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The Use of Market Information in Bank Supervision: Interest Rates on Large Time Deposits

R. Alton Gilbert
Research Department
Federal Reserve Bank of St. Louis
P.O. Box 442
St. Louis, MO 63166
314-444-8559
gilbert@stls.frb.org

Andrew P. Meyer
Banking Supervision and Regulation
Federal Reserve Bank of St. Louis
P.O. Box 442
St. Louis, MO 63166
314-444-4647
ameyer@stls.frb.org

Mark D. Vaughan
Banking Supervision and Regulation
Federal Reserve Bank of St. Louis
P.O. Box 442
St. Louis, MO 63166
314-444-8859
mark.vaughan@stls.frb.org

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Abstract

In theory, information from the prices of bank claims could be used as a complement to off-site surveillance in bank supervision. Unfortunately, the vast majority of banks do not issue claims that are actively traded in secondary markets. These banks do rely heavily on one type of claim that is sensitive, at least to some degree, to bank risk: jumbo CDs. Indeed, the Federal Deposit Insurance Corporation Improvement Act of 1991 (FDICIA) was designed to impose more of the cost of failures on this class of claimants.

We construct an accounting proxy for the default premiums on jumbo CDs that we use to rank banks by the probability that they will experience serious financial problems during future periods. We compare the accuracy of this ranking of banks to a ranking of banks derived from a conventional early warning model. We find that the predictive power of the default premiums on bank CDs is much less than the predictive power of the traditional early warning model.

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1. Introduction

For the past few years, bank supervisors have been considering various means of incorporating market information into supervision. One of the ideas currently receiving a lot of attention in the U.S. would require large banks to issue subordinated debt (Board of Governors, 2000; Kwast, et al, 1999; Meyer, 1999). Advocates of proposals for mandatory subordinated debt argue that investors have information about the risk assumed by banks that is not available to bank supervisors. If investors think that a bank has a relatively high probability of failing, market yields on its subordinated debt would be relatively high, and the bank might not be able to re-issue its subordinated debt when some of it matures. The supervisors could benefit from the information available to investors by monitoring the yields on bank subordinated debt in the secondary markets and observing whether banks re-issue their subordinated debt when it matures. Some proposals would require bank supervisors to take prompt corrective actions based on various indicators of financial distress of banks from the market for their subordinated debt (Evanoff and Wall, forthcoming; and U.S. Shadow Financial Regulatory Committee, 2000).

Recent proposals to enhance the use of market information by supervisors focus on large banking organizations, for the following reasons. The challenges for supervisors of measuring the risk assumed by individual banks using their traditional methods tend to be greatest for the largest banks. In addition, market information on the prices of bank equity and debt are not available for relatively small banking organizations because are usually not publicly traded.

We investigate whether a measure of the interest rates that banks pay on uninsured deposits that can be derived from the quarterly call reports would be useful for surveillance between bank examinations. Uninsured deposits exceed the insurance limit of $100,000 per account. The call reports include the amount of interest that a bank pays on large denomination time deposits each quarter and the average amount of large time deposits over the quarter. Interest paid as a percentage of deposits is the average interest rate that a bank paid on large time deposits during the quarter. We adjust this percentage for the maturity of the time deposits because banks tend to pay higher rates on deposits with longer maturity.

Interest rates on the large time deposits of banks will reflect the risk assumed by the banks only if the depositors think their funds are at risk. The percentage of bank failures in which uninsured depositors lost at least part of their funds rose substantially after passage of the Federal Deposit Insurance Corporation Improvement Act of 1991 (FDICIA), which required the FDIC to resolve cases of bank failure in the manner that would be least costly to the deposit insurance fund (Benston and Kaufman, 1998). Thus, since the early 1990s uninsured depositors have had reason to believe that they would lose at least part of their funds if their banks fail. In addition, there is evidence that the interest rates on large time deposits have become more sensitive to the risk assumed by banks since passage of FDICIA. Hall, King, Meyer and Vaughan (2000) found that a measure of the average interest rate that banks pay on large time deposits derived from the call reports, adjusted for the maturity of the deposits, became slightly more sensitive to measures of risk after 1991.[1] If uninsured depositors have information about the risk

[1] They also find that the *levels* of large time deposits are more sensitive to risk than the cost of funds in the post-FDICIA era. That is, a deposit outflow is more likely than a change in risk premiums in response to

assumed by banks that is not available to the supervisors, the measure of interest rates on large time deposits derived from the call reports might help supervisors predict which banks will experience serious problems in the future.

This paper uses an early warning model to reflect the information available to the supervisors about the condition of banks from the call reports. We compare the ability of the measure of interest rates on large time deposits derived from the call reports and the early warning model to predict which banks will develop serious problems in future periods. We also investigate whether the measure of interest rates on large time deposits would improve the predictive power of the early warning model.

2. Measuring Interest Rates on Large Time Deposits

The ideal measure of depositors' perceptions of bank risk would be the interest rates that banks pay on newly issued large time deposits or the interest rates on the large time deposits in secondary markets. This information, however, is available for only a small percentage of all banks. In keeping with our goal of obtaining the widest possible coverage of banks, we must turn to a somewhat crude proxy for these interest rates.

Interest paid as a percentage of deposits, the measure of interest rates in this study, is an imprecise measure of depositors' perception about the risk assumed by a bank. This percentage reflects the interest rates that a bank paid on its time deposits issued recently and in the past, and interest rate paid on deposits with short and long periods to maturity. Thus, the measure is inherently backward-looking and slow to

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increased risk in a bank. A future extension of this paper will be an exploration of the predictive power of deposit outflows on future bank distress.

respond to changes in current risk and rates on newly-issued CDs. Nevertheless, the usefulness of the measure as a prediction tool is an empirical issue.

We adjust the average interest rate on large time deposits for time to maturity using data from the call reports on the distribution of large time deposits in the following ranges by remaining maturity:[2]

a. Less than three months.
b. Three months to one year.
c. One year to five years.
d. Over five years.

The data on deposits in these ranges for remaining maturity are not ideal for an adjustment of the average interest rate on large time deposits for maturity. Deposits with short remaining maturity in the current period may include deposits issued several years ago with long maturity. These data on remaining maturity, however, are all we have available for making adjustments for the maturity of time deposits.

We make this adjustment by estimating the regression equations in Table 1. The dependent variable in each equation is interest paid on large time deposits in the fourth quarter of each year divided by the average level of large time deposits over the quarter, multiplied by four to derive an annual rate of interest. The model for each year includes an intercept and the following three independent variables:

3 TO 12 -- percentage of large time deposits with remaining maturity between three months and one year.

12 TO 60 -- percentage of large time deposits with remaining maturity between one year and five years.

OVER 60 -- percentage of large time deposits with remaining maturity over five years.

The coefficient on the intercept provides a measure of the average interest rate on large time deposits with remaining maturity less than three months. The coefficient on the intercept plus the coefficient on 3 TO 12 is an estimate of the average interest rate paid on deposits with remaining maturity between three months and one year. The coefficient on the intercept plus the coefficient on 12 TO 60 is an estimate of the average interest rate paid on deposits with remaining maturity between 12 months and five years. The coefficient on OVER 60 has a comparable interpretation.

The signs and magnitudes of the regression coefficients in Table 1 have reasonable values for a model of interest rates on large time deposits. Although the overall explanatory power of each equation is low, the F statistic for the combined explanatory power of the independent variables is significant each year. Estimates of the intercept tend to change with market yields on three-month CDs but reflect the lagged effects of changes in interest rates over time. For instance, the intercept for the fourth quarter of 1991 (5.72 percent) is substantially above the secondary market yield on three-month CDs that quarter (4.91 percent). Because interest rates were lower in the fourth quarter of 1991 than in several prior quarters, the large time deposits with remaining maturity less than three months in the fourth quarter of 1991 included deposits that banks had issued in prior quarters at relatively high interest rates. The signs of the coefficients on the independent variables are consistent with a pattern of higher interest rates on large time deposits with longer maturity.

3. CD Yields as a Supervisory Screen

[2] Call report data on large denomination time deposits changed after 1995. Because of these changes, the data on the interest rates that banks paid on large time deposits in this paper ends in 1995.

In this section we investigate whether the average interest rates that banks pay on large time deposits would serve as a useful screen for identifying the banks most likely to have their supervisory ratings downgraded to problem status in future periods. Supervisors use several screens in surveillance in addition to the predictions of econometric models to identify the banks that should receive relatively close supervision.

We use the residuals of the regression equations in Table 1 as our measure of the risk premium embodied in the interest rates on large time deposits. The residual for an individual bank equals the average interest rate that the bank paid on large time deposits in a quarter minus an estimate of the average rate paid by all banks with the same distribution of large time deposits by remaining maturity. Banks with the largest positive residuals are assumed to be the most risky because they have to pay relatively high interest rates on large time deposits.

The event we want to predict is downgrades of CAMELS composite ratings from 1 or 2 (safe and sound) to 3-5 (problem banks status). Supervisors assign CAMELS composite ratings to banks after examining them. Table 2 interprets the CAMELS composite ratings of 1 through 5. Table 3 indicates that substantial numbers of banks were downgraded to problem status during each year in our sample. We compare the accuracy of downgrade predictions for each of the years 1993 through 1997 based on the residuals of the equations in Table 1 and an early warning model.

We illustrate the predictions of CAMELS downgrades in Figure 1 for the year 1993. The sample of banks for measuring the accuracy of downgrade predictions in 1993 is limited to banks that were rated CAMELS 1 or 2 as of March 1992. These banks were not downgraded to CAMELS 3-5 during April through December 1992 and were examined at least once during 1993. We restrict this sample to banks that were examined during 1993 because supervisors generally change CAMELS ratings after examinations. A bank that was in relatively poor condition during 1993 might have avoided being downgraded to problem status that year if it was not examined.

We use the residuals of the regression equation from Table 1 for the fourth quarter of 1991 to predict which of the banks in the sample will be downgraded to problem status during 1993. We quantify the predictive power of these regression residuals by using figures for the tradeoff of type-1 and type-2 error rates like those in Cole, Cornyn and Gunther (1995). The type-1 error rate is the percentage of downgrades that we fail to predict, while the type-2 error rate is the percentage of healthy banks that we identify incorrectly as downgrade risks. We call the curve that traces out the trade-off of type-1 and type-2 error rates a "power curve." Each power curve tells us the type-1 error rate we must accept for any given type-2 error rate.

The curvature of the power curves provides a basis for comparing the performance of alternative models. We can simultaneously achieve lower type-1 and type-2 error rates using the model with the power curve nearer the origin. A convenient way to quantify the deviation of a power curve from the origin is to calculate the area under the curve as a percentage of all of the area in the box where the power curves are presented. The smaller the area under a power curve, the more accurate the predictions. A useful benchmark is the case in which the banks predicted to be downgraded in the future are selected at random rather than through use of a screen or model. This procedure would produce a power curve with a slope of approximately negative one, starting at the 100 percent type-1 error rate and extending to the 100 percent type-2 error rate. The area under this curve would be approximately 50 percent of the area in the entire box.

The power curve in Figure 1 that is derived from the residuals of the first regression in Table 1 is labeled the CD Spread Model. We derive a power curve for the CD Spread Model by adjusting the number of banks predicted to have their CAMELS ratings downgraded and calculating the type-1 and type-2 error rates. At one extreme, all banks are rated as unlikely to be downgraded. The type-1 error rate would be 100 percent because all of the downgrades would be recorded as errors. The type-2 error rate would be zero because each bank that was not downgraded would be included among those predicted to not be downgraded. Next we assume that the bank with the largest positive residual from the equation in Table 1 for the fourth quarter of 1991 is the one bank predicted to be downgraded during 1993. We calculate the type-1 and type-2 error rates with this one bank predicted to be downgraded. Then we calculate the type-1 and type-2 error rates with the two banks with the largest positive residuals as the only banks predicted to have their CAMELS ratings downgraded to problem status in 1993. We keep adding banks to the group predicted to be downgraded in the order of their residuals from the regression equation in Table 1 and calculating the type-1 and type-2 error rates until we have traced out the entire power curve for the CD Spread Model in Figure 1. With all of the banks predicted to be downgraded, the type-1 error rate is zero and the type-2 error rate is 100 percent.

Figure 1 also presents a power curve derived from an out-of-sample simulation of an early warning model. This model uses logit regression analysis to predict which banks will have their CAMELS ratings downgraded to problem status based on lagged observations from the call reports. The dependent variable in each logit regression has a value of unity if a bank was downgraded, zero if it was not downgraded. Table 4 lists the independent variables used in each logit regression, and Table 5 presents the regression results for each year. The power curve for the Downgrade Model in Figure 1 is based on an out-of-sample simulation of a model that uses call report data as of the fourth quarter of 1989 to predict which banks would be downgraded in 1991. We simulate this model for the same sample of banks used for tracing the power curve in Figure 1 for the CD spread model. We use the coefficients of the first downgrade model in Table 5 and call report data as of the fourth quarter of 1991 to predict which banks will be downgraded to problem status during 1993. The power curve for the Downgrade Model in Figure 1 is based on a ranking of the banks by their estimated probabilities of being downgraded in 1993. The power curves in the other figures are based on comparable timing of observations.

In Figure 1, the power curve for the CD Spread Model is close to the benchmark line for a random ranking of banks by probability of being downgraded throughout the range of tradeoffs between type-1 and type-2 errors. The area under the power curve for the CD Spread Model (47.38 percent) is close to the 50 percent benchmark for random selection. The area under the power curve for the Downgrade Model, in contrast, is 18.52 percent. This contrast of power curves indicates that the CD Spread Model has essentially no power to predict downgrades, and the predictive power of the Downgrade Model dominates the predictive power of the CD Spread Model. Figures 2 through 5 show the same contrast of power curves for prediction of downgrades during the years 1994 through 1997.

4. CD Yields as an Independent Variable in the Early Warning Model

Although our measure of interest rates on large time deposits does not perform well as a screen for surveillance, it may have value as an independent variable in the early warning model. There is evidence that some measures perform poorly as screens but contribute to the explanatory power of early warning models (Gilbert, Meyer and Vaughan, 1999). We investigated this possibility by adding the measure of interest rates on large time deposits (residuals of the regression equations in Table 1) as an independent variable in the equations estimated in Table 5. We added the measure of interest rates to each model with the same timing as the other data from the call reports.[3] In the in-sample estimation of the early warning models, the coefficients on the measure of interest rates were not statically significant (results not shown in this paper). Also, addition of the measure of interest rates on large time deposits did not improve the predictive power of the early warning models in out-of-sample simulations.

5. Conclusion

This paper investigates whether a measure of interest rates on large time deposits derived from the call reports would be useful for bank surveillance. There is evidence that this measure of interest rates became more sensitive to differences among banks in

[3] In results not shown in this paper, we estimated regression equations for the average interest rate on large time deposits as a function of the remaining maturity of the deposits, as in Table 1, with data for the fourth quarters of 1989 and 1990. Residuals from the equation for the fourth quarter of 1989 were included as an independent variable in the early warning model for predicting downgrades in 1991. Out-of-sample simulations of this model used call report data as of the fourth quarter of 1991, including the residuals of the first equation in Table 1, to predict downgrades during 1993. Residuals from the equation for the fourth quarter of 1990 were used in estimation of the equation for predicting downgrades during 1992, and the coefficients of that equation were used for predicting downgrades during 1994 in an out-of-sample simulation of the model.

the risk they assume after the early 1990s. Depositors may have access to information about the condition of banks that is not available to supervisors through examinations and surveillance of financial ratios derived from the call reports. In that case, supervisors might be able to use the measure of interest rates on large time deposits to predict which banks will be classified as problem banks in future periods.

We compare the ability of two models to predict which of the banks that supervisors currently rate as safe and sound will have their ratings downgraded to problem status in future periods. The predictive power of the measure of interest rates on large denomination time deposits is dominated by the predictive power compared of an econometric model early warning model. In addition, the measure of interest rates on large time deposits does not improve the predictive power of the early warning model in the in-sample estimation or out-of-sample simulations. The measure of interest rates on large time deposits derived from the call reports would not help supervisors identify the banks that are likely to experience serious problems in future periods.

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Table 1: How are CD yields related to their remaining maturities?

This table shows the results from a regression of the average interest rate of each bank's large time deposits regressed on the proportion of their time deposits in assorted maturity pools. The coefficient on the intercept provides a measure of the average interest rate on large time deposits with remaining maturity less than three months. The coefficient on the intercept plus the coefficient on 3 TO 12 is an estimate of the average interest rate paid on deposits with remaining maturity between three months and one year. The coefficient on the intercept plus the coefficient on 12 TO 60 is an estimate of the average interest rate paid on deposits with remaining maturity between 12 months and five years. The coefficient on OVER 60 has a comparable interpretation.

Note that in each year, the estimated interest rate rises as the time-to-maturity increases.

Three stars indicate statistical significance at the 1 percent level, two stars indicate statistical significance at the 5 percent level, and one stars indicates statistical significance at the 10 percent level

Regression coefficients (Standard errors in parentheses)

	Fourth quarter of:				
Independent variables	**1991**	**1992**	**1993**	**1994**	**1995**
Intercept	0.0572***	0.0367***	0.0332***	0.0433***	0.0538***
	(0.0006)	(0.0005)	(0.0004)	(0.0004)	(0.0006)
3 TO 12	0.0090***	0.0122***	0.0060***	0.0012	0.0051***
	(0.0013)	(0.0009)	(0.0008)	(0.0008)	(0.0010)
12 TO 60	0.0256***	0.0276***	0.0253***	0.0117***	0.0091***
	(0.0021)	(0.0012)	(0.0009)	(0.0009)	(0.0012)
OVER 60	0.0137	0.0470***	0.0290***	0.0085*	0.0182**
	(0.0113)	(0.0065)	(0.0045)	(0.0047)	(0.0082)
Adjusted R^2	0.0149	0.0531	0.0690	0.0164	0.0070
F-statistic for significance of the three independent variables	59.338	208.245	264.166	57.65	23.68
Percentage of deposits with remaining maturity					
Within 3 months	53.17%	48.93%	45.90%	45.01%	45.62%
3 to 12 months	29.43	30.00	30.38	31.35	33.8
12 to 60 months	15.99	18.94	21.32	21.88	19.11
Over 60 months	1.41	2.13	2.41	1.76	1.47
Yield on three-month CDs in the secondary market	4.91%	3.44%	3.28%	5.86%	5.72%

Table 2: What are CAMELS composite ratings?

A CAMELS rating is an acronym for six components of safety and soundness—capital protection (C), asset quality (A), management competence (M), earnings strength (E), liquidity risk (L), and sensitivity to market risk (S). Supervisors assign a grade of 1 (best) through 5 (worst) to each component. They also use these six scores to award a composite rating, also expressed on a 1 through 5 scale.

The following is a brief description of the individual CAMELS composite ratings. In the view of supervisors, a bank with a rating of 1 or 2 is usually considered safe and sound, and when it is downgraded to a 3 or worse, it is considered a problem bank. Therefore, in this paper, we concentrate our efforts on comparing each model's ability to predict movements from safe and sound status to problem status, i.e. from a 1 or 2 to a 3, 4, or 5 rating.

	CAMELS Composite Rating	Description
Safe and Sound	1	Financial institutions with a composite 1 rating are sound in every respect and generally have individual component ratings of 1 or 2.
	2	Financial institutions with a composite 2 rating are fundamentally sound. In general, a 2-rated institution will have no individual component ratings weaker than 3.
Problem Bank Status	3	Financial institutions with a composite 3 rating exhibit some degree of supervisory concern in one or more of the component areas.
	4	Financial institutions with a composite 4 rating generally exhibit unsafe and unsound practices or conditions. They have serious financial or managerial deficiencies that result in unsatisfactory performance.
	5	Financial institutions with a composite 5 rating generally exhibit extremely unsafe and unsound practices or conditions. Institutions in this group pose a significant risk the deposit insurance fund and their failure is highly probable.

Source: *Federal Reserve Commercial Bank Examination Manual*

Table 3: How many banks suffered safety and soundness downgrades in the 1990s?

This table shows the number of sample banks that were ranked as safe and sound (CAMELS 1 or 2) in March of each year that were downgraded to problem status (CAMELS 3, 4 or 5) in the following 10 to 21 months. We excluded from the sample any banks that received downgrades to problem status within 9 months of the CAMELS 1 or 2 observation because those downgrades were included in the previous year's count.

Date of Rating (Year of Downgrade)	CAMEL Rating	Number of Banks	Number of Banks Downgraded to Problem Status	Percentage of Banks Downgraded to Problem Status
March 1992 (1993)	1	1,978	17	0.86
	2	5,246	295	5.62
March 1993 (1994)	1	2,046	14	0.68
	2	5,040	185	3.67
March 1994 (1995)	1	2,363	13	0.55
	2	4,463	129	2.89
March 1995 (1996)	1	2,596	13	0.50
	2	3,964	136	3.43
March 1996 (1997)	1	2,655	13	0.49
	2	3,394	157	4.63

Table 4: What factors help predict safety and soundness problems?

This table lists the independent variables used in the downgrade regression model. The signs indicate the hypothesized relationship between each variable and the likelihood of a safety-and-soundness problem. For example, the negative sign for the net worth ratio indicates that other things equal, a higher net worth reduces the likelihood of a future failure, a future CAMELS downgrade, or a bad current CAMELS rating.

	Symbol	Description **Independent Variables**	Hypothesis about the sign of the coefficient for predicting safety and soundness problems.
Capital	NET-WORTH	Total net worth (equity capital minus goodwill) as a percentage of total assets.	–
Capital	ROA	Return on average assets.	–
Credit Risk Variables	PAST-DUE-30	Loans past due 30-89 days as a percentage of total assets.	+
Credit Risk Variables	PAST-DUE-90	Loans past due 90+ days as a percentage of total assets.	+
Credit Risk Variables	NONACCRUING	Nonaccrual loans as a percentage of total assets.	+
Credit Risk Variables	COMMERCIAL-LOANS	Commercial and industrial loans as a percentage of total assets.	+
Credit Risk Variables	RESIDENTIAL-LOANS	Residential real estate loans as a percentage of total assets.	–
Credit Risk Variables	OREO	Other real estate owned as a percentage of total assets.	+
Liquidity	SECURITIES	Book value of securities as a percentage of total assets.	–
Liquidity	LARGE-TIME-DEPOSITS	Deposits > $100M (jumbo CDs) as a percentage of total assets.	+
Control	SIZE	Natural logarithm of total assets, in thousands of dollars.	
Control	CAMELS-2	Dummy variable equal to 1 if bank has a CAMELS rating of 2.	
Control	POOR-MANAGE	Dummy variable equal to 1 if the bank's Management rating is worse than composite CAMELS rating.	–

Table 5: How well did the CAMELS downgrade model fit the data in-sample?

This table presents the estimated regression coefficients for the model estimating downgrades from safe-and-sound status to problem status. The dependent variable equals "1" for a downgrade and "0" for no downgrade for calendar year *t* with call report data from the fourth quarter of year *t-2*. Standard errors appear in parentheses below the coefficients. One asterisk denotes significance at the ten percent level, two asterisks denote significance at the five percent level, and three asterisks denote significance at the one percent level. Shading highlights coefficients that were significant with the predicted sign in all six years. (See table 4.) The pseudo-R^2 gives an approximation of the proportion of the total variance of the dependent variable explained by the model.

Overall, the evidence suggests that the logit model predicted in-sample downgrades well. Ten of the 13 regression variables are significant with the predicted sign in all five years, and all of the variables were significant in at least some years. Note that by most measures of in-sample fit, the model declines in power in each year, primarily because of the decrease in the number of downgrades. (See table 3.)

	Years of downgrades in CAMELS ratings:		
Independent Variables	**1991**	**1992**	**1993**
Intercept	-3.280***	-0.678	1.033
	(0.018)	(0.555)	(0.775)
COMMERCIAL-LOANS	0.018***	0.029***	0.024***
	(0.005)	(0.006)	(0.008)
RESIDENTIAL-LOANS	-0.005	-0.001	-0.005
	(0.004)	(0.005)	(0.007)
LARGE-TIME-DEPOSITS	0.033***	0.035***	0.035***
	(0.005)	(0.006)	(0.009)
NET-WORTH	-0.093***	-0.081***	-0.083***
	(0.020)	(0.022)	(0.029)
PAST-DUE-90	0.646***	0.541***	0.552***
	(0.075)	(0.078)	(0.103)
PAST-DUE-30	0.203***	0.248***	0.208***
	(0.041)	(0.043)	(0.058)
NONACCRUING	0.362***	0.236***	0.652***
	(0.057)	(0.064)	(0.079)
ROA	-0.443***	-0.487***	-0.298***
	(0.072)	(0.081)	(0.096)
SECURITIES	-0.041***	-0.045***	-0.038***
	(0.004)	(0.004)	(0.006)
OREO	0.295***	0.200***	0.236***
	(0.057)	(0.066)	(0.064)
SIZE	0.125***	-0.139***	-0.242***
	(0.031)	(0.038)	(0.057)
CAMELS-2	1.210***	0.995***	1.130***
	(0.134)	(0.165)	(0.266)
BAD-MANAGE	0.839***	0.650***	0.884***
	(0.100)	(0.113)	(0.143)
Number of Observations	7,120	6,973	7,255
Pseudo-R^2	0.223	0.213	0.213
-2 log likelihood testing whether all coefficients (except the intercept) = 0	4677.663***	3651.350***	2025.375***

Table 5 (Continued): What was the in-sample fit of the downgrade model?

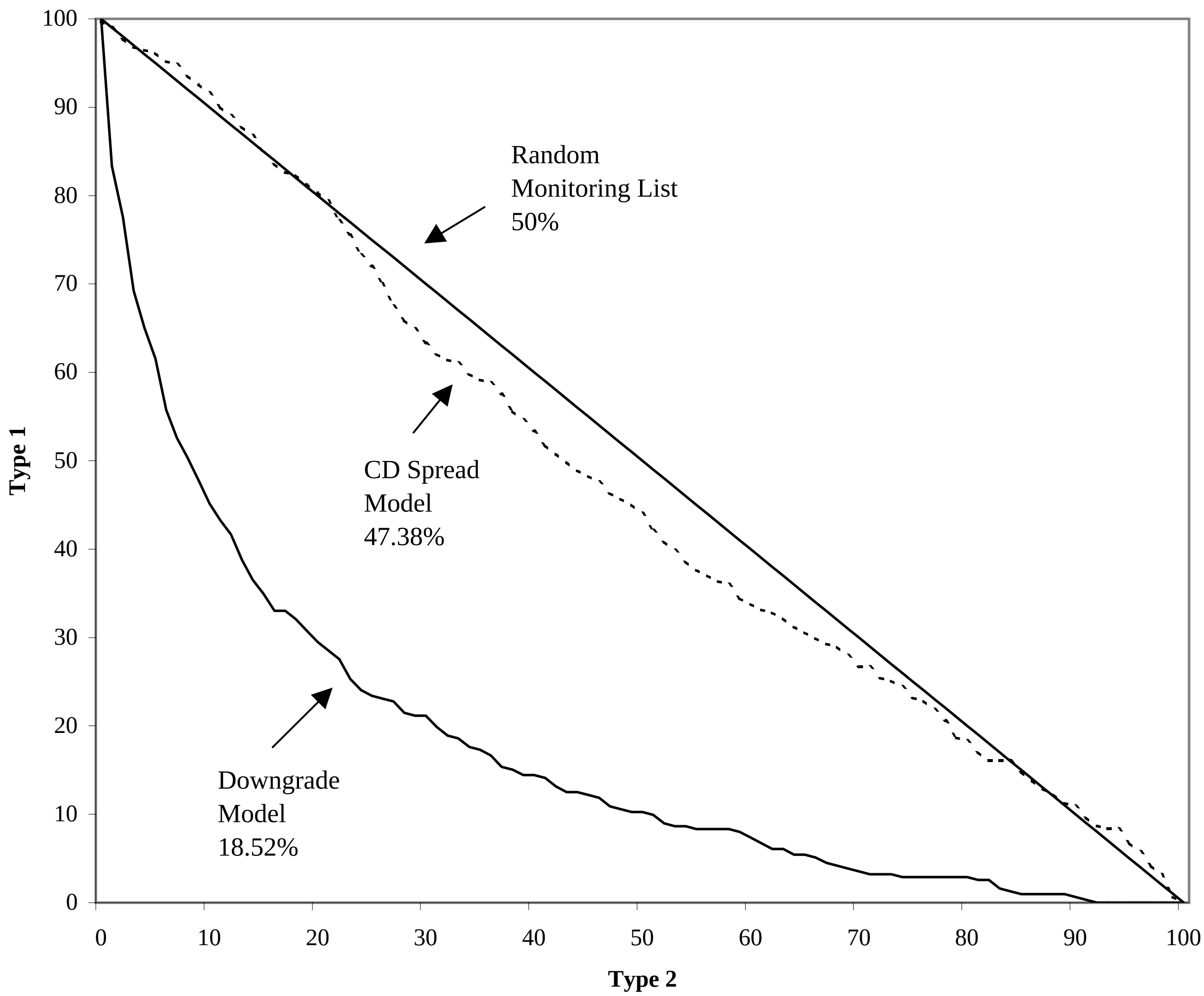
	Years of downgrades in CAMELS ratings:	
Independent Variables	**1994**	**1995**
Intercept	0.157	-0.979
	(0.942)	(1.067)
COMMERCIAL-LOANS	0.004	0.007
	(0.012)	(0.013)
RESIDENTIAL-LOANS	-0.014	-0.003
	(0.008)	(0.009)
LARGE-TIME-DEPOSITS	0.039***	0.060***
	(0.011)	(0.013)
NET-WORTH	-0.102***	-0.026
	(0.033)	(0.034)
PAST-DUE-90	0.424***	0.366**
	(0.121)	(0.142)
PAST-DUE-30	0.264***	0.204**
	(0.084)	(0.081)
NONACCRUING	0.272**	0.396***
	(0.107)	(0.118)
ROA	-0.471***	-0.410***
	(0.110)	(0.132)
SECURITIES	-0.017***	-0.019**
	(0.006)	(0.008)
OREO	0.263***	0.321***
	(0.098)	(0.098)
SIZE	-0.334***	-0.350***
	(0.074)	(0.088)
CAMELS-2	1.143***	1.225***
	(0.281)	(0.308)
BAD-MANAGE	0.853***	0.801***
	(0.166)	(0.196)
Number of Observations	7,118	6,852
Pseudo-R^2	0.121	0.130
-2 log likelihood testing whether all coefficients (except the intercept) = 0	1615.532***	1215.478***

COMMERCIAL-LOANS	Commercial and industrial loans as a percentage of total assets	NONACCRUING	Loans on nonaccrual status as a percentage of total loans
RESIDENTIAL-LOANS	Residential real-estate loans as a percentage of total assets	ROA	Net income as a percentage of total assets.
LARGE-TIME-DEPOSITS	Large denomination time deposit liabilities as a percentage of total assets.	SECURITIES	Book value of securities as a percentage of total assets
		OREO	Other real estate owned as a percentage of total assets
NET-WORTH	Equity less goodwill as a percentage of total assets	SIZE	Natural logarithm of total assets, in thousands of dollars.
PAST-DUE-90	Loans over 90 days past due as a percentage of total loans	CAMELS-2	Dummy variable equal to 1 if bank has a CAMELS rating of 2.
PAST-DUE-30	Loans over 30 days past due as a percentage of total loans	BAD-MANAGE	Dummy variable equal to 1 if the bank's Management rating is worse than composite CAMELS rating.

Figure 1: How well do the models predict out-of-sample CAMELS downgrades?

1993 Downgrade Predictions Using Year-end 1991 Data

This graph shows that the econometric downgrade model clearly dominates the CD spread model in predicting future problem-bank status. In fact, the use of CD spreads alone in choosing which banks to monitor is barely better than a random selection of banks.

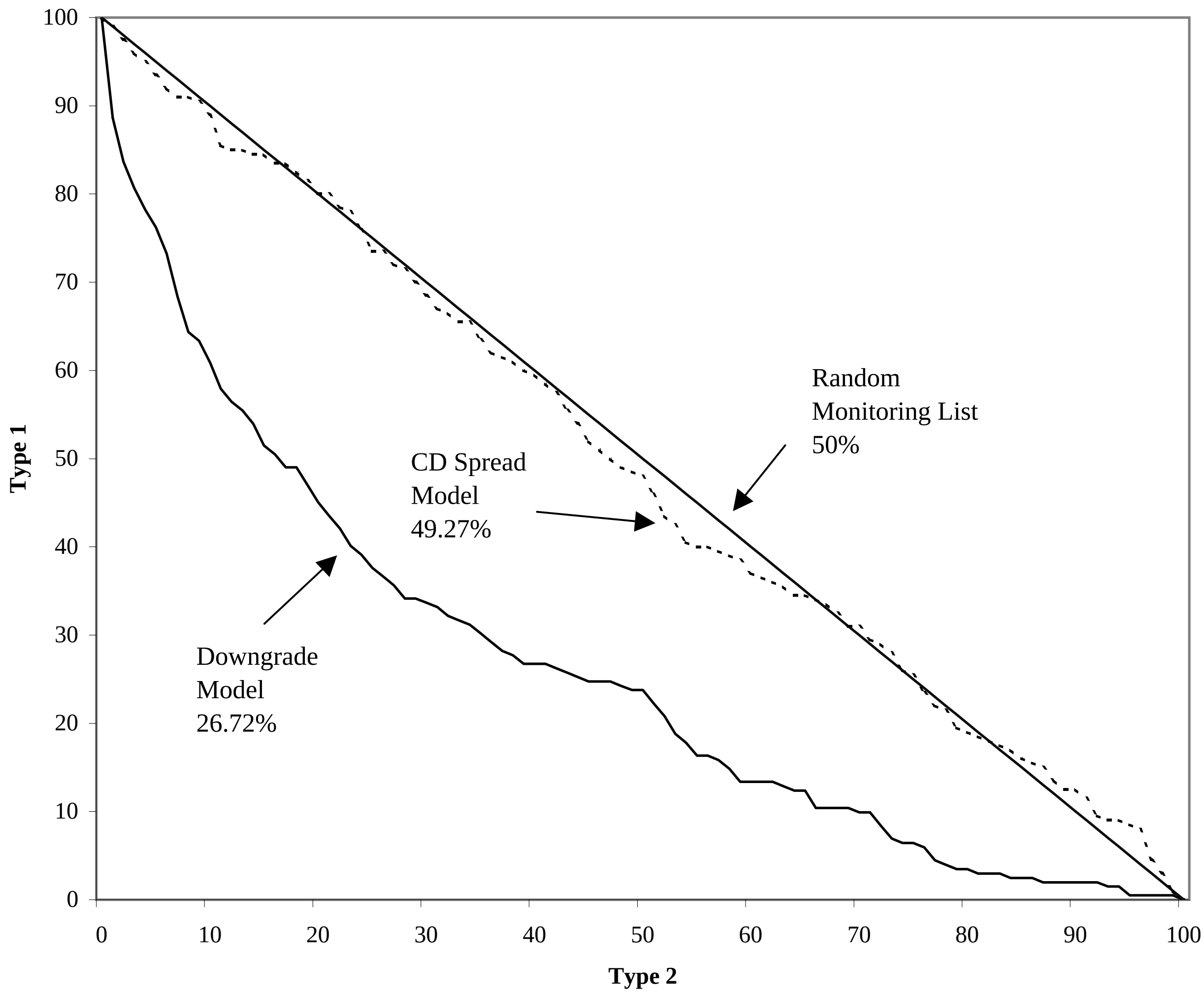


This figure shows the trade-off between the type-1 error rate and the type-2 error rate. The type-1 error rate is the percentage of banks rated CAMEL-1 or -2 that were subsequently downgraded by supervisors but were not identified. The type-2 error rate is the percentage of banks rated CAMEL-1 or -2 that were not subsequently downgraded but were misidentified as a downgrade risk. A desirable early-warning system minimizes the level of type-2 errors for any given level of type-1 errors. A convenient way to express this difference in performance is to calculate the percentage of the area in the figure that is under each curve. Smaller areas are more desirable because they imply simultaneously low levels of both types of errors. The 50 percent line indicates the type 1 and type 2 errors we could expect if banks were examined on a random basis.

Figure 2: How well do the models predict out-of-sample CAMELS downgrades?

1994 Downgrade Predictions Using Year-end 1992 Data

As in the previous year, this graph shows that the econometric downgrade model again dominates the CD spread model in predicting future problem-bank status. Again, the use of CD spreads alone in choosing which banks to monitor is barely better than a random selection of banks.

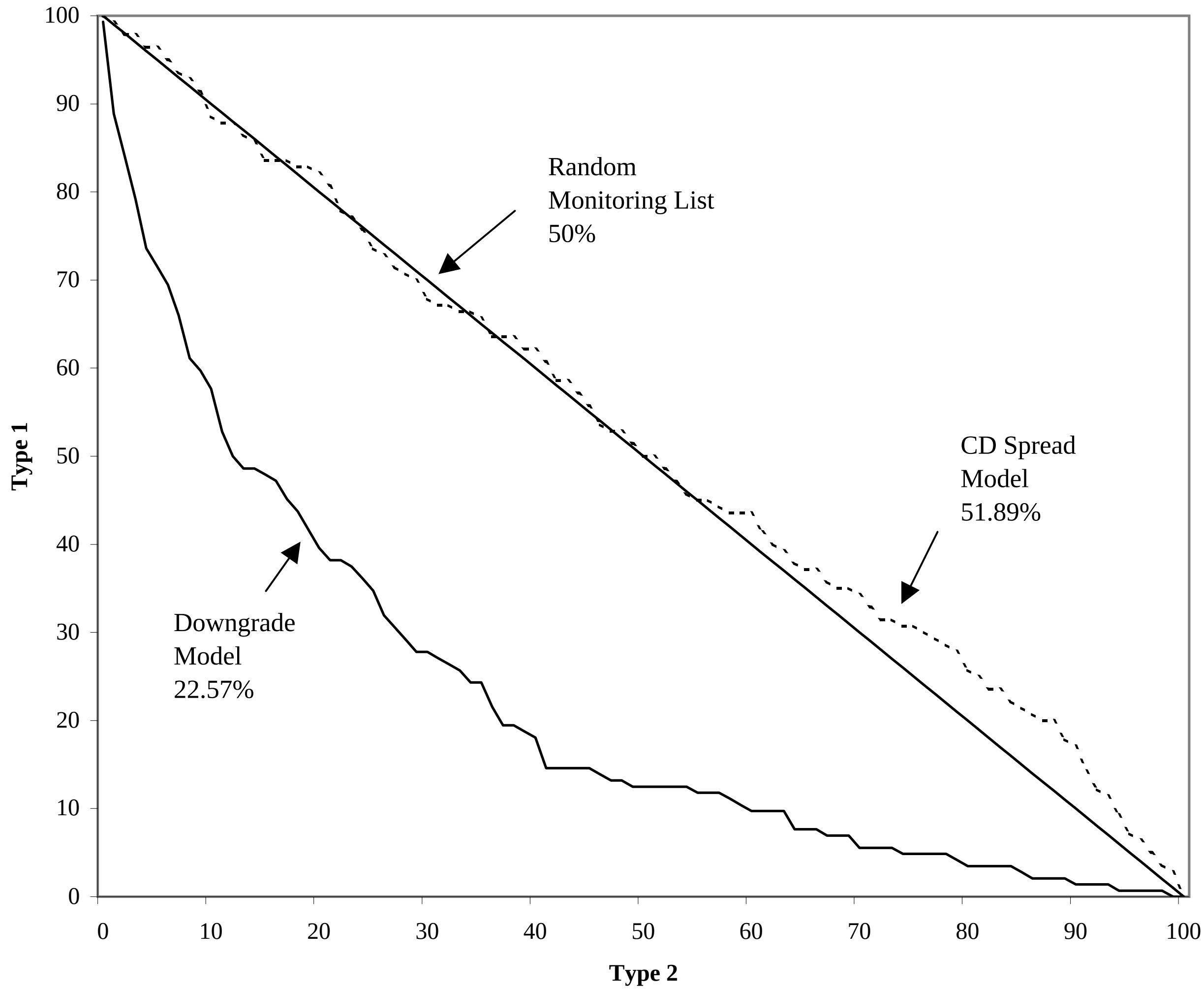


This figure shows the trade-off between the type-1 error rate and the type-2 error rate. The type-1 error rate is the percentage of banks rated CAMEL-1 or -2 that were subsequently downgraded by supervisors but were not identified. The type-2 error rate is the percentage of banks rated CAMEL-1 or -2 that were not subsequently downgraded but were misidentified as a downgrade risk. A desirable early-warning system minimizes the level of type-2 errors for any given level of type-1 errors. A convenient way to express this difference in performance is to calculate the percentage of the area in the figure that is under each curve. Smaller areas are more desirable because they imply simultaneously low levels of both types of errors. The 50 percent line indicates the type 1 and type 2 errors we could expect if banks were examined on a random basis.

Figure 3: How well do the models predict out-of-sample CAMELS downgrades?

1995 Downgrade Predictions Using Year-end 1993 Data

In this graph, the CD-spread model actually produces a worse ranking of banks than a random monitoring list. Again, the econometric downgrade model clearly dominates the CD spread model in predicting future problem-bank status.

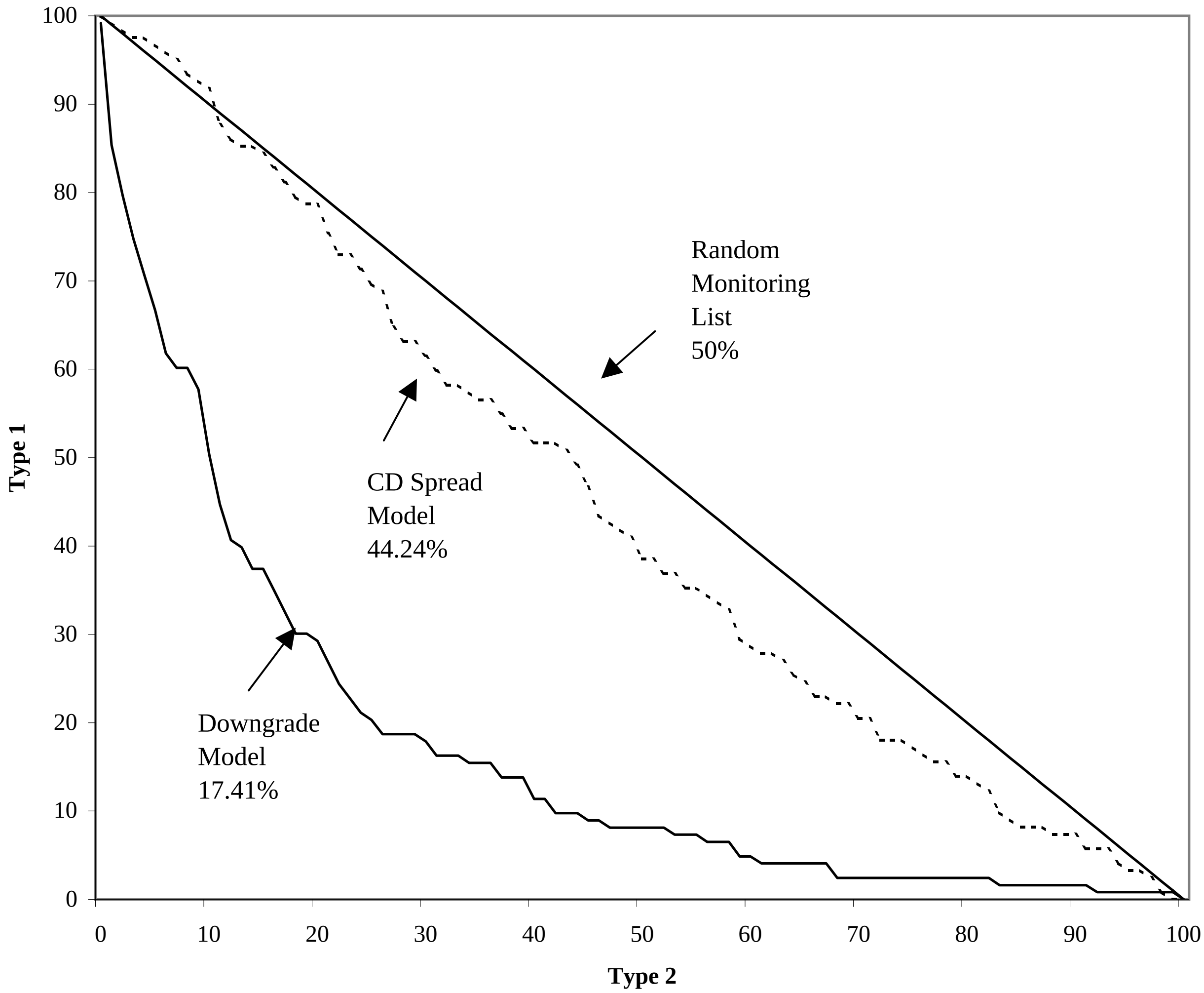


This figure shows the trade-off between the type-1 error rate and the type-2 error rate. The type-1 error rate is the percentage of banks rated CAMEL-1 or -2 that were subsequently downgraded by supervisors but were not identified. The type-2 error rate is the percentage of banks rated CAMEL-1 or -2 that were not subsequently downgraded but were misidentified as a downgrade risk. A desirable early-warning system minimizes the level of type-2 errors for any given level of type-1 errors. A convenient way to express this difference in performance is to calculate the percentage of the area in the figure that is under each curve. Smaller areas are more desirable because they imply simultaneously low levels of both types of errors. The 50 percent line indicates the type 1 and type 2 errors we could expect if banks were examined on a random basis.

Figure 4: How well do the models predict out-of-sample CAMELS downgrades?

1996 Downgrade Predictions Using Year-end 1994 Data

Although the CD-spread model shows some improvement in this year, it is still clearly dominated by the econometric downgrade model in predicting future problem-bank status.

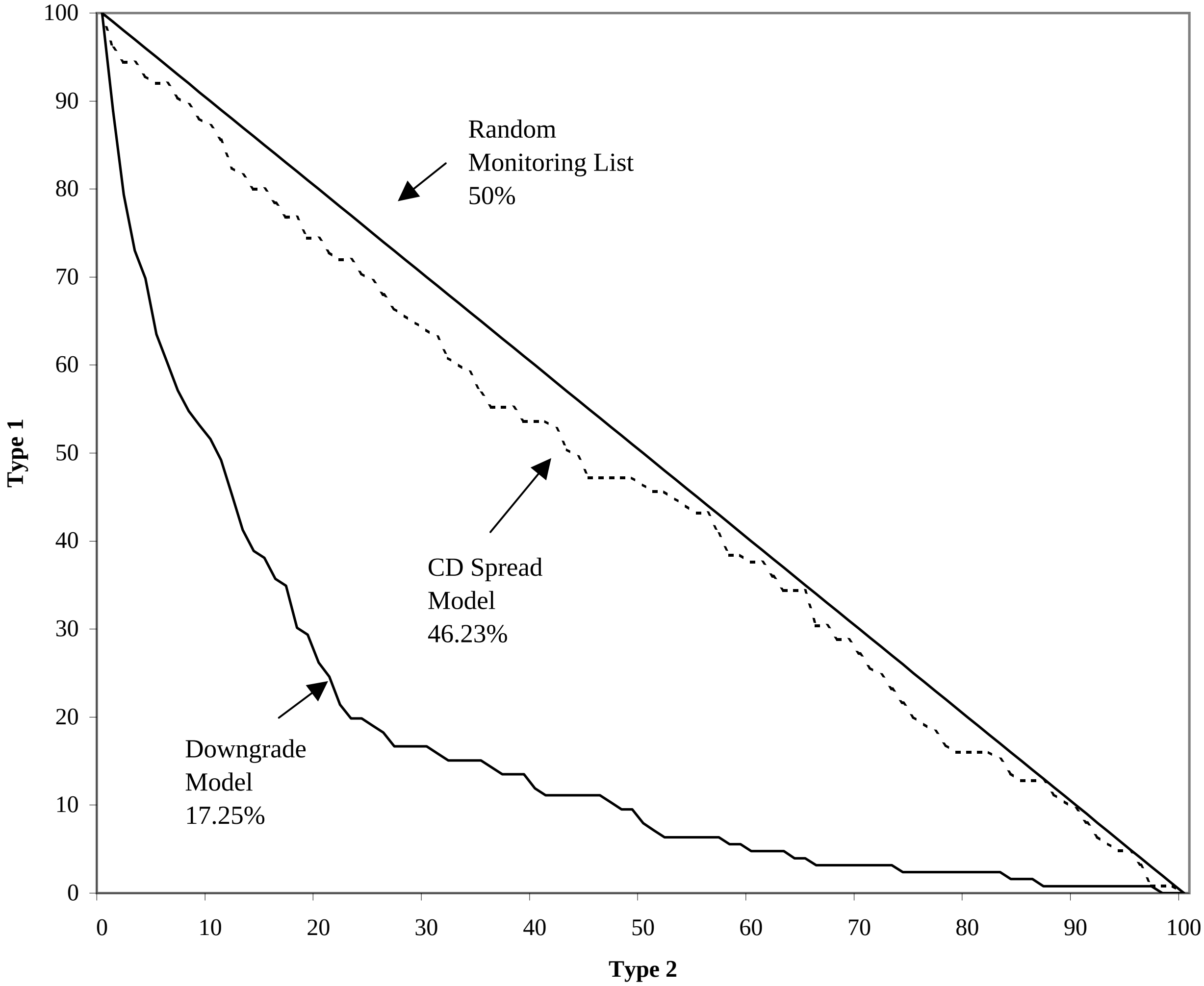


This figure shows the trade-off between the type-1 error rate and the type-2 error rate. The type-1 error rate is the percentage of banks rated CAMEL-1 or -2 that were subsequently downgraded by supervisors but were not identified. The type-2 error rate is the percentage of banks rated CAMEL-1 or -2 that were not subsequently downgraded but were misidentified as a downgrade risk. A desirable early-warning system minimizes the level of type-2 errors for any given level of type-1 errors. A convenient way to express this difference in performance is to calculate the percentage of the area in the figure that is under each curve. Smaller areas are more desirable because they imply simultaneously low levels of both types of errors. The 50 percent line indicates the type 1 and type 2 errors we could expect if banks were examined on a random basis.

Figure 5: How well do the models predict out-of-sample CAMELS downgrades?

1997 Downgrade Predictions Using Year-end 1995 Data

Once again, this graph shows that the econometric downgrade model clearly dominates the CD spread model in predicting future problem-bank status.



This figure shows the trade-off between the type-1 error rate and the type-2 error rate. The type-1 error rate is the percentage of banks rated CAMEL-1 or -2 that were subsequently downgraded by supervisors but were not identified. The type-2 error rate is the percentage of banks rated CAMEL-1 or -2 that were not subsequently downgraded but were misidentified as a downgrade risk. A desirable early-warning system minimizes the level of type-2 errors for any given level of type-1 errors. A convenient way to express this difference in performance is to calculate the percentage of the area in the figure that is under each curve. Smaller areas are more desirable because they imply simultaneously low levels of both types of errors. The 50 percent line indicates the type 1 and type 2 errors we could expect if banks were examined on a random basis.