16] The original model was an "expert system" in that its parameter values were assigned on the basis of professional judgment rather than statistical analysis. Weights were assigned to a number of growth-related variables in an attempt to identify those institutions most in danger of a downgrade in CAMELS ratings. In the late 1990s, the FDIC developed a new version of this model using statistical techniques. This newer version of GMS, implemented in 2000, uses a logit model of downgrades, much like more traditional models, estimating which institutions that are currently rated satisfactory are most likely to be classified as problem banks at the end of three years. Rather than using credit-quality measures as independent variables, GMS includes forward-looking variables that can be precursors of problems that have yet to become manifest.

The nine variables in the model are indicated in Table 3.[17] Two variables have the most effect on the results: loan growth and noncore funding. Although the coefficient magnitudes vary somewhat over time, they are significant both statistically and economically. More rapid loan growth and heavy dependence on noncore funding generally lead to higher estimated default probabilities.

Back testing of GMS shows that the model has significant forecasting power.[18] Between 1996 and 2000 approximately 30 percent of the banks with GMS rankings at or above the 98th percentile received a rating of 3 or worse over the next five years.[19] Among the banks with rankings at the 79th percentile or lower, just 8 percent were downgraded, so banks in the top 2 percentiles were approximately two-and-a-half times more likely to receive a rating of 3 or worse.

The performance of GMS is even better when flagging more severe problems. Banks with GMS rankings at or above the 98th percentile either were downgraded to a CAMELS 4 or 5 or failed 9.5 percent of the time; in contrast, banks with GMS ratings in the lower 79th percentile either were downgraded to a rating of 4 or 5 or failed only 1.3 percent of the time. Finally, banks with GMS rankings at or above the 98th percentile were over eight times more likely to fail (0.76 percent) than banks with rankings in the 79th percentile or lower (0.09 percent). It should be noted that although the GMS model has notable success in identifying risky institutions, many banks with high GMS rankings are never downgraded. For this reason, the results of the GMS model are probably most useful in determining which banks need a closer review at the next examination.

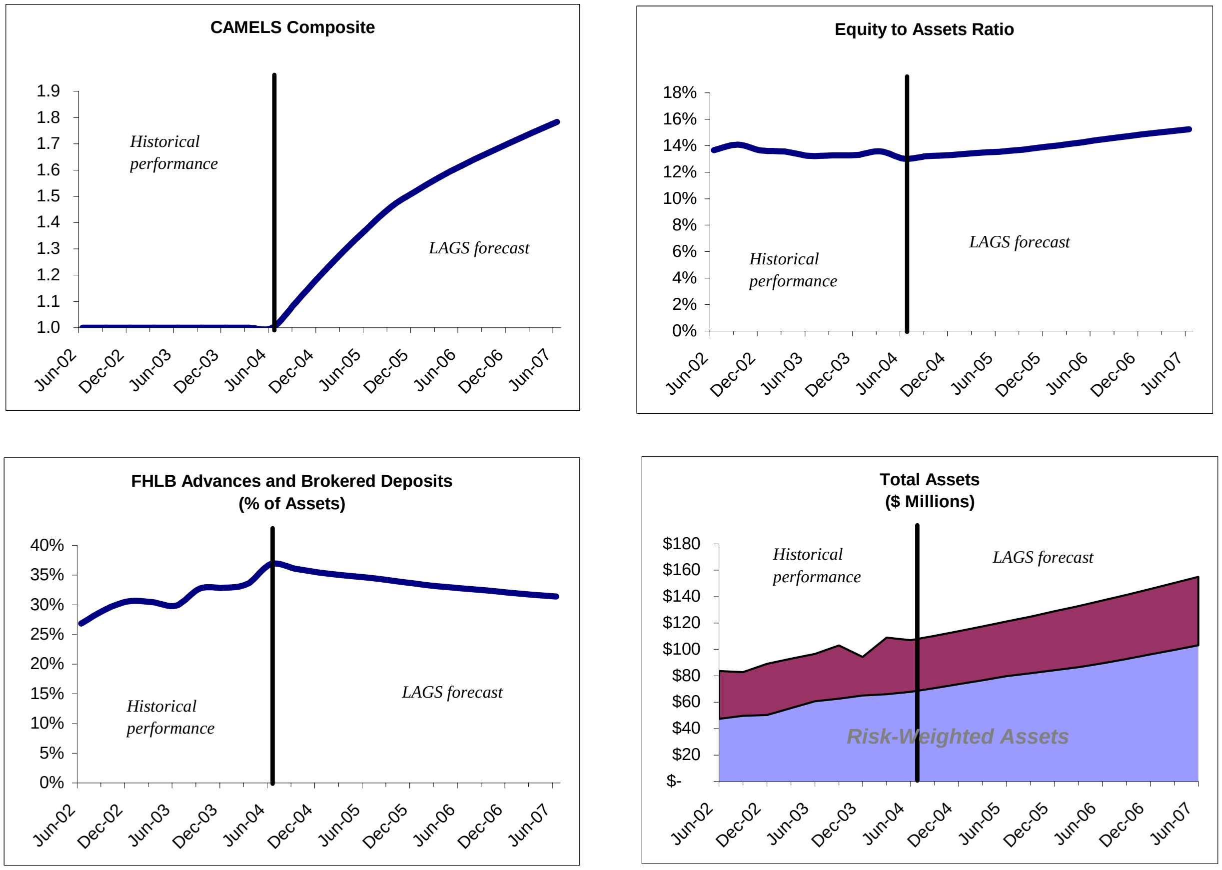
2.2.1.2. Liquidity and Asset Growth Screen

Like GMS, LAGS attempts to flag banks that use particular funding vehicles to fuel rapid asset growth.[20] The central idea is that a bank that experiences a combination of falling capital ratios and rapid asset growth funded with noncore, non-risk-priced funding exhibits the classic characteristics of moral hazard.

The LAGS model consists of ten separate panel vector autoregressions (VARs), identical in their variables but estimated on banks of different inflation-adjusted asset classes. The four dependent variables in the VARs are the quarterly growth rate of risk-weighted assets, weighted by the risk-weighted-to-total-assets ratio; the ratio of brokered deposits and FHLB advances to total assets; the CAMELS composite score; and the ratio of equity to total assets.[21] The equations are estimated on rolling samples of quarterly data, updated every three months to include the most recent figures available. The key variable in the model is the CAMELS score. Banks that have worse forecasted CAMELS ratings over a three-year horizon are interpreted as being in greater danger of risk induced by moral hazard.

The charts in Figure 3 show how LAGS works for an anonymous bank as of June 2004. In each of the four panels, the data to the left of the vertical black lines represent the bank's behavior over the previous two years. To the right of the black lines, the graphs show the LAGS forecasts. LAGS predicts that the sample bank's CAMELS score will rise from its present level of 1 to 1.78 over the next three years.

Figure 3. LAGS Forecasts for an Anonymous Bank as of June, 2004



A closer look at the sample bank's recent history gives us an idea of why the model predicts such a dramatic rise in risk. The bank grew rapidly between June 2002 and June 2004, increasing its assets by half and ratcheting up its risk-weighted-asset ratio. The bank funded a substantial portion of this growth with FHLB advances and brokered deposits. As of June 2004, these liabilities supported over 35 percent of the bank's total assets, a ratio that rose more than 10 percentage points during the previous two years. Meanwhile, capital declined by about 100 basis points. The bank therefore displays key moral-hazard characteristics.

Given the narrow focus of the LAGS model, we would not expect its performance to be as impressive as that of a more comprehensive model like SEER, yet LAGS does display significant discriminatory ability. Between March 1998 and June 2001, 21.7 percent of CAMELS-2 banks with LAGS scores at the 90th percentile or above either were downgraded to 3, 4, or 5 or failed within the following three years. In addition, 47.1 percent of the 2-rated banks at the 99th percentile or above were downgraded or failed within three years. By contrast, only 12.7 percent of banks below the 90th percentile either were subsequently downgraded or failed.[22]

2.2.2. Risk-Focused Models

In addition to becoming more forward looking, bank-distress models are also evolving to accommodate the relatively new risk-focused framework. Several off-site monitoring devices have already been developed by the FDIC and the Fed, and more are in development. We describe two of these models here.

2.2.2.1. Real Estate Stress Test

Real estate crises have been persistent causes of bank failure.[23] In 2000, the FDIC implemented a Real Estate Stress Test (REST) that attempts to identify those banks and thrifts that are most vulnerable to problems in real estate markets.[24]

The REST model incorporates the experience of the New England real estate crisis of the early 1990s. Conceptually, the model subjects banks to the same stress as that crisis and forecasts the resulting CAMELS ratings. REST was developed by regressing performance data for New England banks in December 1990 on performance and portfolio data for the same banks in December 1987. These regressions identify the factors that were observable in 1987 that later were associated with concerns about safety and soundness. A concentration in construction and developments loans is the primary risk factor, but there are a host of secondary factors, such as concentrations in commercial mortgages, commercial and industrial loans, mortgages on multifamily housing, reliance on noncore funding, and rapid growth. These regressions are used to forecast measures of bank performance, which are then translated to CAMELS ratings by the use of the SCOR model. The result is a REST rating that ranges from 1 to 5. The output from the model is distributed to FDIC examiners as well as examiners from other federal and state banking agencies. The model has been validated with data from other real estate downturns; it can identify banks that are vulnerable from real estate exposure three to seven years in advance.

Because of the long horizon, banks with poor REST ratings are not an immediate concern. More importantly, the model does not consider the underwriting standards and other aspects of risk management that a bank uses to control its exposure to real estate downturns. Consequently, examiners use the output from the REST model for examination planning. The model produces a set of "weights" indicating which variables are the most responsible for the poor rating, giving examiners a sense of the aspects of a bank's operations that deserve the most attention.

2.2.2.2. Interest Rate Risk

The savings and loan crisis of the 1980s heightened the banking industry's awareness of interest rate risk. Many thrifts became insolvent following the sharp rise in interest rates in the early 1980s. Bank supervisors were challenged to stay abreast of the industry's ability to take on interest rate risk. Economists at the Board of Governors responded by developing a duration-based measure of interest rate risk that could be used for surveillance and risk-scoping purposes.[25] The model, titled the Economic Value Model (EVM), became operational in the first quarter of 1998 when it produced a confidential quarterly surveillance report (called the Focus report) for each commercial bank.

The charge for economists at the Board of Governors was to build a model that, on the one hand, was more sophisticated than the simple repricing models used by most banks at the time but, on the other hand, did not place an undue reporting burden on banks. To ease the regulatory burden, the Fed's EVM uses call-report data, most of which are recorded at historical cost. The EVM aggregates balance-sheet items into various groupings. The model then uses the duration from a proxy financial instrument for each grouping to calculate the "risk weight," or the change in economic value of those items to a 200 basis point instantaneous rise in rates. For example, the EVM places all residential mortgages that reprice or mature within five to fifteen years in the same grouping. If the risk weight for the five- to fifteen-year mortgages were 7.0, the value of the five- to fifteen-year mortgages would be estimated to decline by 7.0 percent following an immediate 200 basis point rate hike. The change in economic value is repeated for each balance-sheet grouping. The predicted change in economic value of the bank's equity, then, is the difference between the predicted change in assets and the predicted change in liabilities.

Recent research by Sierra and Yeager (2004) shows that the model effectively ranks banks by their exposure to rising interest rates. That is, banks that the model predicts to be the most vulnerable to rising interest rates suffer the largest declines in income and equity following an interest rate hike. These banks also show the largest gains in income and equity following interest rate declines. Bank supervisors can use the model's output to rank banks by interest rate risk. If a bank is found to be an outlier, the examiner-in-charge will emphasize that risk in the upcoming exam.

3. Conclusion

After their introduction in the 1970s, studies on the causes of bank distress made rapid progress, fueled by considerable academic interest. In recent years, this interest has waned outside the regulatory community, a waning that may reflect the belief that the causes of bank distress are well understood. However, significant legislative, technological, and financial innovations may make it necessary to supplement the prevailing academic and regulatory models with a new generation of risk-focused monitoring systems. Indeed, banks that failed between 1995 and 2003 had quite different characteristics from banks that failed in the 1980s. The banking industry and the deposit insurance fund may pay a high price if researchers wait for the next round of failures before moving to the next generation of early-warning systems.

The continued advancements in computing power, the desire for supervisors to be more forward looking, and the switch to the risk-focused supervisory approach have led to new generations of models within supervisory agencies. Forward-looking early-warning models at the FDIC and the Fed include the Growth Monitoring System and the Liquidity and Asset-Growth Screen, respectively. Risk-focused screens include the Real Estate Stress Test and the Economic Value Model. In addition, ongoing work is focusing on other aspects of risk, such as liquidity risk. By describing current and evolving surveillance models, we hope to bridge the gap between regulatory and academic banking research and broaden the search for the causes and detection of bank distress.

Of course, the use of a variety of models in bank supervision requires judgment by supervisors to determine which models are the most relevant in a given set of circumstances. Nonetheless, the improvements in off-site monitoring devices give supervisors a deeper tool kit with which to detect and contain problem banks.

References

Altman, Edward I. 1968. "Financial Ratios, Discriminant Analysis, and the Prediction of Corporate Bankruptcy." *Journal of Finance* 23 (September): 589–609.

———. 1977. "Predicting Performance in the Savings and Loan Association Industry." *Journal of Monetary Economics* 3 (October): 443–66.

Avery, Robert B., and Gerald A. Hanweck. 1984. "A Dynamic Analysis of Bank Failure." Board of Governors of the Federal Reserve System, Research Papers in Banking and Financial Economics 74 (September): 39.

Barth, J., D. Brumbaugh, Daniel Sauerhaft, and George H. K. Wang. 1989. "Thrift Institution Failures: Estimating the Regulator's Closure Rule." In *Research in Financial Services,* edited by George Kaufman, 1-23. Greenwich, CT: JAI Press.

Billet, Matthew T., Jon A. Garfinkle, and Edward S. O'Neal. 1998. "The Cost of Market vs. Regulatory Discipline in Banking." *Journal of Financial Economics* 48:333–58.

Bovenzi, John F., James A. Marino, and Frank E. McFadden. 1983. "Commercial Bank Failure Prediction Models." Federal Reserve Bank of Atlanta *Economic Review* (November): 14–26.

Claessens, Stijn, Thomas Glaessner, and Daniela Klingebiel. 2002. "Electronic Finance: Reshaping the Financial Landscape around the World." *Journal of Financial Services Research* 22 (August–October): 29–61.

Cole, Rebel A. 1993. “When Are Thrift Institutions Closed? An Agency-Theoretic Model.” *Journal of Financial Services Research* 7 (December): 283–307.

Cole, Rebel A., Barbara G. Cornyn, and Jeffery W. Gunther. 1995. “FIMS: A New Monitoring System for Banking Institutions.” Federal Reserve *Bulletin* (January): 1–15.

Cole, Rebel A., and Jeffery W. Gunther. 1998. “Predicting Bank Failures: A Comparison of On- and Off-Site Monitoring Systems.” *Journal of Financial Services Research* 13 (April): 103–17.

Collier, Charles, Sean Forbush, Daniel A. Nuxoll, and John O’Keefe. 2003a. “The SCOR System of Off-Site Monitoring.” *FDIC Banking Review* 15 (3rd Quarter): 17–32.

Collier, Charles, Sean Forbush, and Daniel A. Nuxoll. 2003b. “The Vulnerability of Banks and Thrifts to a Real Estate Crisis.” *FDIC Banking Review* 15 (4th Quarter): 19–36.

Cornett, Marcia M., Hamid Mehran, and Hassan Tehranian. 1998. “The Impact of Risk-Based Premiums on FDIC-Insured Institutions.” *Journal of Financial Services Research* 13 (April): 153–69.

Demirgüç-Kunt, Asli. 1989. “Modeling Large Commercial-Bank Failures: A Simultaneous-Equations Analysis.” Working Paper 8905, Federal Reserve Bank of Cleveland.

Embersit, James A., and James V. Houpt. 1991. “A Method for Evaluating Interest Rate Risk in U.S. Commercial Banks.” Federal Reserve *Bulletin* (August): 625–37.

Evanoff, Douglas D., and Larry D. Wall. 2001. “Sub-Debt Yield Spreads and Bank Risk Measures.” *Journal of Financial Services Research* 20 (October–December): 121–45.

Fan, Rong. 2003. "Getting the Most out of a Mandatory Subordinated Debt Requirement." *Journal of Financial Services Research* 24 (October–December): 149–79.

Federal Deposit Insurance Corporation (FDIC). 1997. *History of the Eighties: Lessons for the Future.* Vol. 1, *An Examination of the Banking Crises of the 1980s and Early 1990s.* Washington, DC: FDIC.

Flannery, Mark J. 1998. "Using Market Information in Prudential Bank Supervision: A Review of the U.S. Empirical Evidence." *Journal of Money, Credit, and Banking* 30:273–305.

———. 2001. "The Faces of 'Market Discipline.'" *Journal of Financial Services Research* 20 (October–December): 107–19.

Flannery, Mark J., and K. Rangan. 2003. "Market Forces at Work in the Banking Industry: Evidence from the Capital Buildup of the 1990s." Working paper, University of Florida, Gainesville, FL.

Flannery, Mark J., and Soren Sorescu. 1996. "Evidence of Bank Market Discipline in Subordinated Debenture Yields: 1983–1991." *Journal of Finance* 51 (March): 1347–77.

Gilbert, R. Alton, Andrew P. Meyer, and Mark D. Vaughan. 1999. "The Role of Supervisory Screens and Econometric Models in Off-Site Surveillance." Federal Reserve Bank of St. Louis *Review* 81 (November/December): 2–27.

———. 2002. "The Role of a CAMELS Downgrade Model in Bank Surveillance." Federal Reserve Bank of St. Louis *Review* 84 (January/February): 47–63.

Goldberg, Lawrence, and Sylvia Hudgins. 2002. "Depositor Discipline and Changing Strategies for Regulating Thrift Institutions." *Journal of Financial Economics* 63 (February): 263–74.

Hall, John R., Thomas B. King, Andrew P. Meyer, and Mark D. Vaughan. 2002. "Did FDICIA Enhance Market Discipline at Community Banks?" In *Research in Financial Services,* vol. 14, edited by George G. Kaufman, 63–94. Greenwich, CT: JAI Press.

Hannan, Timothy H., and Robin A. Prager. 1998. "The Relaxation of Entry Barriers in the Banking Industry: An Empirical Investigation." *Journal of Financial Services Research* 14 (December): 171–88.

Hanweck, Gerald A. 1977. "Predicting Bank Failure." Board of Governors of the Federal Reserve System, Research Papers in Banking and Financial Economics (November).

Helwege, Jean. 1996. "Determinants of Savings and Loan Failures: Estimates of a Time-Varying Proportional Hazard Function." *Journal of Financial Services Research* (December): 373–92.

Herring, Richard J., and Susan M. Wachter. 1999. "Real Estate Booms and Banking Busts—An International Perspective." Occasional Paper No. 58, Group of Thirty.

Hirtle, Beverly J., and Jose A. Lopez. 1999. "Supervisory Information and the Frequency of Bank Examinations," Federal Reserve Bank of New York *Economic Policy Review* (April): 1–19.

Hooks, Linda M. 1995. "Bank Asset Risk: Evidence from Early-Warning Models." *Contemporary Economic Policy* 13 (October): 36–50.

Houpt, James V., and Wright, David M. 1996. "An Analysis of Commercial Bank Exposure to Interest Rate Risk." Federal Reserve *Bulletin* (February): 115–28.

King, Thomas B. 2003. "Discipline and Liquidity in the Market for Federal Funds." Working Paper 2003-02, Federal Reserve Bank of St. Louis.

King, Thomas B., Mark D. Vaughan, and Timothy J. Yeager. 2004. "Detecting Moral Hazard at Commercial Banks: The Liquidity and Asset-Growth Screen," Working Paper 2004-06, Federal Reserve Bank of St. Louis.

Korobow, Leon, and David P. Stuhr. 1983. "The Relevance of Peer Groups in Early Warning Analysis." Federal Reserve Bank of Atlanta *Economic Review* (November): 27–34.

Korobow, Leon, David P. Stuhr, and Daniel Martin. 1976. "A Probabilistic Approach to Early Warning of Changes in Bank Financial Condition." Federal Reserve Bank of New York *Quarterly Review* (July): 187–94.

———. 1977. "A Nationwide Test of Early Warning Research in Banking." Federal Reserve Bank of New York *Quarterly Review* (Autumn): 37–52.

Lane, William R., Stephen W. Looney, and James W. Wansley. 1986. "An Application of the Cox Proportional Hazards Model to Bank Failure." *Journal of Banking and Finance* 10:511–31.

Marino, James A., and Rosalind L. Bennett. 1999. "The Consequences of National Depositor Preference." *FDIC Banking Review* 12 (October): 19–38.

Martin, Daniel. 1977. "Early Warning of Bank Failure: A Logit Regression Approach." *Journal of Banking and Finance* 1 (November): 249–76.

Meyer, Paul A., and Howard W. Pifer. 1970. "Prediction of Bank Failure." *Journal of Finance* (September): 853–68.

Pantalone, Coleen C., and Marjorie B. Platt. 1987. "Predicting Commercial Bank Failure since Deregulation." Federal Reserve Bank of Boston *New England Economic Review* (July/August): 37–47.

Pettway, Richard H., and Josepeh F. Sinkey, Jr. 1980. "Establishing On-Site Bank Examination Priorities: An Early-Warning System Using Accounting and Market Information." *Journal of Finance* 35 (March): 137–50.

Putnam, Barron H. 1983. "Early Warning Systems and Financial Analysis in Bank Monitoring." Federal Reserve Bank of Atlanta *Economic Review* (November): 6–14.

Rose, Peter S., and James W. Kolari. 1985. "Early Warning Systems as a Monitoring Device for Bank Condition." *Quarterly Journal of Business and Economics* 24 (Winter): 43–60.

Rose, Peter S., and William L. Scott. 1978. "Risk in Commercial Banking: Evidence from Postwar Failures." *Southern Economic Journal* 45 (July): 90–106.

Santomero, Anthony M., and Joseph D. Vinso. 1977. "Estimating the Probability of Failure for Commercial Banks and the Banking System." *Journal of Banking and Finance* 1:185–205.

Schuermann, Til. 2004. "Why Were Banks Better Off in the 2001 Recession?" Federal Reserve Bank of New York *Current Issues in Economics and Finance*10:1–7.

Sierra, Gregory E., and Timothy J. Yeager. 2004. "What Does the Federal Reserve's Economic Value Model Tell Us about Interest Rate Risk at U.S. Community Banks?" Federal Reserve Bank of St. Louis *Review* 86 (November/December):45–60.

Sinkey, Joseph F., Jr. 1975. "A Multivariate Statistical Analysis of the Characteristics of Problem Banks." *Journal of Finance* 30 (March): 21–36.

———. 1978. "Identifying 'Problem' Banks: How Do the Banking Authorities Measure a Bank's Risk Exposure?" *Journal of Money, Credit, and Banking* 10:184–93.

Stojanovic, Dusan, Mark D. Vaughan, and Timothy J. Yeager. 2001. "Do Federal Home Loan Bank Advances and Membership Lead to More Bank Risk?" In *The Financial Safety Net: Costs, Benefits, and Implications for Regulations,* Proceedings of the 37th Annual Conference on Bank Structure and Competition, 165–96.

Stuhr, David P., and Robert van Wicklen. 1974. "Rating the Financial Condition of Banks: A Statistical Approach to Aid Bank Supervision." Federal Reserve Bank of New York *Monthly Review* (September): 233–8.

Thomson, James B. 1992. "Modeling the Bank Regulator's Closure Option: A Two-Step Logit Regression Approach." *Journal of Financial Services Research* 6 (May): 5–23.

Wang, George H. K., and Daniel Sauerhaft. 1989. "Examination Ratings and the Identification of Problem/Non-Problem Thrift Institutions." *Journal of Financial Services Research* 2 (October): 319–42.

West, Robert Craig. 1985. "A Factor-Analytic Approach to Bank Condition." *Journal of Banking and Finance* 9 (June): 253–66.

Whalen, Gary. 1991. "A Proportional Hazards Model of Bank Failure: An Examination of Its Usefulness as an Early Warning Tool." Federal Reserve Bank of Cleveland *Economic Review* 27 (1st Quarter): 20–31.

Whalen, Gary, and James B. Thomson. 1988. "Using Financial Data to Identify Changes in Bank Condition." Federal Reserve Bank of Cleveland *Economic Review* 24 (2nd Quarter): 17–26.

White, Eugene N. 1992. *The Comptroller and the Transformation of American Banking, 1960–1990*. Washington DC: U.S. Office of the Comptroller of the Currency.

Notes

[1] See, for example, Meyer and Pifer (1970), Sinkey (1975), Altman (1977), Martin (1977), Santomero and Vinso (1977), Sinkey (1978), Pettway and Sinkey (1980), West (1985), and Lane et al. (1986).

[2] Before 1976 the frequency of call-report filing varied, but it has been at least semiannual for every bank in the country since 1960. A strand of literature complementary to the one we focus on looks at the ability of market data to forecast banking problems. Indeed, this strand has led to recent calls for mandatory issuance of publicly traded subordinated debt at large banks (see Evanoff and Wall, 2001; Fan, 2003). See Flannery (1998, 2001) for comprehensive overviews.

[3] One strand of the literature models the regulator's closure decision as endogenous and considers institutional factors that may alter the probability of closure. See Thomson (1992) and Cole (1993). We do not consider these models here, but they support our basic point: that the regulatory environment, among other things, may affect the behavior of banks as they head for failure.

[4] See Korobow and Stuhr (1983), Korobow et al (1976, 1977), Stuhr and van Wicklen (1974).

[5] Korobow et al. (1977) was also notable for being one of the first to emphasize the role of bank size in determinations of overall risk, a finding that would be replicated and used in many subsequent papers.

[6] Another output of the NBSS was known as the Bank Performance Report (BPR). This product and the FDIC's Comparative Bank Performance Report formed the bases for the Federal Financial Institutions Examination Council's (FFIEC) Uniform Bank Performance Report (UBPR), which remains an important component of informal off-site surveillance.

[7] Before 1979, the three federal regulatory agencies assigned banks scores for capital (1–4), asset quality (A–D), and management (S, F, or P), as well as a composite score (1–4).

[8] CAMELS is used throughout the paper to refer to the rating system, although before 1997, there was no S component.

[9] Two other, related, lines of research begun in this period involve modeling time to failure (rather than failure probability) and regulatory closure-decision rules. Examples of the time-to-failure models, which typically involve Cox proportional-hazard specifications, can be found in Lane et al. (1986), Whalen (1991), and Helwege (1996). For models of supervisory closure behavior see Barth et al. (1989), Demirgüç-Kunt (1989), Thomson (1992), and Cole (1993).

[10] West (1985) and Wang and Sauerhaft (1989) model supervisory ratings in a factor-analytic framework. Supervisory ratings were previously used to measure composite risk in a discriminant-analysis study by Stuhr and van Wicklen (1974).

[11] See Collier et al. (2003a).

[12] Cole and Gunther (1998) show that a probit model similar to the failure-predictor component of SEER does a better job of forecasting failures in the late 1980s than even supervisor-assigned CAMELS scores.

[13] Hooks (1995) and Helwege (1996) provide evidence on the parameter instability of traditional early-warning models over time.

[14] Billet et al. (1998).

[15] Stojanovic et al. (2001) provide further discussion of why the FHLB might create incentives for abnormal risk taking and what the evidence is that supports this hypothesis. Wang and

Sauerhaft (1989) show that thrift reliance on FHLB advances and brokered deposits was associated with worse supervisory ratings in the 1980s.

[16] See FDIC (1997), ch. 13.

[17] Noncore funding, loans to total assets, and assets per employee are adjusted for size peers. The growth variables and the change in loan mix are not adjusted because there is no evidence that the size peers differ. All growth rates are measured year-over-year in order to avoid problems of seasonal adjustment. The growth rates of loans and assets are adjusted for mergers, but the growth rates in noncore funding and equity are not. This adjustment means that the model ignores acquisitions unless the acquisitions have eroded equity or made the bank more dependent on noncore funding.

[18] The GMS system has also had particular success identifying recent failures due to fraud, although the exact reasons for this success require further investigation.

[19] Of course, the full five years have not passed for ratings assigned in the year 2000. The results are for those banks that survived five years or that filed a September 2003 call report.

[20] For more details on LAGS, see King et al. (2004).

[21] Eight quarterly lags of each of these four variables are included as regressors in each of the four equations. The equations also include intercept terms. In toto, then, LAGS consists of forty linear regression equations each containing thirty-six variables. Banks are excluded from the sample if they are less than eight quarters old or have merged with another institution within the previous eight quarters. As of June 30, 2004, the dataset included approximately 175,000 observations.

[22] As noted, the LAGS coefficients are reestimated every quarter. The numbers reported in this paragraph reflect the estimates actually used in each quarter (rather than, say, the most recent set). In other words, they reflect out-of-sample forecasting ability.

[23] See Herring and Wachter (1999).

[24] See Collier et al., 2003b.

[25] See Embersit and Houpt (1991) and Houpt and Wright (1996) for details.