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*Senior Economist*

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# What Do Early Warning Models Tell Us About Asset Risk and Bank Failures?

Linda M. Hooks
Economist

Financial Industry Studies Department
Federal Reserve Bank of Dallas

Banking difficulties rose dramatically during the 1980s, as the rate of U.S. bank failures reached levels not observed since the Great Depression. While Eleventh District banks showed signs of recovery in 1991, banking difficulties have persisted in some regions of the country. The financial turmoil experienced during the past decade has prompted renewed interest in predicting bank failures. Early warning models are econometric tools designed to estimate the impact of a set of relevant explanatory variables on the probability of bank failure. These models can help regulators identify potential problem banks and thereby help to limit potential losses to the Federal Deposit Insurance Corporation (FDIC) resulting from bank failures. Bank managers could also use similar techniques to provide information for managing portfolio risk.

An important element of early warning models of bank failure is the riskiness of bank assets. The accurate measurement of a bank's risk posture remains a complex issue, however. Many analysts have focused on specific aspects of a bank's portfolio that identify some portion of asset riskiness, but few have examined a more comprehensive picture of a bank's overall risk exposure.

Using data on banks in Eleventh District states, this article investigates how information on the contents of a bank's asset portfolio can be used to evaluate asset risk in the context of an early warning model.[1] The findings highlight the importance of risk-taking in explaining recent bank failures. The results indicate that asset risk measures were more important for predicting bank failures in the mid-1980s than in the late 1980s. Risk-taking was reflected in ex ante measures of asset risk in 1985, before the most severe regional economic difficulties. In 1987 and 1989, however, the effects of this risk-taking were manifested in ex post measures, such as low equity-to-asset ratios. This shift occurred as adverse regional economic conditions led banks to write off problem loans.

## Eleventh District Banking Conditions

The profitability cycle experienced by Eleventh District banks in the 1980s is one of the most pronounced on record. Chart 1 shows movements in the return on assets over the past decade for banks in each state in the District. The dramatic decline in the return on assets at Texas banks through 1988 is echoed, to a lesser degree, by Louisiana banks over the same period. New Mexico banks experienced less drastic changes in profitability. These swings in profitability were primarily attributable to the interaction between changes in the economic environment in which District banks operated and changes in the riskiness of bank portfolios.

Changes that occurred in the District's economic environment are illustrated in Chart 2, which shows growth in the annual averages of nonagricultural employment levels for the District states compared with the United States over the past decade. Employment in Texas and Louisiana decreased in the early 1980s, then grew again through 1985. Employment then declined more severely through 1987. These movements mirror the changes in bank

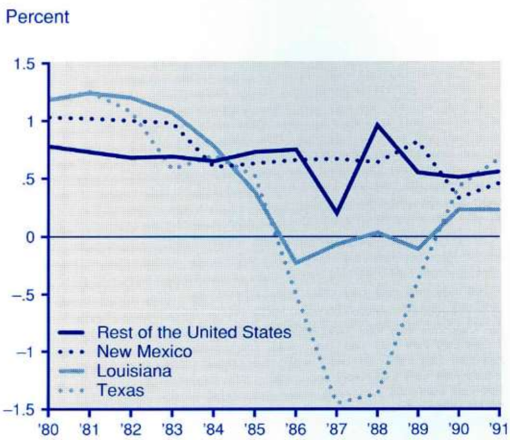
[1] The Eleventh District comprises Texas, northern Louisiana, and southern New Mexico. This article considers the banking industries of these three District states.

profitability shown in Chart 1. Because the years 1985 and 1987 mark high and low points in District economic activity, the early warning models examined later are estimated for both years, and for 1989. These estimates facilitate comparisons of the importance of measures of asset risk in predicting bank failures under different local economic conditions.

In addition to reflecting changes in economic conditions, movements in bank profitability also reflect the underlying composition of banks' portfolios. Chart 3 shows a breakdown of the average loan-to-asset ratio at year-end 1985, before the strong downturn in the regional economy. District banks held a higher average concentration of commercial and industrial loans than banks elsewhere in the nation, together with a greater share of assets in both construction loans and loans backed by commercial real estate. Texas banks, in particular, also held a relatively low proportion of assets in residential real estate loans. The average loan-to-asset ratio was higher for each of the District states than for the rest of the nation.

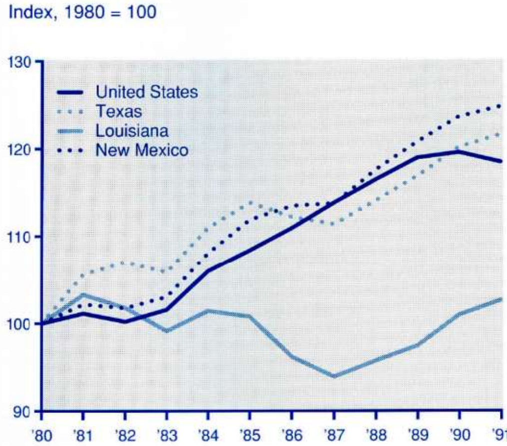
The increase in District states' bank failures that followed the abrupt changes in

**Chart 1**
Return on Assets for Insured Commercial Banks, 1980–91




SOURCE: Report of Condition and Income.

**Chart 2**
Nonagricultural Employment, 1980–91




SOURCE: CITIBASE, Citibank Economic Database.

District bank profitability is shown in Chart 4. Bank failures in Texas and Louisiana mounted rapidly over the decade, peaking in 1989, while bank failures in New Mexico were spread over the mid-1980s and early 1990s. The increase in bank failures, both in the District states and in many other regions in the country, has heightened interest in developing accurate early warning models of bank failures. Early warning models can identify potential problem banks and, thus, help avoid bank failures.

By 1991, District banks' loan portfolios were more evenly divided among the various loan categories than earlier in the decade. While Chart 3 showed that District banks held fairly concentrated loan portfolios in 1985, Chart 5 shows a more diverse composition of the average loan portfolio for banks in the District by the end of 1991. A comparison of Charts 3 and 5 also shows that banks in Texas and Louisiana held a substantially smaller proportion of their assets in loans in 1991 compared with the rest of the nation. The proportion of loans relative to total assets decreased because banks were more cautious in lending, and fewer borrowers sought bank loans. The cautious lending positions reflected additional loan write-downs taken during the period of financial difficulties, and the declining demand for loans reflected the regional economic downturn.

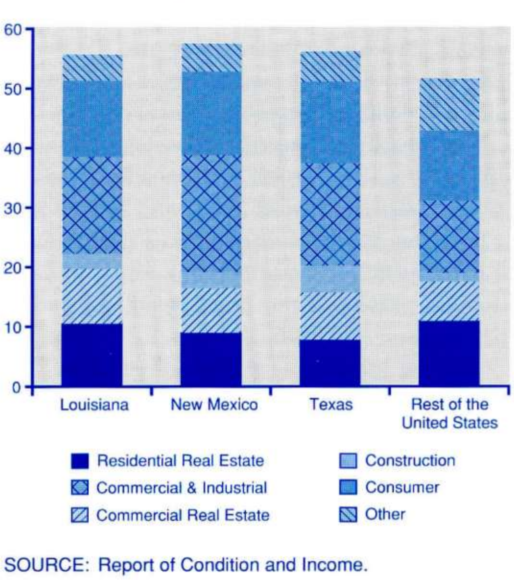
## Shortcomings of Existing Asset Risk Measures

Measures of asset risk are particularly important components of an early warning model, since asset risk can profoundly affect bank survivability. Asset risk measures generally are more forward-looking than other types of explanatory variables and, therefore, may significantly aid in the identification of potential bank failures. A more accurate measure of asset risk also would help bank managers to control risk exposure more effectively.

Bank analysts sometimes quantify asset risk by examining the share of loans or assets in a specific loan category. Users of this method presume that the chosen loan share category contributes substantially to portfolio risk. For example, commercial and industrial loans may be perceived as a particularly risky loan category. Because this method fails to take into account components of the portfolio other than the chosen loan category, it produces an inaccurate assessment of risk.[2]

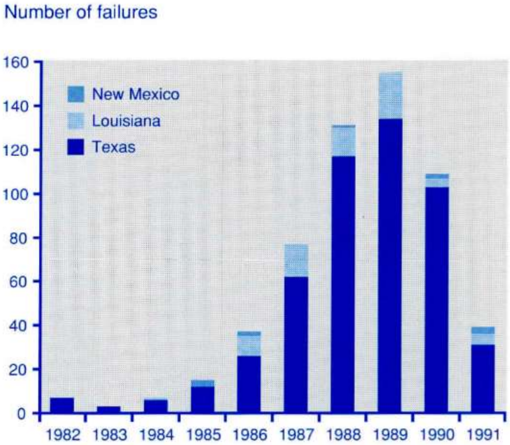
A second approach to measuring bank asset risk by evaluating loan concentrations is known as the *Herfindahl Index*. This index measures asset risk by identifying appropriate loan categories, forming the ratio of each loan category to total assets, and summing the squares of those ratios.[3] The Herfindahl Index method fails to account

**Chart 3**
Average Lending Concentration, 1985




SOURCE: Report of Condition and Income.

**Chart 4**
Bank Failures, 1982–91




NOTE: There were no bank failures in Texas, Louisiana, or New Mexico in 1980 or 1981.

SOURCE: Federal Deposit Insurance Corporation.

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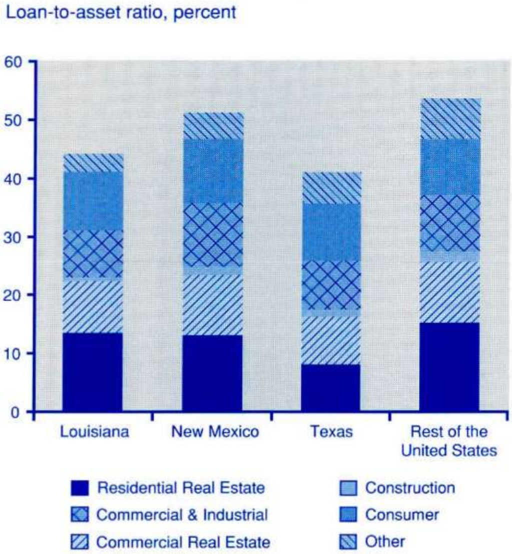
[2] For example, a particular loan category may be risky in the sense that it generates volatile, or unstable, returns, but the movement in those returns may be offset by movements in the returns of another component of the portfolio. In such cases, the return to the overall portfolio may be relatively stable, even though the returns to each component of the portfolio are quite volatile when viewed in isolation.

[3] The formula for this measure is $(\textit{real estate loans to total assets})^2 + (\textit{commercial and industrial loans to total assets})^2 + (\textit{consumer loans to total assets})^2 + (\textit{commercial and industrial loans to total assets})^2 + (\textit{foreign loans to total assets})^2 + (\textit{agricultural loans to total assets})^2 + (\textit{depository institution loans to total assets})^2$. Thomson (1991) demonstrates the use of this measure in an early warning model.

**Chart 5**
Average Lending Concentration, 1991




SOURCE: Report of Condition and Income.

for differing risk levels among the loan share categories. Each loan category is given the same weight, even though risk may differ across categories.[4]

## Finance Theory and Measures of Asset Risk

While no perfectly accurate measure of asset risk exists, finance theory can address some problems. Modern finance theory shows that a portfolio's riskiness depends on both the loan shares in a portfolio and the covariation among the returns to the different shares. Financial analysts considering the riskiness of investments in the stock market often calculate a risk measure called *beta,* derived from finance theory, that accounts for these factors. Of course, any measure of asset risk will suffer from some degree of error, but an understanding of the beta risk measure offers some methods for improving the measurement of asset risk in early warning models of bank failures.

Beta summarizes information about the riskiness of a particular stock that is conveyed by movements in the market-determined price of that stock. Beta measures the covariance of the returns to a particular stock with the returns to the stock market overall.[5] This covariance is relevant because it measures the portion of risk that arises from an individual stock, or the contribution of a particular stock to portfolio risk.[6] For example, consider an investor who holds a portfolio of two stocks. If the returns to both stocks move in tandem with the returns to the stock market overall, then the returns to the portfolio will be volatile, or the portfolio will be risky, because returns to both components of the portfolio will move up or down simultaneously. If, instead, the returns to only one of the stocks parallel the returns to the stock market overall, while the returns to the other stock move inversely with the market, then the returns to the portfolio will be less volatile and the portfolio less risky because changes in the returns offset each other. A portfolio composed of several stocks has a beta that is simply the sum of the betas for the individual investments, weighted by the proportion of the portfolio in each investment.

For bank assets, a beta-type measure can be constructed using beta measures for each asset category. A bank's asset risk is then measured as the sum of these proxy betas, scaled by the corresponding loan shares. Two methods of incorporating these beta risk weights are the nonsample information

[4] For example, a bank with a high concentration of loans in a risky loan category would be identified as having the same level of asset risk as a bank with a high concentration of loans in a less risky loan category.

[5] Formally, beta for investment $i$ is defined by the formula covariance $(R_i R_m)$/variance $(R_m)$, where $R_i$ denotes the returns to investment $i$ and $R_m$ denotes the returns to the market overall. Sharpe (1964) provides a formal derivation of the capital asset pricing model; Copeland and Weston (1988) give a useful exposition of the beta measure.

[6] Beta measures systematic risk, the reaction of an asset to general market movements. A measure incorporating systematic and nonsystematic asset risk, the variance of the portfolio, might be used instead.

method and the in-sample information method.[7]

The nonsample weighting method calculates risk weights from data external to the sample. Each loan share category is matched with a similar industry from the stock market; the beta for this stock market industry serves as a proxy for the loan category's beta. The beta of a bank's loan portfolio is the sum of these individual proxy betas weighted by the proportion of the asset portfolio invested in each loan category. In other words, a bank's portfolio beta is a risk-weighted sum of the loan shares in the portfolio, where the risk weights are betas from related industries.

The different weights on loan shares reflecting their differing riskiness can alternatively be calculated from data within the sample under consideration. This technique requires that each loan share be included as an explanatory variable when the early warning model is estimated. The risk weights will be the coefficients on each loan share in the model after it has been estimated with the sample data.

If the additional information used in the nonsample weighting method is relevant to bank portfolio risk, then an early warning model using the nonsample method should yield better predictions of bank failures than one using the in-sample method. If the additional nonsample information is irrelevant, then this erroneous information biases the results of an early warning model, and the nonsample weighting method would produce less accurate predictions of bank failures than the in-sample method would. For example, the nonsample information may not be helpful if the stock market proxies chosen for the loan categories are inadequate representations of the returns on the actual loans.

While the in-sample weighting measure and the nonsample weighting measure, in theory, improve the measurement of risk, in practice, these measures are subject to errors in implementation just as other measures are. It is important, then, to examine the extent to which these alternate measures actually improve the predictions of estimated early warning models. The next section examines this issue by comparing estimates of early warning models using the in-sample weighting and nonsample weighting asset risk measures with estimates of early warning models using two other measures, the Herfindahl Index and the loan-to-asset ratio.

## Early Warning Model Accuracy

Estimates of the early warning model measure asset risk in four alternate ways to assess their impact on the accuracy of the model. These four methods are the in-sample risk weighting measure, the nonsample risk weighting measure, the Herfindahl Index measure, and the loan-to-asset ratio. For comparison, a fifth version of the model that does not include an explicit measure of asset risk is also estimated; this serves as a benchmark from which the other models can be judged. The box titled "Overview of Early Warning Models" explains the remaining variables used in the early warning models.

The usefulness of an estimated early warning model can be evaluated by examining the model's ability to predict whether a given bank will fail. Two types of errors may arise when an estimated model is used to predict bank failure. First, a bank that actually fails during the time period under consideration may be incorrectly predicted to survive; this is referred to as a *Type I error*. Secondly, a bank that actually survives during the specified time period may be incorrectly predicted to fail; this is a *Type II error*. A Type I error means that the model has faltered in its early warning capacity, since it misclassified a bank that actually failed as one that would not fail; for this reason, a Type I error is often considered the more serious error.

Type I and Type II errors vary inversely

[7] Schaefer (1987) proposes a related risk measure based on finance theory.

## Overview of Early Warning Models

Early warning models provide a framework for analyzing a bank's financial condition. These econometric models estimate the relationship between a set of relevant explanatory variables, such as bank capital, and the likelihood of bank failure. The estimated relationship can then be used to forecast future bank failures. An important measure of the accuracy of an early warning model is the proportion of failed banks that are correctly identified by the model as potential failures.

Most early warning models use a similar set of explanatory variables.[1] The model in this article includes among its explanatory variables proxies for the components of the CAMEL rating used by examiners to evaluate the financial condition of a bank.[2] For the model estimated below, capital adequacy is measured by the ratio of equity capital to assets. Asset quality is measured by the ratio of net charge-offs to total loans.[3] Management expertise is approximated by the ratio of overhead expenses (noninterest expenses) to assets and by the ratio of loans extended to bank officers to assets. Earnings are represented by the ratio of net income to assets, while liquidity is measured by the ratio of cash and securities to assets. Asset risk measures are incorporated in several different ways, as explained in the main article.

Finally, the early warning model includes several additional explanatory variables to control for other influences on bank failures. A dummy variable controlling for the impact of a bank's corporate structure takes on the value of one for a bank holding company, and zero otherwise. The model includes total assets of the bank to account for the possible impact of bank size on failure. Because a bank's access to low-cost funds may be important to its financial condition, the ratio of core deposits to total deposits also is included. The model allows for the impact of local economic conditions by including the percentage change in the county-level annual average per-capita personal income and employment levels.

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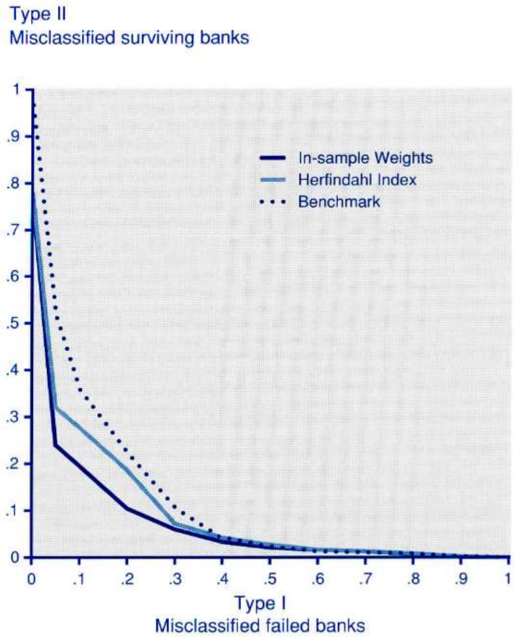
[1] Avery and Hanweck (1984), Pantalone and Platt (1987), Thomson (1991), and Whalen (1991) estimate early warning models using various combinations of the variables mentioned. For a survey of the results of several different models, see Demirguc–Kunt (1989).

[2] CAMEL stands for capital, asset quality, management, earnings, and liquidity.

[3] Estimates of early warning models sometimes use the ratio of nonperforming assets to total assets instead of net charge-offs. Regressions not reported here indicate that this substitution does not qualitatively alter the results.

for an estimated early warning model. Type I error, the proportion of failed banks classified as survivors, falls as Type II error, the proportion of surviving banks classified as failures, rises. Curves depicting this trade-off between the proportions of the two types of errors can be used to compare the accuracy of competing early warning models. Given an acceptable level of Type I error, the model with the lowest Type II error would be preferred. That is, analysts desire early signals about potentially excessive risk exposure in banks, so they want an early warning model with a low Type I error (that correctly identifies a large proportion of the banks that fail); but for a given level of Type I error, analysts prefer a model that correctly classifies more surviving banks than other models do. Generally, one model performs better than another if it produces a curve that fits closer to the graph's axes at each point of the curve; the closer fit of the curve means that one model has lower Type II errors for each level of Type I errors compared with the other model.

**Chart 6**
1985 Model Prediction Errors for Bank Failures, 1986–87




**Accuracy of the 1985 early warning model.** The first sample data set consists of all banks in Louisiana, Texas, and New Mexico in 1985. The model estimates the relationship between the 1985 values of the explanatory variables for the banks and the failure or survival of these banks over the period 1986–87. The risk posture of banks in 1985, as they headed into the economic downturn, would be expected to affect their profitability during the downturn.

Chart 6 shows the trade-off curve between Type I errors and Type II errors associated with different early warning models for the period 1986–87. Because the model's most important function is to predict bank failures correctly, the acceptable Type I error level chosen should be relatively low. Choosing the 5-percent level of Type I error, for example, means that each model correctly identifies 95 percent of the banks that fail. When each model misclassifies only 5 percent of the failed banks, which proportion of the surviving banks does it misclassify? Chart 6 shows that, at the 5-percent level of Type I error, the model using in-sample risk weighting misclassifies 24 percent of the surviving banks, while the model using the Herfindahl Index misclassifies 32 percent of the surviving banks. In comparison, the benchmark model that uses none of the asset risk measures misclassifies 50 percent of the surviving banks. The remaining models produce Type II misclassification rates between 24 percent and 50 percent.[8]

While the in-sample and nonsample risk weight models generate fewer errors than the other models with risk measures, all

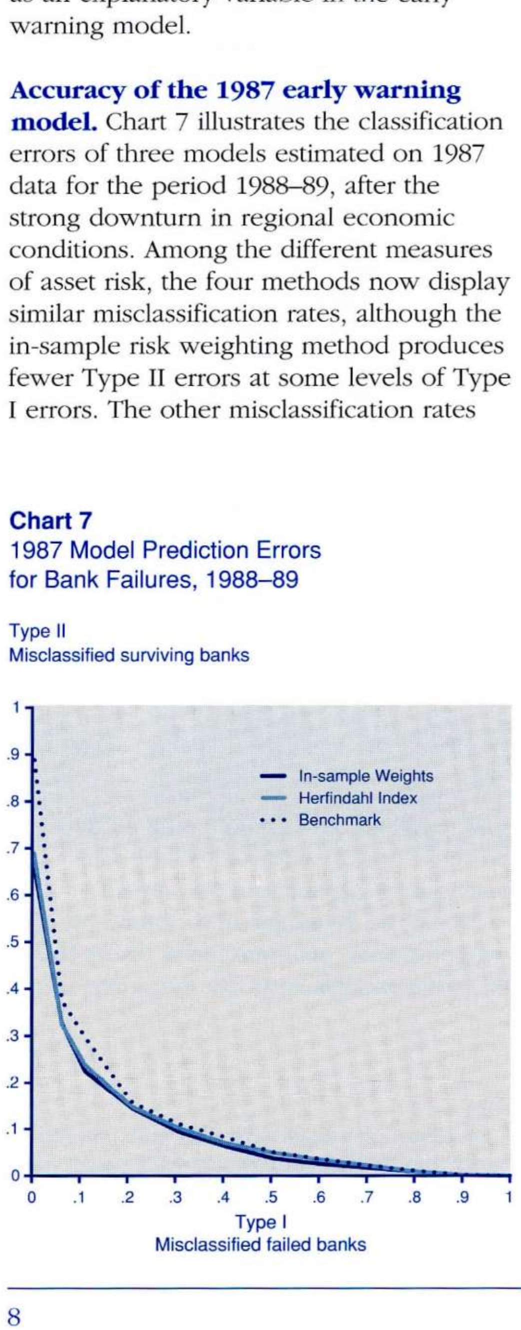
[8] For clarity, each figure depicts the error trade-off curves only for the benchmark model, the most accurate asset risk model, and the least accurate risk model. The Appendix titled "Regression Results" contains tables with prediction errors for each model.

four models that incorporate a risk measure yield fewer prediction errors than the benchmark model. Especially at lower levels of Type I errors, the models for each of the risk measures outperform the benchmark. These results indicate that asset risk measures were important in predicting banking difficulties in the 1986–87 period; errors in predicting bank failures occur more frequently if asset risk is not included as an explanatory variable in the early warning model.

**Accuracy of the 1987 early warning model.** Chart 7 illustrates the classification errors of three models estimated on 1987 data for the period 1988–89, after the strong downturn in regional economic conditions. Among the different measures of asset risk, the four methods now display similar misclassification rates, although the in-sample risk weighting method produces fewer Type II errors at some levels of Type I errors. The other misclassification rates are close in value to those of the benchmark model that does not explicitly incorporate asset risk as an explanatory variable. While asset risk adds substantially to the predictive power of early warning models for 1985, the magnitude of this difference fades when the early warning model is reestimated with 1987 data.

The decrease in the predictive power of asset risk variables indicates that later in the downturn, bank capital levels reflected asset quality problems more completely than earlier. During this later period, past asset risk difficulties were resolved through loan write-downs, so that bank capital ratios incorporated past asset quality problems more fully than measures of current asset risk. The relatively good performance of the benchmark model with the 1987 data indicates that a bank's capital position and other variables are as effective as its asset risk position in explaining a bank's condition during the period 1988–89.

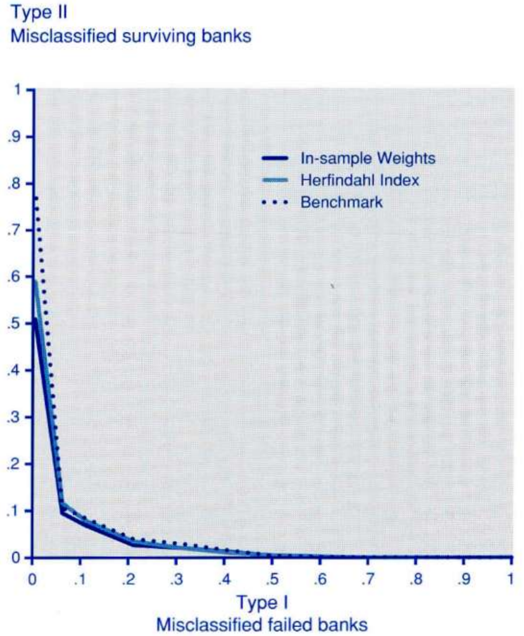
**Chart 7**
1987 Model Prediction Errors for Bank Failures, 1988–89




**Accuracy of the 1989 early warning model.** The decline in the predictive power of asset risk measures persists for the 1989 model estimates. Chart 8 shows the error trade-off curve for early warning models estimated on 1989 values for banks that survived or failed in 1990 and 1991. The benchmark model that does not explicitly include a measure of asset risk performs about as well as the models incorporating asset risk measures. At low levels of Type I error, the Type II errors of the benchmark model are smaller than some of the models with measures of asset risk.

At low levels of Type I error, each 1989 model has notably lower Type II errors than the corresponding 1985 and 1987 models, which indicates that each model generally made more accurate predictions in 1989 than it did in 1985 or 1987. By 1989, the variables included in the early warning models more precisely captured past risk positions than they did in earlier models. Thus, the early warning models based on this information have greater predictive power than the earlier models.

**Chart 8**
1989 Model Prediction Errors
for Bank Failures, 1990–91




Ideally, an early warning model would provide a truly *early* warning of potential problems. Instead, the more accurate predictions of the 1989 models relative to the 1985 and 1987 models imply that these models identify potential bank failures most accurately after the onset of financial difficulties.

In sum, results for the 1985 early warning models confirm that an accurate measure of asset risk is an important component for predicting a bank's financial condition before the significant deterioration in local economic conditions. The better performance of the in-sample and nonsample risk weights for loan shares demonstrates that riskiness should be viewed in terms of the entire bank portfolio, and not in terms of only a few components of the portfolio. In the late 1980s and early 1990s, District banks resolved many of their earlier asset quality problems. As banks recognized troubled assets and wrote off problem loans, measures of capital became more reflective of past risk postures. The early warning models estimated confirm that asset risk measures served as early indicators of banking difficulties, but as asset quality problems were resolved, measures of capital became more important indicators of banking difficulties.

## Conclusion

The results of the early warning models estimated above show that financial difficulties were first reflected in measures of ex ante asset risk, and later in measures of ex post asset risk. In 1985, before the severe regional economic downturn, the best predictors of future bank failures in Eleventh District states include ex ante measures of a bank's asset riskiness. After the downturn had occurred, however, measures of current bank asset risk become less important, and the bank's asset quality and capital position, reflecting past risk positions, become more important.

The lower prediction errors of the 1989 models relative to the 1985 and 1987 models indicate that ex ante measures of asset risk used in the 1985 and 1987 models foreshadow potential bank problems imprecisely. Ex post measures of bank risk-taking improve the predictive power for the 1989 models, but, by their nature, they were reflective of declining banking conditions only after financial difficulties had arisen, and hence do not contribute significantly to early warnings. These results highlight the difficulty early warning models have in providing accurate signals of problems that have not yet emerged.

The imprecision associated with risk predictions based on call report data highlights concerns about the assignment of fixed weights to asset categories for the risk-based capital guidelines. Although it is desirable to assign different weights to different asset categories, the estimates of the early warning models in this article suggest that it is difficult to do so accurately over long periods of time. As the relationship between a given asset category and the probability of bank failure fluctuates over time, the fixed weight on that asset category will at times be appropriate, too low, or too high.[9] Moreover, the asset categories themselves provide only a rough basis for characterizing risk, since a single category can contain assets with differing risk characteristics. Hence, for both bank managers and regulators, the risk weights should be viewed as imperfect guidelines to the degree of bank risk exposure. This technique is only one of many elements used to determine the overall riskiness of a bank.

Fortunately, most banks in the Eleventh District states now are well-positioned to meet the recently imposed risk-based capital guidelines. The return on District banking assets rebounded over the past two years, and the District's bank failure rate subsided. These developments suggest that the severe problems of the late 1980s have been resolved and that banks in the District states are poised for profitable growth.

[9] Bradley, Wambeke, and Whidbee (1991) address some of the difficulties of assigning accurate risk weights under the new risk-based capital guidelines for thrifts.

## Appendix

### Regression Results

This appendix summarizes the estimates of early warning models used in the text to generate the models' prediction error rates.[1] Because the dependent variable for the model is one if the bank fails and zero if it does not fail, the models are estimated using the probit technique instead of ordinary least squares. The models are estimated for 1985, 1987, and 1989.

The estimates of the early warning models indicate that the coefficients generally have their predicted signs. The coefficients on the capital-to-asset ratio and the net-income-to-asset ratio, for example, are both significantly negatively related to the probability of failure. The coefficients on the asset risk variables are positive and sometimes statistically significant. The coefficient on the nonsample risk weights measure is significantly positive in the 1985 model, while the coefficient on the Herfindahl Index measure is not significant in any model. The results of the regressions incorporating the in-sample risk weights show that the coefficients on the separate loan categories vary in sign and magnitude across the 1985, 1987, and 1989 models.

One unexpected coefficient sign is the occasionally significantly negative sign on the ratio of noninterest expenses to assets. Supplementary regressions indicate that the coefficient on the salary-to-asset component of noninterest expenses has a negative sign, while the coefficient on the premise-expenses-to-asset component has the expected positive sign. A second counterintuitive relationship is the significantly negative sign on the ratio of net charge-offs to loans in the 1989 model estimates. This negative relationship is reported in similar estimates of early warning models, like Thomson (1991), and may arise from mismatched timing of these charges with financial difficulties.

Tables A1, A2, and A3 summarize prediction errors for each model; these tables correspond to Charts 6, 7, and 8 in the main text. Each table lists the Type II errors for the models at a given level of Type I errors.

[1] Complete regression results are available from the author upon request.

*(Continued on the next page)*

## Regression Results—*Continued*

**Table A1**
1985 Model Prediction Errors for 1986–87 Bank Failures

| Type I errors (Percentage of misclassified failed banks) | Type II errors (Percentage of misclassified surviving banks) In sample weights | Non sample weights | Herfindahl Index | Loans to assets | Benchmark |
|---|---|---|---|---|---|
| 5 | 24 | 30 | 32 | 29 | 50 |
| 10 | 19 | 24 | 28 | 22 | 35 |
| 30 | 6 | 6 | 7 | 7 | 10 |
| 50 | 2 | 3 | 3 | 2 | 2 |
| 70 | 1 | 1 | 1 | 1 | 1 |
| 90 | 0 | 0 | 0 | 0 | 0 |

**Table A2**
1987 Model Prediction Errors for 1988–89 Bank Failures

| Type I errors (Percentage of misclassified failed banks) | Type II errors (Percentage of misclassified surviving banks) In sample weights | Non sample weights | Herfindahl Index | Loans to assets | Benchmark |
|---|---|---|---|---|---|
| 5 | 33 | 33 | 32 | 30 | 39 |
| 10 | 22 | 24 | 24 | 25 | 29 |
| 30 | 9 | 10 | 10 | 10 | 11 |
| 50 | 4 | 5 | 5 | 4 | 5 |
| 70 | 2 | 2 | 2 | 2 | 2 |
| 90 | 0 | 0 | 0 | 0 | 0 |

**Table A3**
1989 Model Prediction Errors for 1990–91 Bank Failures

| Type I errors (Percentage of misclassified failed banks) | Type II errors (Percentage of misclassified surviving banks) In sample weights | Non sample weights | Herfindahl Index | Loans to assets | Benchmark |
|---|---|---|---|---|---|
| 5 | 9 | 13 | 12 | 11 | 12 |
| 10 | 7 | 7 | 8 | 8 | 6 |
| 30 | 2 | 2 | 2 | 2 | 3 |
| 50 | 0 | 1 | 0 | 0 | 0 |
| 70 | 0 | 0 | 0 | 0 | 0 |
| 90 | 0 | 0 | 0 | 0 | 0 |

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# Banking Difficulties and Discount Window Operations:

## *Is Monetary Policy Affected?*

Kenneth J. Robinson
Senior Economist

Financial Industry Studies Department
Federal Reserve Bank of Dallas

An important function of the Federal Reserve at its inception in 1913 was to serve as lender of last resort. This role relates to the question of how a central bank should respond to financial crises. In particular, under what conditions should the Fed provide liquidity to the financial system to avert widespread financial panics? The classic treatment of this lender-of-last-resort function can be traced to the writings of Henry Thornton in *An Enquiry into the Nature and Effects of the Paper Credit of Great Britain*, published in the early nineteenth century, and Walter Bagehot's definitive work, *Lombard Street*, published in 1873. Bagehot summed up what is required of a lender of last resort: "Theory suggests, and experience proves, that in a panic the holders of the ultimate Bank reserves should lend to all that bring good securities quickly, freely, and readily."

The Federal Reserve System has carried out its lender-of-last-resort responsibilities primarily through its discount window operations.[1] Federal Reserve advances to depository institutions are grouped into three broad categories. *Adjustment credit* represents short-term loans extended to depository institutions when other sources of funds "...are not reasonably available and when the need for credit is appropriate. Guidelines for administering adjustment credit are fairly general, in recognition of the wide range of circumstances that may give rise to borrowings by institutions that differ in size, in the nature of their business, and in the economic environments in which they operate."[2]

The second category of discount window advances is *seasonal credit*, which is available to depository institutions of relatively small size that generate a clear pattern of recurring swings in funding needs. The Federal Reserve established the seasonal program in the early 1970s because of some small banks' lack of access to national money markets. Under this program, institutions "may obtain longer-term funds from the discount window during periods of seasonal need so they can carry fewer liquid assets during the rest of the year and can make more funds available for local lending."[3]

The third category of discount window loans is known as *extended credit*. Extended credit is issued to depository institutions experiencing "...special difficulties arising from exceptional circumstances or practices involving individual institutions or from liquidity strains affecting a broad range of depository institutions."[4] The extended credit category of discount window advances most closely approximates central bank operations under the traditional concept of lender of last resort.

While the lender-of-last-resort function remains vital, the most essential role of the central bank today can be found in its monetary policy objectives. That is, the

[1] The Federal Reserve could also carry out its lender-of-last-resort function through open market operations. Before 1980, discount window advances were available only to banks that were members of the Federal Reserve System. Since passage of the Depository Institutions Deregulation and Monetary Control Act of 1980, all depository institutions are eligible for discount window loans.

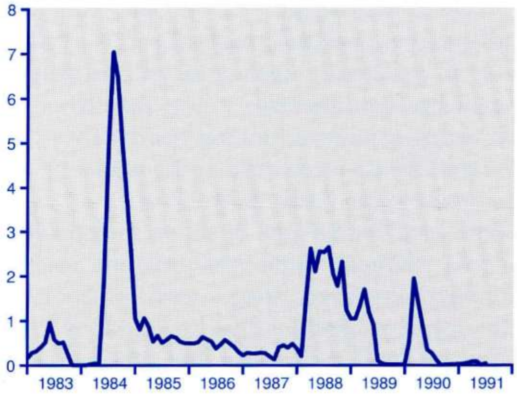
[2] Federal Reserve System, 1990.

[3] Federal Reserve System, 1990.

[4] Federal Reserve System, 1990.

**Chart 1**
Extended Credit

Billions of dollars




SOURCE: CITIBASE, Citibank Economic Database.

central bank is also charged with the responsibility of controlling the growth of the nation's money supply. The exercise of lender-of-last-resort responsibilities to cope with liquidity needs could lead to a temporary abrogation of these monetary policy responsibilities. Repeated bank and thrift failures in the 1980s resulted in the more frequent use of extended credit. Extended credit, in effect, adds to bank reserves, and, thus, can potentially alter the course of monetary policy. "Because there is not the same need to repay such borrowing promptly as there is with traditional short-term adjustment credit," the *Federal Reserve Bulletin* states, "the money market impact of extended credit is similar to that of nonborrowed reserves."[5] Thus, as Bagehot stressed, any liquidity assistance by the central bank should be short-term in nature, mainly to ensure that the effect on monetary policy goals is inconsequential.[6] Humphrey (1975, 4) points out, though, that a conflict between lender-of-last-resort and monetary policy goals is not inevitable:

> There need be no conflict between the monetary control and lender of last resort functions, however, since the first refers to the long run and the second to temporary periods of emergency. If the central bank, in its role as lender of last resort, responds appropriately to the threat of a liquidity crisis, the panic will be averted quickly. Consequently, the deviation of the money stock from its long-run target path will be small, both in magnitude and duration.

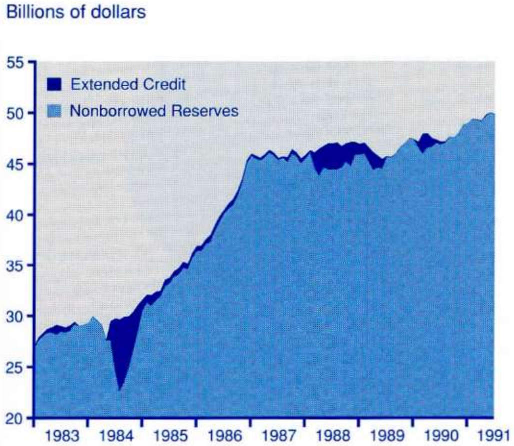
The issue of interest in this article is whether the Federal Reserve's role as lender of last resort has affected its role in controlling the nation's money supply. To examine this issue, the behavior of extended credit is analyzed from November 1982 through July 1991. I chose this period because extended credit was issued very infrequently before November 1982, since financial-sector difficulties were relatively rare. The November 1982 to July 1991 period includes a time of consistent Federal Reserve operating procedures—mainly the borrowed-reserves operating regime.[7] Empirical results suggest that the Federal Reserve's role as lender of last resort did not alter the course of monetary policy—whether measured by movements in interest rates or by movements in the money supply. Before examining these results, I offer some background on the Federal Reserve's use of extended credit in the next section. Then, I describe the statistical techniques used to judge the potential conflict between lender-of-last-resort and monetary policy

[5] See *Federal Reserve Bulletin*, notes to RESERVES AND BORROWINGS, Depository Institutions Table.

[6] This article focuses on the narrow category of extended credit. For more on the role and functions of lender of last resort, see Humphrey (1975) and Garcia and Plautz (1988).

[7] Before the early 1980s, extended credit was, for the most part, not issued. The exception was in 1974, when extended credit increased sharply. While individual institutions are not identified as recipients of extended credit, the timing of this spike in extended credit coincided with the difficulties of the Franklin National Bank.

**Chart 2**
Nonborrowed Reserves and Extended Credit




SOURCE: CITIBASE, Citibank Economic Database.

objectives, and I present the results. The final section offers conclusions from and policy implications of these findings.

## The Federal Reserve's Use of Extended Credit

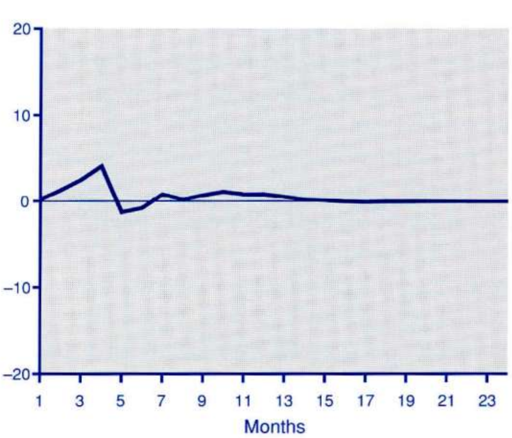
Under the Federal Reserve's Regulation A, extended credit is available to banks and other depository institutions when similar assistance is not readily available from other sources and where exceptional circumstances or practices are adversely affecting an individual depository institution. Regulation A states, "Exceptional circumstances would include situations where an individual depository institution is experiencing financial strains arising from particular circumstances or practices affecting that institution—including sustained deposit drains, impaired access to money market funds, or sudden deterioration in loan repayment performance." Applicants for extended credit are required to make full use of other reasonably available sources of funds, including special industry lenders before turning to the discount window. Furthermore, to ensure effective coordination, requests for extended credit will be reviewed jointly by the Federal Reserve and other responsible supervisory agencies. Finally, Federal Reserve assistance is provided only if a plan for eliminating the institution's liquidity shortfall is in place or is being worked out with the Federal Reserve and other relevant authorities. An interest rate above the basic discount rate may be applied to loans made under other extended credit, subject to review and determination by the Board of Governors.[8]

Provisions of extended credit can affect monetary policy because they can affect the amount of total reserves outstanding. Total reserves are the sum of borrowed reserves, which include extended credit, and nonborrowed reserves, which are supplied by open market operations. On average, extended credit is a very small component of total reserves—less than 3 percent. However, extended credit tends to be very volatile. In fact, extended credit exhibits roughly forty times more volatility than does the category of nonborrowed reserves.[9] Chart 1 shows movements in extended credit over the period of this analysis. While individual borrowers are not publicly identified as recipients of extended credit, the timing of sudden swings

[8] Title 1 of The Federal Deposit Insurance Corporation Improvement Act of 1991 places limits on Federal Reserve discount window advances to undercapitalized insured depository institutions. The Federal Reserve can now lend to an undercapitalized institution for a maximum of sixty days in any 120-day period. Discount window loans to undercapitalized institutions may exceed this limit provided that the institution's regulator or the chairman of the Federal Reserve certifies the institution's viability. Lending to undercapitalized institutions could continue beyond sixty days without this certification, but the Federal Reserve would be exposed to potential losses from such loans. A similar set of criteria applies to Federal Reserve loans to critically undercapitalized institutions that extend for more than five days. These discount window provisions are effective two years after date of enactment of the legislation.

[9] Volatility here is expressed in terms of standard deviations. The standard deviation of changes in extended credit is 90.2, while the standard deviation of changes in nonborrowed reserves is 2.4.

**Chart 3**
Response of Federal Funds Rate
to Movements in Extended Credit




SOURCE: CITIBASE, Citibank Economic Database.

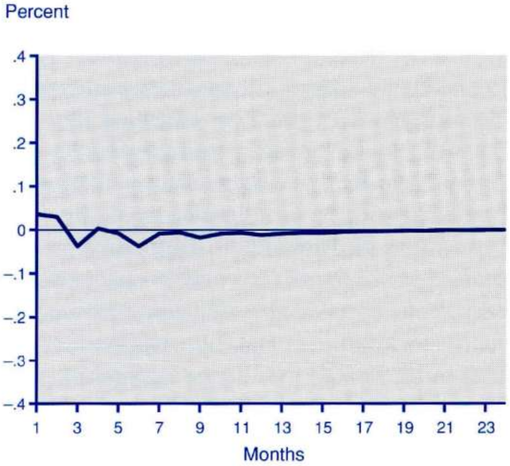
in extended credit suggests three possibilities: that the big spike in extended credit in 1984 corresponded to the difficulties associated with Continental Illinois National Bank, that the run-up in extended credit in the late 1980s coincided with banking difficulties in Texas, and that the greater use of extended credit in 1990 coincided with banking difficulties in New England.

Provisions of extended credit add to total reserves but do not necessarily alter the course of monetary policy. The Federal Reserve can adjust its open market operations to offset the provision of extended credit. Open market operations affect the supply of nonborrowed reserves and are undertaken to keep monetary policy on course. If the amount of extended credit increases, then the provision of nonborrowed reserves through open market operations would be reduced correspondingly. However, the volatility of extended credit over very short periods of time could conceivably make it more difficult for the monetary authorities to achieve the desired level of nonborrowed reserves plus extended credit, thereby providing the potential for conflict between the lender-of-last-resort and monetary policy functions. Chart 2 (on previous page) shows that the Federal Reserve attempted to offset the provision of extended credit with reductions in the supply of nonborrowed reserves. During those periods of rapid growth in extended credit, nonborrowed reserves appeared to shrink. More formal statistical tests are available to determine if the Federal Reserve was successful in these defensive open market operations.

## The Lender of Last Resort and Monetary Policy: Is There A Conflict?

The policy variables I analyzed to judge the effect on monetary policy that arises from the provision of extended credit are movements in the federal funds rate and the narrow monetary aggregate, M1.[10] This combination allows me to judge the effect of the volatility of extended credit on both interest rates and a particular measure of the money supply. I chose the federal

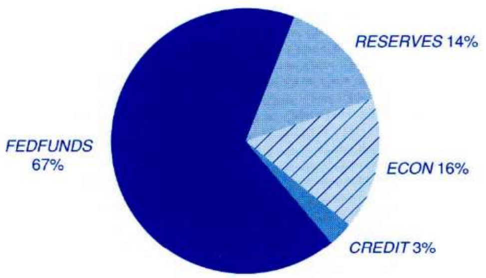
**Chart 4**
Response of M1 Growth
to Movements in Extended Credit




SOURCE: CITIBASE, Citibank Economic Database.

[10] M1 consists mainly of currency plus checking accounts.

**Chart 5**
Forecast Error in Predicting Federal Funds Rate




SOURCE: CITIBASE, Citibank Economic Database.

funds rate because a regime of targeting borrowed reserves can be viewed as a variation on a federal funds rate targeting procedure.[11] Although the Federal Reserve now sets target ranges for the broad monetary aggregate, M2, I chose the narrow monetary aggregate because this measure of the money supply tends to be more closely related to reserve growth than are the broader monetary aggregates since the major components of M1 are subject to reserve requirments.[12] In the statistical analysis, the investigation centers on what *independent* effect movements in extended credit exerted on both the federal funds rate and M1. To accomplish this task, it is necessary to control for other factors that might have affected these variables. These other factors include the supply of nonborrowed reserves, economic activity, and prior movements in the funds rate and M1 themselves.[13]

Charts 3 and 4 show what happens over time to the federal funds rate and M1 growth from shocks or innovations in extended credit, again after accounting for reserves, economic activity, and previous movements in the funds rate and in M1. Neither the federal funds rate nor the narrow monetary aggregate appears to be affected by movements in extended credit. Chart 3 shows that changes in extended credit caused, at most, about a four-basis-point increase in the federal funds rate. Chart 4 shows that changes in extended credit led to, at most, less than a one-tenth-of-one-percent increase in M1. These results indicate that the Federal Reserve was successful in not allowing its role of lender of last resort to conflict with its monetary policy objectives.

Another gauge of the impact of extended credit on monetary policy can be found in Charts 5 and 6. These charts show how much of the error in predicting both the federal funds rate and M1 results from shocks in extended credit and in the other potential influences on these variables. As evident in Chart 5, only 3 percent of the prediction error in the federal funds rate can be explained by shocks or innovations in extended credit, while from Chart 6 only 2 percent of the error in forecasting M1 is accounted for by the volatility in extended credit. Past innovations in the federal funds rate and M1 themselves account for most of the errors in trying to forecast these variables. This is often the case with economic variables that are highly correlated over time, as both of these variables are.

## Conclusions

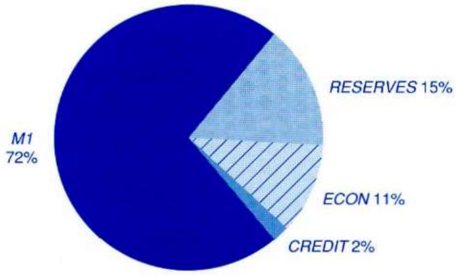
Inherent in a fractional-reserve banking system is the potential for liquidity problems

[11] For more on this procedure, see Thornton (1988).

[12] See Gilbert (1992).

[13] More formally, a four-variable vector autoregression (VAR) is estimated. VARs are atheoretical dynamic models that use only the observed time series properties of the data to test formally theories that imply particular behavior of the variables in the model. To investigate whether defensive open market operations completely offset issues of extended credit, Butkiewicz and Lewis (1991) estimate a bivariate VAR model that includes only measures of reserves. These authors find that the Federal Reserve does offset its use of extended credit with defensive open market operations. For more on the VAR model estimated in this article, see the Appendix, "A Vector Autoregression Model of Extended Credit."

**Chart 6**
Forecast Error in Predicting M1




SOURCE: CITIBASE, Citibank Economic Database.

to develop at banks and other depository institutions, if financial difficulties emerge. The Federal Reserve's role as lender of last resort represents a vital central bank function needed to ensure the stability of the banking system. A lender of last resort stands ready to avert potential panics by providing reserves to banks experiencing liquidity pressures. The central bank's role of lender of last resort, though, could conflict with its monetary policy objectives. Evidence presented here suggests that the Federal Reserve's responsibility for providing emergency liquidity to financial institutions did not conflict with its role in conducting monetary policy. The Federal Reserve was successful in mitigating the effect on reserves when providing liquidity to troubled depository institutions. Neither the federal funds rate nor the money supply was significantly affected by shocks to extended credit. These results suggest that efforts to deal with the banking difficulties of the past decade proceeded without significantly altering the course of monetary policy.

## Appendix

### A Vector Autoregression Model of Extended Credit

To determine whether the Federal Reserve's lender-of-last-resort function conflicted with its monetary policy goals, two vector autoregression (VAR) models were estimated. *VAR models* are atheoretical models that use only the observed time series properties of the data to study relationships among different economic variables. The results in this article are derived from two VAR models, one that captures the effect of extended credit on the federal funds rate and the other that captures how extended credit may have affected M1. Because it is necessary to control for other factors that might affect the federal funds rate and the money supply, each VAR contains four variables. In addition to including extended credit and the policy variable of interest (either the federal funds rate, or M1), each model includes a measure of economic activity, as well as the amount of reserves supplied by the Federal Reserve through its open market operations. These variables are present because they can also affect the path of interest rates and the money supply. The VAR models estimated are

(A1) *[ECON CREDIT FEDFUNDS RESERVES]*

and

(A2) *[ECON M1 CREDIT RESERVES],*

where *ECON* is the Industrial Production Index, *CREDIT* is extended credit, *FEDFUNDS* is the federal funds rate, *RESERVES* is the amount of nonborrowed reserves, and *M1* is the narrow monetary aggregate. Monthly data for all variables were obtained from CITIBASE.[1] Unit root tests indicated that all variables were nonstationary in their levels, indicating that each series contained one unit root. Tests for the presence of co-integration along the lines suggested in Engle and Yoo (1987) revealed that co-integration is not indicated in the models estimated. Finally, a test for appropriate lag length, described in Sims (1980) suggested the use of relatively short lag lengths for the VARs. Therefore, the VAR models were estimated as

(A1.1)
$$ECON_t = \beta_0 + \sum_{i=1}^{4} \beta_i ECON_{t-i} + \sum_{i=1}^{4} \beta_{i+4} FEDFUNDS_{t-i}$$
$$+ \sum_{i=1}^{4} \beta_{i+8} RESERVES_{t-i} + \sum_{i=0}^{4} \beta_{i+13} CREDIT_{t-i} + \varepsilon_{1t}.$$

[1] The use of monthly averages of daily figures for extended credit could overstate the volatility of extended credit. Under a regime of targeting borrowed reserves, extended credit can be treated like nonborrowed reserves in determining the needed volume of open market operations. That is, the projected demand for total reserves minus a targeted level for borrowed reserves equals the sum of nonborrowed reserves plus extended credit that must be supplied. A better measure of the volatility of extended credit would be the daily volatility of such credit, particularly late in each reserve maintenance period. Such data are not publicly available, however.

*(Continued on the next page)*

## **Appendix**—*Continued*

### A Vector Autoregression Model of Extended Credit

(A1.2)
$$CREDIT_t = \alpha_0 + \sum_{i=1}^{4} \alpha_i CREDIT_{t-i} + \sum_{i=1}^{4} \alpha_{i+4} ECON_{t-i}$$
$$+ \sum_{i=0}^{4} \alpha_{i+9} FEDFUNDS_{t-i} + \sum_{i=0}^{4} \alpha_{i+14} RESERVES_{t-i} + \varepsilon_{2t}.$$

(A1.3)
$$FEDFUNDS_t = \delta_0 + \sum_{i=1}^{4} \delta_i FEDFUNDS_{t-i} + \sum_{i=1}^{4} \delta_{i+4} ECON_{t-i}$$
$$+ \sum_{i=0}^{4} \delta_{i+9} CREDIT_{t-i} + \sum_{i=0}^{4} \delta_{i+14} RESERVES_{t-i} + \varepsilon_{3t}.$$

(A1.4)
$$RESERVES_t = \xi_0 + \sum_{i=1}^{4} \xi_i RESERVES_{t-i} + \sum_{i=1}^{4} \xi_{i+4} ECON_{t-i}$$
$$+ \sum_{i=0}^{4} \xi_{i+9} CREDIT_{t-i} + \sum_{i=0}^{4} \xi_{i+14} FEDFUNDS_{t-i} + \varepsilon_{4t}.$$

and

(A2.1)
$$ECON_t = a_0 + \sum_{i=1}^{4} a_i ECON_{t-i} + \sum_{i=1}^{4} a_{i+4} RESERVES_{t-i}$$
$$+ \sum_{i=1}^{4} a_{i+8} M1_{t-i} + \sum_{i=0}^{4} a_{i+13} CREDIT_{t-i} + e_{1t}.$$

(A2.2)
$$M1_t = b_0 + \sum_{i=1}^{4} b_i M1_{t-i} + \sum_{i=1}^{4} b_{i+4} ECON_{t-i}$$
$$+ \sum_{i=0}^{4} b_{i+9} RESERVES_{t-i} + \sum_{i=0}^{4} b_{i+14} CREDIT_{t-i} + e_{2t}.$$

(A2.3)
$$CREDIT_t = d_0 + \sum_{i=1}^{4} d_i CREDIT_{t-i} + \sum_{i=1}^{4} d_{i+4} ECON_{t-i}$$
$$+ \sum_{i=0}^{4} d_{i+9} RESERVES_{t-i} + \sum_{i=0}^{4} d_{i+14} M1_{t-i} + e_{3t}.$$

(A2.4)
$$RESERVES_t = g_0 + \sum_{i=1}^{4} g_i RESERVES_{t-i} + \sum_{i=1}^{4} g_{i+4} ECON_{t-i}$$
$$+ \sum_{i=0}^{4} g_{i+9} CREDIT_{t-i} + \sum_{i=0}^{4} g_{i+14} M1_{t-i} + e_{4t}.$$

Qualitatively identical results were obtained when a maximum of two lags of each variable were included in the models. Also, since the ordering of the variables in the VAR can affect the results, different specifications of Models A1 and A2 were estimated. The results were not sensitive to the ordering of the variables. Charts 3 and 4 are the impulse functions calculated from the VAR models, while Charts 5 and 6 are the two-year-ahead squared prediction errors, or the variance decompositions, derived from models A1 and A2.

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