Early Warning Models in Real Time

Jeffery W. Gunther and Robert R. Moore
Federal Reserve Bank of Dallas

Abstract. Each quarter, banks file a call report, or Report of Condition and Income, containing hundreds of accounting items pertaining to their financial condition. Because call reports are filed quarterly, whereas banks are typically examined about once every twelve to eighteen months, statistical early warning models using call report data potentially provide a more up-to-date picture of a bank's condition than on-site exams alone. Often neglected, however, is the fact that call report data are subject to revision. We find evidence of a strong relationship between on-site exams and call report revisions. In addition, we evaluate a major class of early warning models using both originally published and revised data to assess whether model accuracy in real time is appreciably lower than accuracy measured using revised data. The findings indicate revised data overstate the accuracy of early warning models. The substantial effect of revisions on the accuracy of early warning models, coupled with the finding of a relationship between revisions and exams, points to a substantial auditing role for on-site exams. More generally, our findings point to the need for care in the use of call report data for research in which the real-time flow of financial information is of some concern.

Corresponding author: Jeffery W. Gunther, Financial Industry Studies Department, Federal Reserve Bank of Dallas, 2200 N. Pearl St., Dallas, TX 75201.

E-mail: jeffery.w.gunther@dal.frb.org.

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1. Introduction

Efforts requiring banks to divulge information on their financial condition have a long history. In the early 1800s, some states required banks to file reports of condition with the governor or legislature, arguing the state was a shareholder in the banks and therefore entitled to the information (Robertson 1995). However, the reports contained only broad breakdowns of assets and liabilities and no information bank directors did not wish to disclose. In 1869, Congress empowered the comptroller of the currency to "call" for a full statement of condition from national banks several times a year. Regulators since have made many changes to the resulting *call report*, but its purpose remains the same—to provide timely information regarding the condition of banks.

The modern call report, or Report of Condition and Income, is filed quarterly by all banks and contains hundreds of accounting items that regulators and private analysts use to characterize the financial condition of both individual banks and the industry. Call reports now include detailed measures of assets, liabilities, revenues, expenses, and off-balance-sheet activity. The level of detail is somewhat greater for large banks than for small ones, but even small banks file an extensive report.

Because call reports are filed quarterly, whereas banks are typically examined about once every twelve to eighteen months, call report data potentially provide a more up-to-date picture of a bank's condition than on-site exams alone. For this reason, both regulators and private-sector analysts use call report data extensively in a variety of efforts to monitor banks' condition. One such effort involves the construction and implementation of statistical early warning models to identify emerging financial problems. These statistical systems typically rely heavily on call report data for input variables. However, if call report information does not accurately reflect

financial conditions when published, the report's usefulness in tracking financial developments between on-site exams could be reduced. Additionally, if inaccuracies in the call report data are ultimately corrected, analysis based on the revised data might overstate the report's usefulness in tracking financial developments in real time, as Cole and Gunther (1998) point out.

These considerations suggest the need for analyzing whether the accuracy of early warning models in identifying financial problems in real time is appreciably lower than accuracy measured using revised data. Toward this end, we estimate a type of early warning model designed to predict the results of on-site exams. Cole, Cornyn, and Gunther (1995) present a model of this type employed by the Federal Reserve to monitor financial conditions at individual banks. An example from the academic literature is Wang and Sauerhaft (1989). Our analysis distinguishes itself by estimating the model using real-time data, in addition to revised data. The findings indicate revised data overstate the accuracy of early warning models, as the relationship between call report data and the results of supervisory exams is significantly weaker for real-time data than for revised data. Out-of-sample results also indicate a relatively low level of accuracy for real-time data. The substantial effect of revisions on the accuracy of early warning models, coupled with the finding of a relationship between revisions and exams, points to a substantial auditing role for on-site exams. More generally, our findings point to the need for care in the use of call report data for research in which the real-time flow of financial information is of some concern.

2. Background

Deterioration in loan portfolios typically has been the primary proximate cause of downturns in the banking sector. Reflecting this stylized fact, variables related to asset quality

generally have a large role in early warning models. The banking industry uses a specialized system to account for loan quality problems, at the heart of which is the allowance for loan and lease losses (ALLL). Through provision for loan and lease losses, banks add funds to ALLL. These provisions are an expense item and reduce a bank's net income. The ALLL balance is subtracted from total loans, so that loans on the balance sheet are reported net of ALLL. When loans are charged off, total loans are reduced by the amount of the losses, but the losses are charged against ALLL, leaving net loans unaffected. If a bank recovers some of the losses on loans previously charged off, the recoveries are added back to ALLL.

When a bank charges off a loan, the resulting loss does not affect reported profitability, since the charge-off is against ALLL. Credit quality problems affect reported profitability when a bank incurs the provision expense, since the expense directly reduces net income. As a result, timely disclosure of information on credit quality and its impact on overall operating results depends on the degree to which provisions are made in anticipation of, or concurrent with, actual impairment in the loan portfolio. If adequate provisions are made only after the impairment occurs, profitability prior to the provisions is overstated. Because of their close relationship with credit quality difficulties, provisions are an obvious candidate for inclusion in early warning models.[1]

[1] In first-quarter 1998, banks began reporting provision for credit losses and no longer reported provision for loan and lease losses. The new provision covers loan and lease losses but also includes provisions for losses on certain types of off-balance-sheet activity. For simplicity, we refer to provision expense in all years as provision for loan and lease losses. Banks continue to report ALLL and now also report an allowance for credit losses, which includes the allowance for losses on off-balance-sheet activity. Comparing the two quantities makes it possible to estimate the size of the provision for losses on off-balance-sheet activity. The provision for losses on this activity is very small overall in comparison with the provision for loan and lease losses, and for the vast majority of banks the provision for off-balance-sheet losses is zero.

One factor that might prompt banks to set an insufficient level of ALLL and provision expense involves regulatory or market-based penalties for a deterioration in financial condition. Risk-based capital requirements allow banks to count ALLL only in Tier 2 capital and only up to 1.25 percent of risk-weighted assets. By not making the necessary provisions, banks with asset-quality problems can raise reported net income and retained earnings, thereby boosting Tier 1 capital and potentially avoiding the numerous restrictions regulators typically place on troubled banks.

Given the current institutional framework, which assigns regulators a large role in the monitoring and disciplining of banks, the incentive to underreport provisions provides a particularly strong reason for regulatory exams. The Commercial Bank Examination Manual states that "the examiner's responsibility to determine the adequacy of a bank's ALLL is one of the most important functions of any examination" (Federal Reserve Board of Governors 1999). In verifying the adequacy of ALLL, examiners consider information obtained during the current and prior exams, loan quality trends and peer group data, processes for internal credit review, past-due and restructured loans, and economic conditions. If, after considering these factors, an examiner finds that a bank's ALLL is too low, the institution normally is required to increase its provision expense and raise ALLL to the desired level.[2]

[2] In addition to examiner review, a bank's loan-loss accounting may be reviewed by independent auditors. While all commercial banks are subject to exams, not all are subject to external audits. The Federal Reserve requires bank holding companies with consolidated assets of $500 million or more to have an annual external audit. New banks are also required to have external audits. The Securities and Exchange Commission requires audits for publicly traded companies, including bank holding companies. Finally, the Federal Deposit Insurance Corporation Improvement Act of 1991 requires annual external audits for any bank insured by the Federal Deposit Insurance Corp. with assets greater than $500 million (Federal Reserve Board of Governors 1994).

Several studies support the view that troubled banks often have insufficient ALLL and that exams are important in helping correct the problem. The General Accounting Office (1990, 1991) finds troubled or failing banks often have insufficient ALLL. Similarly, Berger, King, and O'Brien (1991) discuss the potential for insufficient ALLL, particularly when a bank has not been examined recently.

Setting provisions requires detailed knowledge about a bank's loan portfolio. Regulators and, especially, bank managers are more likely than outsiders to have such detailed knowledge. If an exam aligns provision expense and ALLL with credit quality, it may facilitate the public communication of important bank-specific information and thereby enhance banking system transparency.

Consistent with this view, Docking, Hirschey, and Jones (1997) find a bank's announcement of loan-loss provisions adversely affects both that bank's stock price and sometimes the stock price of other banks as well. Berger and Davies (1998) provide evidence that quarterly financial statements are a conduit for transmitting exam findings to financial markets. And Flannery and Houston (1999) find exams affect the relationship between a bank holding company's market and book value, possibly reflecting the improved accuracy of financial statements following an exam or a certification effect whereby exams serve as a stamp of approval on published financial statements.

Other researchers have reached a different conclusion, however, arguing essentially that outsiders can see through a bank's loan-loss accounting and discern the true quality of its loans, even if provisions and ALLL are lower than necessary. Wall and Koch (2000) cite several studies that indicate investors often do not react to announcements of loan-loss provisions,

presumably having already effectively estimated the extent of the deterioration in bank loan portfolios. If, without substantial cost, outsiders can accurately estimate losses in a bank's loan portfolio on the basis of other information, the benefits of exams in assessing loan quality and the sufficiency of ALLL may be limited mostly to the supervisory process itself, as opposed to the promotion of financial transparency in general.

The potential importance of provision expense in early warning models suggests call report revisions, insofar as they reflect exam findings pointing to the need for further provisions, may affect the measured accuracy of early warning models. If examiners determine that the provision expense a bank reports is inadequate, they may require the bank to make additional provisions and refile one or more recent call reports to reflect the change.[3] In this case, a potentially significant gap arises between the real-time and revised data. If the originally published data report a level of provisions that is subsequently found to be too low, then the revised data, which reflects more adequate provisions, would provide a more accurate view of credit quality and, as a result, might generate more accurate predictions regarding supervisory outcomes. Previous studies have only used revised data to assess the accuracy of early warning models.

3. Data

3.1. Revisions and sample design

The quarterly data this study uses are limited to commercial banks, 1996–98. The originally reported data are from files transmitted from the Federal Reserve Board, seventy to

[3] Not all exam findings on provisions necessarily require call report revisions. If additional provisions are necessary, the expense may simply be reflected on a bank's subsequent call report.

eighty days following the report dates. The revised data are for the same report dates but were transmitted from the Board in May 2000. Any differences between the original data and the data obtained in May reflect revisions made sometime after the data were published as "final," which typically occurs about sixty-five days after the report date.[4]

Several additional restrictions frame the analysis. First, the sample is limited to banks that received a satisfactory rating on the last exam prior to the report date. Satisfactory status corresponds to a safety and soundness rating of 1 or 2. Safety and soundness ratings of 3, 4, and 5 are considered unsatisfactory. Focusing on banks entering a period with a satisfactory rating facilitates an assessment of whether new or emerging problems are freely divulged by banks or reported only at the behest of examiners. In addition, banks less than four years old are excluded, since young banks typically exhibit unique financial characteristics and are not directly comparable to more mature banks. The resulting sample contains 100,222 call reports for the period from 1996 through 1998.

3.2. Variables

The early warning model we use to predict the results of bank exams includes seven financial ratios related to the major elements of financial condition considered by examiners. Each of the seven variables is measured relative to total assets. Total capital (*CAP*) is our measure of capital adequacy. High values for this variable should reduce the chances of an unsatisfactory exam rating. Problem loans are represented by loans past due 90 days or more and still accruing (*PD90*) and nonaccrual loans (*NON*). Provision expense (*PRO*) is also included in

[4] As regulators process call report data, substantial effort is devoted to validating the reported information. The primary goal is to ensure the data are accurate before they are published as "final." While the data are typically published about sixty-five days after the report date, revisions can be made for up to five years.

the model. High values of the three variable measuring credit problems should increase the chances of a problem exam rating. Earnings are represented by the return on assets (*ROA*) and are expected to reduce the chances of an inferior exam rating. As a measure of liquidity, investment securities (*SEC*) should reduce the chances of a problem exam rating, whereas a high reliance on large CDS (*LCD*) is expected to have the opposite effect.

Besides the financial ratios, two additional variables are included to capture the potential effects of supervisory status and bank size. If a bank received a rating of 2 on its most recent prior exam, the variable *SUP2* is equal to one, and zero otherwise. This variable should be positively associated with downgrades, since 2-rated banks are closer to problem status than 1-rated banks. The log of total assets, *SIZE*, may reduce the chances of a downgrade if largeness provides financial strength, through either a greater ability to diversify risk or a closer relationship with the broader financial market.

3.3. Averages by revision category

Table 1 displays average values for each of the seven financial ratios. For each ratio, an average is calculated for the cases in which the underlying data were not revised. For cases where a ratio is higher based on the revised data than on the original data, averages are calculated using both sets of data. Two sets of averages are also calculated for cases in which revisions result in a lower value of a ratio. The number of cases of no revision, an upward revision, and a downward revision are shown in parentheses. To allow for potential seasonality in revisions, the data are separated into four groups by calendar quarter. The data for each quarter span three years. Income statement data for the first three quarters are annualized.

As shown in Table 1, the originally submitted call report data are revised only infrequently. However, the fourth quarter call report is subject to a noticeably larger number of revisions than the others, possibly reflecting heightened attention to the year-end income statement covering an entire four quarters. For this reason, we continue to analyze the data by quarter throughout our investigation.

The revisions are small on average. However, a notable exception to this latter observation are upward revisions to the provision expense ratio. For the first and second quarters, *PRO*, the ratio of provision expense to total assets, doubles on average when it is revised upward. In addition, the lower portion of Table 1 shows the incidence and magnitude of changes in *PRO* associated with revisions to the level of loan loss provisions; that is, changes in *PRO* resulting from revisions to the reported level of total assets, but not loan loss provisions, are included in the category of no revision. For this subset of total revisions, the magnitude of upward revisions is even greater, in the lowest case more than doubling and in the highest increasing by a factor of seven.

4. Results

4.1. Exams and revisions

The number of upward revisions in our sample is fairly small. However, these were good times for the banking industry. Because financial problems were few, the need for increases in provisions, for example, could be expected to have been low. As a first step in analyzing the effect of data revisions on early warning models, we investigate the degree to which revisions are associated with emerging financial difficulties.

In Table 2, we divide the observations into three groups corresponding to the banks' exam status in the subsequent quarter. The first group contains banks not examined in the subsequent quarter. The second group was examined and remained in nonproblem status, while the third group was examined and received an unsatisfactory rating. We then compare across groups the incidence of upward revisions to provision expense. Banks receiving an unsatisfactory rating had a much higher incidence of upward revisions than banks that were not examined or were examined but remained in satisfactory status. Looking at the fourth quarter, 36 percent of the downgraded banks revised upward their originally reported level of provision expense. For each of the four quarters, the incidence of upward revisions is highest for the problem group of banks. The null hypothesis of no association between exam and revision category is rejected for each quarter at the 1-percent significance level.

The association between exam results and call report revisions raises the likelihood that the accuracy of early warning models used to predict exam findings is lower for real-time data than for the revised data typically employed in research. While revisions are few in our sample, they are associated with supervisory downgrades, the very outcome the early warning models we use are designed to predict.

In addition, the significant relationship between exams and revisions is direct evidence of a significant role for exams in uncovering financial problems and ensuring bank accounting statements reflect them. To the extent outsiders use provisions and ALLL in assessing loan quality, these results support the view that exams are important in the public dissemination of accurate information on banks' financial condition.

4.2. Regressions

The explanatory variables are used to explain supervisory downgrades to problem status in the quarter following the report date. As such, the model uses a bank's most recent accounting data to predict whether the bank is likely to receive a substandard rating during an on-site supervisory exam. The estimation sample is limited to banks examined in the subsequent quarter. We use the probit model in our estimations.

The probit regression results based on the originally reported data are shown in Table 3. Most of the variables are significant and possess the expected sign in each quarter. The exceptions are *CAP*, which is insignificant in three of the four regressions, and *SEC* and *LCD*, which are insignificant in the fourth quarter.

Estimation results using the revised data are shown in Table 4. Again, most of the variables are significant and possess the expected sign in each quarter. The exceptions are *CAP*, which is again insignificant in three of the four regressions, *SEC*, which is again insignificant in the fourth quarter, and *LCD*, which is now insignificant in the second and fourth quarters. The lack of consistent significance for *CAP* suggests book-value capitalization, while important in determining a bank's long-run viability, does not necessarily register problems in the early stages of financial deterioration.

Overall, the two sets of regressions are highly similar. Any substantial impact of data revisions on predictive accuracy is not immediately apparent from the coefficient estimates themselves.

4.3. In-sample error rates

Figure 1 shows the in-sample error rates associated with using first quarter data to predict second quarter downgrades. The percentage of problem banks identified as nonproblem banks is referred to as the type-1 error rate. The percentage of nonproblem banks identified as problem banks is referred to as the type-2 error rate. A low type-1 error rate for a given rate of type-2 error indicates superior predictive performance.[5] The model using revised data is clearly superior to the one using original data. At a type-2 error rate of 10 percent, the revised and original data produce type-1 error rates of 29.3 and 37.4 percent, respectively. Using probabilities from the binomial distribution, this substantial difference in type-1 error rate is statistically significant at the 5-percent level.

Figures 2, 3, and 4 show in-sample error rates for the second, third, and fourth quarter data, respectively. The predictive superiority of the revised data remains evident for the second quarter data shown in Figure 2, though the performance gap is considerably narrower than for the first quarter data. For the third quarter data, the original and revised data perform equally well. However, a large difference in performance reemerges when the fourth quarter data are used, as shown in Figure 4. At a type-2 error rate of 10 percent, the revised and original data produce type-1 error rates of 29.7 and 38.1 percent, respectively. And this difference is statistically significant at the 5-percent level.

Combining the observations from all four quarters results in the tradeoff in error rates shown in Figure 5. Based on this summary measure, the revised data predict supervisory

[5] For early warning models in banking, the most relevant levels of type-2 error arguably are in the range of 5 to 20 percent.

downgrades more accurately than the originally reported data. At a type-2 error rate of 10 percent, the revised and original data produce type-1 error rates of 31 and 36 percent, respectively. This difference in type-1 error rate is statistically significant at the 1-percent level.

4.4. Out-of-sample error rates

The revised data match up with supervisory outcomes much better than the originally reported data. As an additional test of predictive capacity, we compare out-of-sample error rates across the two sets of data. Quarterly models estimated using revised data for 1996 and 1997 are applied to both original and revised data for 1998.[6] Because only one set of regression coefficients is estimated for each quarter, any difference in forecasts using the 1998 data are attributable entirely to data revisions and not to differences in coefficient estimates.[7]

As shown in Figure 6, the revised data forecast supervisory outcomes more accurately than the originally reported data. At a type-2 error rate of 10 percent, the revised and original data produce type-1 error rates of 45.2 and 49.4 percent, respectively. This difference in type-1 error rate is statistically significant at the 5-percent level.

5. Conclusion

The findings reported here demonstrate the importance of revisions to banking data. We find evidence of a strong relationship between on-site exams and call report revisions. And while few banks have revised their call report in recent years, the revisions that have occurred have tended to be substantial. Rank orderings of banks, based on the indices underlying our

[6] Only revised data are used in estimating the models, under the assumption that the revised data for 1996 and 1997 were available one year after the report date.

[7] Even for the in-sample results, where the coefficients were allowed to differ across the two sets of data, the differences in predictive performance are almost entirely the result of differences in the data values themselves, as opposed to differences in the estimated coefficients.

probit models of exam results, differ substantially depending on whether the original or revised data are applied to the estimated coefficients. The difference in rank orderings manifests itself in noticeably different error rates in predicting supervisory outcomes. The revised data overstate the accuracy of early warning models considerably. We note though, that while accuracy is substantially lower in real time than the revised data would suggest, the real-time data nevertheless are useful in predicting downgrades.

Overall, the substantial effect of revisions on the accuracy of early warning models, coupled with the finding of a relationship between revisions and exams, points to a substantial auditing role for on-site exams. Call report revisions, and particularly revisions to loan loss provisions, provide a unique window through which to view the results of exam activity. The linkage between supervisory downgrades and upward revisions to provisions supports a significant role for exams in uncovering financial problems and ensuring bank accounting statements reflect them.

The final implication of our results that we wish to emphasize concerns the extensive use of call report data in banking research. Researchers that intend on using accounting data as it was reported, which is required by event studies and other investigations dependent on the real-time flow of information, must be aware of and control for the substantial call report revisions that tend to occur among troubled banks, as documented here.

Table 1
Variable Means by Type of Revision, 1996–98

	Revision	First Quarter		Second Quarter		Third Quarter		Fourth Quarter	
CAP	None:	10.24	(24,985)	10.29	(24,794)	10.42	(24,508)	10.19	(22,940)
	Positive:	10.52	10.89 (248)	10.91	11.29 (172)	10.40	11.29 (125)	10.55	10.72 (636)
	Negative:	9.95	9.75 (362)	10.36	10.15 (263)	10.18	10.00 (246)	10.27	10.08 (943)
PD90	None:	.22	(25,190)	.23	(24,920)	.23	(24,662)	.20	(23,539)
	Positive:	.35	.41 (208)	.33	.40 (157)	.41	.49 (103)	.40	.41 (451)
	Negative:	.54	.45 (197)	.50	.39 (152)	.47	.33 (114)	.42	.34 (529)
NON	None:	.35	(25,193)	.35	(24,939)	.35	(24,652)	.32	(23,504)
	Positive:	.58	.70 (213)	.51	.62 (158)	.43	.55 (115)	.56	.65 (490)
	Negative:	.63	.61 (189)	.73	.64 (132)	.74	.66 (112)	.59	.55 (525)
PRO	None:	.15	(25,222)	.16	(24,932)	.17	(24,654)	.18	(23,433)
	Positive:	.24	.53 (190)	.28	.56 (173)	.21	.31 (125)	.35	.52 (640)
	Negative:	.35	.30 (183)	.29	.24 (124)	.35	.30 (100)	.29	.28 (446)
ROA	None:	1.28	(25,010)	1.30	(24,785)	1.31	(24,514)	1.24	(22,959)
	Positive:	1.17	1.33 (261)	1.20	1.33 (201)	1.43	1.67 (118)	1.20	1.31 (601)
	Negative:	1.26	.92 (324)	1.25	.96 (243)	1.26	1.08 (247)	1.15	.98 (959)
SEC	None:	29.32	(25,114)	29.11	(24,878)	28.42	(24,619)	28.25	(23,347)
	Positive:	27.62	27.86 (241)	26.51	26.77 (178)	27.39	27.65 (126)	25.80	25.88 (586)
	Negative:	28.59	28.28 (240)	27.17	26.41 (173)	29.17	28.50 (134)	28.13	28.01 (586)
LCD	None:	9.73	(25,114)	9.77	(24,879)	9.99	(24,620)	9.90	(23,346)
	Positive:	10.96	11.12 (241)	11.10	11.43 (190)	11.48	11.80 (133)	11.79	11.92 (589)
	Negative:	11.38	11.11 (240)	10.84	10.52 (160)	10.67	10.45 (126)	11.74	11.63 (584)
Revisions to the Level of Loan Loss Provisions									
PRO	None:	.15	(25,536)	.16	(25,145)	.17	(24,814)	.18	(24,232)
	Positive:	.25	1.81 (35)	.31	1.20 (54)	.31	.66 (38)	.42	.87 (245)
	Negative:	.58	.20 (24)	.29	.09 (30)	.22	.05 (27)	.37	.19 (42)

NOTE: For revisions, the first entry is calculated using the originally reported call report data, the second using subsequently revised data. The number of instances is shown in parentheses. The variables are multiplied by 100.

Table 2
Number of Revisions to Loan Loss Provisions, 1996–98

Revision	Not Examined	Nonproblem	Problem	Not Examined	Nonproblem	Problem
	First Quarter			Second Quarter		
None	20,645 (100)	4,801 (100)	90 (91)	20,210 (100)	4,847 (99)	88 (87)
Positive	12 (0)	14 (0)	9 (9)	23 (0)	18 (0)	13 (13)
Negative	21 (0)	3 (0)	0 (0)	23 (0)	7 (0)	0 (0)
		$\chi^2 = 77.8$			$\chi^2 = 99.2$	
	Third Quarter			Fourth Quarter		
None	20,796 (100)	3,923 (99)	95 (94)	19,218 (99)	4,939 (98)	75 (64)
Positive	20 (0)	12 (0)	6 (6)	134 (1)	69 (1)	42 (36)
Negative	18 (0)	9 (0)	0 (0)	28 (0)	13 (0)	1 (1)
		$\chi^2 = 47.4$			$\chi^2 = 267.2$	

NOTE: Exam status refers to the results of exams in the first quarter following the call report date. Column percentages are in parentheses (may not sum to 100 due to rounding). The likelihood ratio chi-square test statistic under each frequency table is for the null hypothesis of no association between exam and revision category; each has four degrees of freedom and is significant at the 1-percent level.

Table 3
Probit Regression Results Using Original Data

	First Quarter	Second Quarter	Third Quarter	Fourth Quarter
Constant	-.4821	-.8508	-.3311	-.7166
	(.6018)	(.5828)	(.5936)	(.5516)
SUP2	.4470*	.7232*	.3063†	.6757*
	(.1361)	(.1734)	(.1268)	(.1372)
SIZE	-.0217*	-.1233*	-.1389*	-.1727*
	(.0465)	(.0440)	(.0465)	(.0447)
CAP	-3.602	-4.310†	-3.137	-.8921
	(1.988)	(1.930)	(2.539)	(1.333)
PD90	28.64*	49.95*	30.66*	26.90*
	(7.30)	(6.76)	(8.11)	(6.73)
NON	28.77*	26.37*	33.51*	36.75*
	(6.11)	(6.43)	(6.08)	(5.74)
PRO	22.47*	21.00*	33.32*	43.80*
	(8.11)	(6.27)	(8.91)	(8.37)
ROA	-20.60*	-22.59*	-41.79*	-13.35†
	(7.25)	(7.20)	(8.37)	(5.21)
SEC	-1.962*	-1.237*	-.9423†	-.7361
	(.444)	(.449)	(.4231)	(.3947)
LCD	1.850*	1.624†	3.015*	1.149
	(.666)	(.725)	(.662)	(.629)

NOTE: Standard errors are in parentheses. * significant at the 1-percent level. † significant at the 5-percent level.

Table 4
Probit Regression Results Using Revised Data

	First Quarter	Second Quarter	Third Quarter	Fourth Quarter
Constant	-.5589	-.6786	-.2927	-.5773
	(.6166)	(.5932)	(.5976)	(.5914)
SUP2	.4166*	.6934*	.2932†	.6598*
	(.1406)	(.1758)	(.1271)	(.1470)
SIZE	-.1104†	-.1207*	-.1402*	-.1881*
	(.0473)	(.0446)	(.0468)	(.0477)
CAP	-3.958	-5.069†	-3.089	-1.857
	(2.079)	(2.024)	(1.964)	(1.591)
PD90	28.91*	45.04*	30.04*	23.12*
	(7.49)	(6.94)	(8.02)	(6.99)
NON	31.88*	24.75*	32.59*	37.41*
	(6.10)	(6.59)	(6.12)	(5.80)
PRO	24.51*	25.13*	36.74*	60.85*
	(7.61)	(6.39)	(8.81)	(7.93)
ROA	-24.26*	-29.09*	-44.26*	-16.50*
	(6.54)	(7.79)	(8.32)	(5.71)
SEC	-1.988*	-1.332*	-.9218†	-.4981
	(.461)	(.460)	(.4241)	(.4136)
LCD	1.746†	1.442	2.934*	1.117
	(.687)	(.746)	(.669)	(.658)

NOTE: Standard errors are in parentheses. * significant at the 1-percent level. † significant at the 5-percent level.

References

Berger, Allen N., and Sally M. Davies (1998), "The Information Content of Bank Exams," *Journal of Financial Services Research* 14 (October): 117-44.

Berger, Allen N., Kathleen Kuester King, and James M. O'Brien (1991), "The Limitations of Market Value Accounting and a More Realistic Alternative, *Journal of Banking and Finance* 15 (September): 753-83.

Cole, Rebel A., Barbara G. Cornyn, and Jeffery W. Gunther (1995), "FIMS: A New Monitoring System for Banking Institutions, *Federal Reserve Bulletin* 81 (January): 1-15.

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

Docking, Diane Scott, Mark Hirschey, and Elaine Jones (1997), "Information and Contagion Effects of Bank Loan-Loss Reserve Announcements," *Journal of Financial Economics* 43 (February): 219-39.

Federal Reserve Board of Governors (1994), "Internal Control," *Commercial Bank Examination Manual*, November.

_____ (1999), "Allowance for Loan and Lease Losses," *Commercial Bank Examination Manual*, November.

Flannery, Mark J., and Joel F. Houston (1999), "The Value of a Government Monitor for U.S. Banking Firms," *Journal of Money, Credit, and Banking* 31 (February): 14-34.

General Accounting Office (1990), "Bank Insurance Fund: Additional Reserves and Reforms Needed to Strengthen the Fund," GAO/AFMD-90-100, September.

_____ (1991), "Failed Banks: Accounting and Auditing Reforms Urgently Needed," GAO/AFMD-91-43, April.

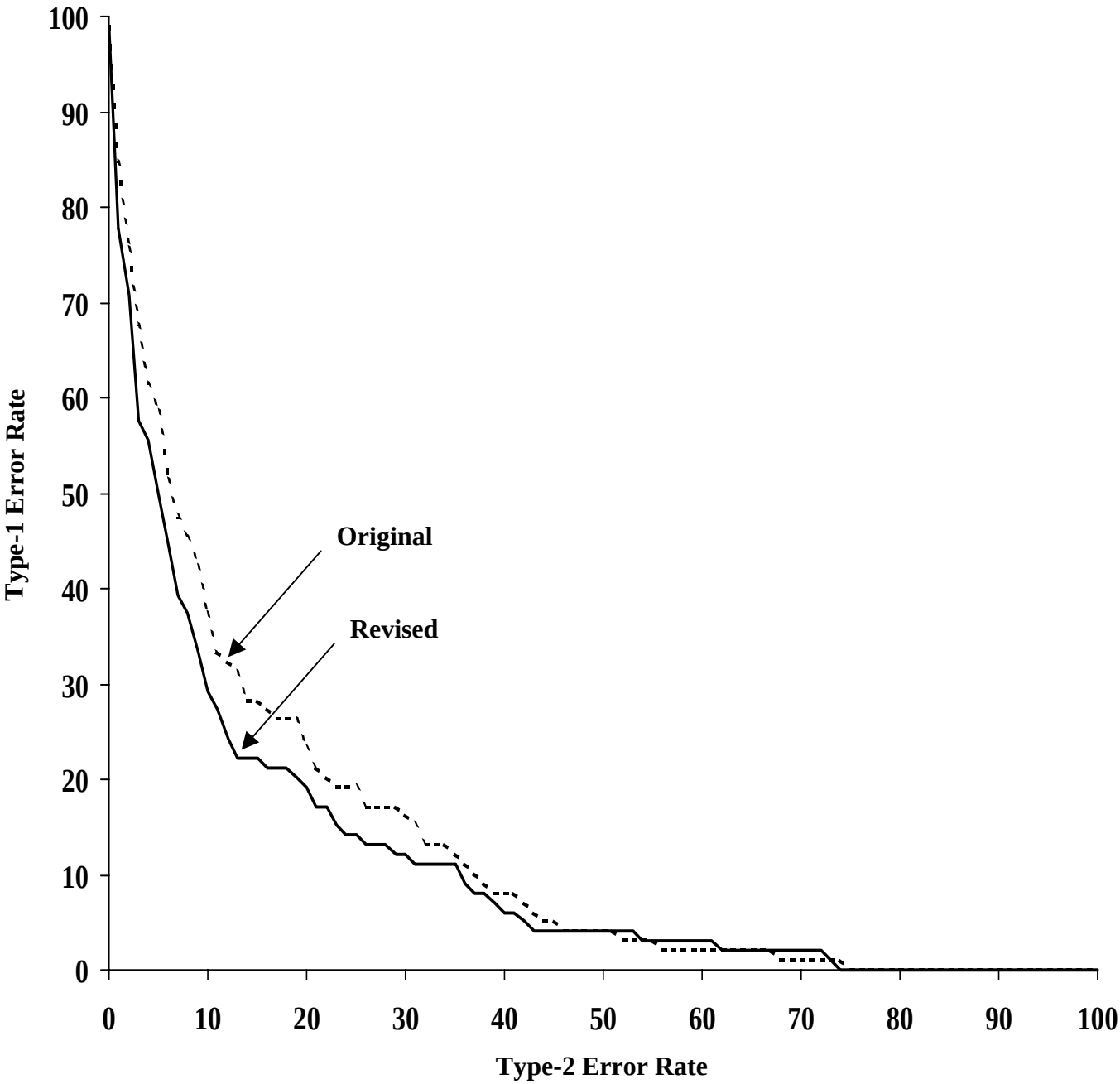
Robertson, Ross M. (1995), *The Comptroller and Bank Supervision: A Historical Appraisal*, (Washington, D.C.: Office of the Comptroller of the Currency).

Wall, Larry D., and Timothy W. Koch (2000), "Bank Loan-Loss Accounting: A Review of Theoretical and Empirical Evidence," Federal Reserve Bank of Atlanta *Economic Review* 85 (Second Quarter): 1-19.

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

Figure 1

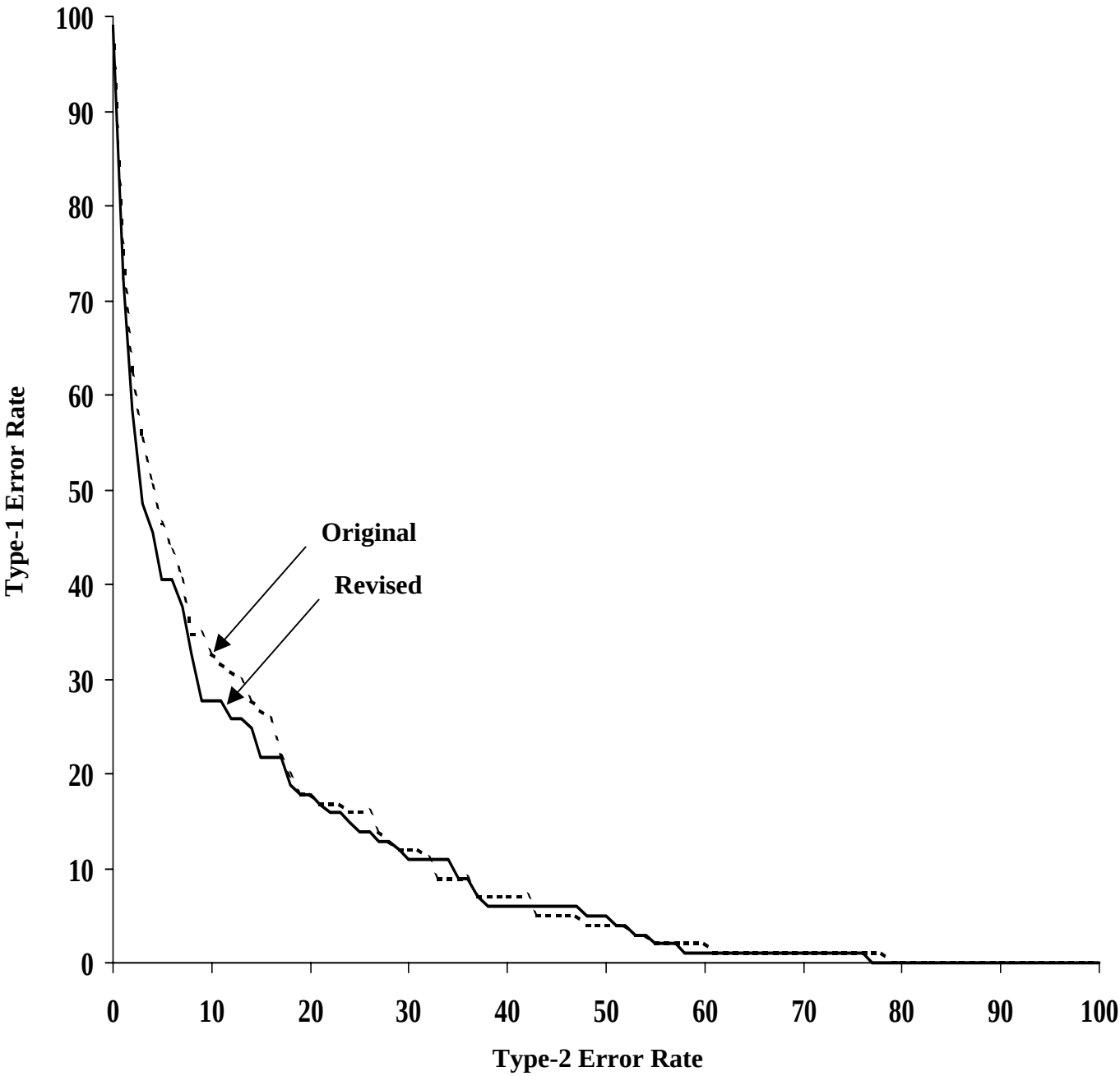
Error Rates Using First Quarter Data to Predict Second Quarter Downgrades



Note: The type-1 error rate is the percentage of problem banks identified as nonproblem banks. The type-2 error rate is the percentage of nonproblem banks identified as problem banks. The call report data are for 1996-98. The original data are from the date on which the data were first published as "final" or closely thereafter. The revised data are from May 2000.

Figure 2

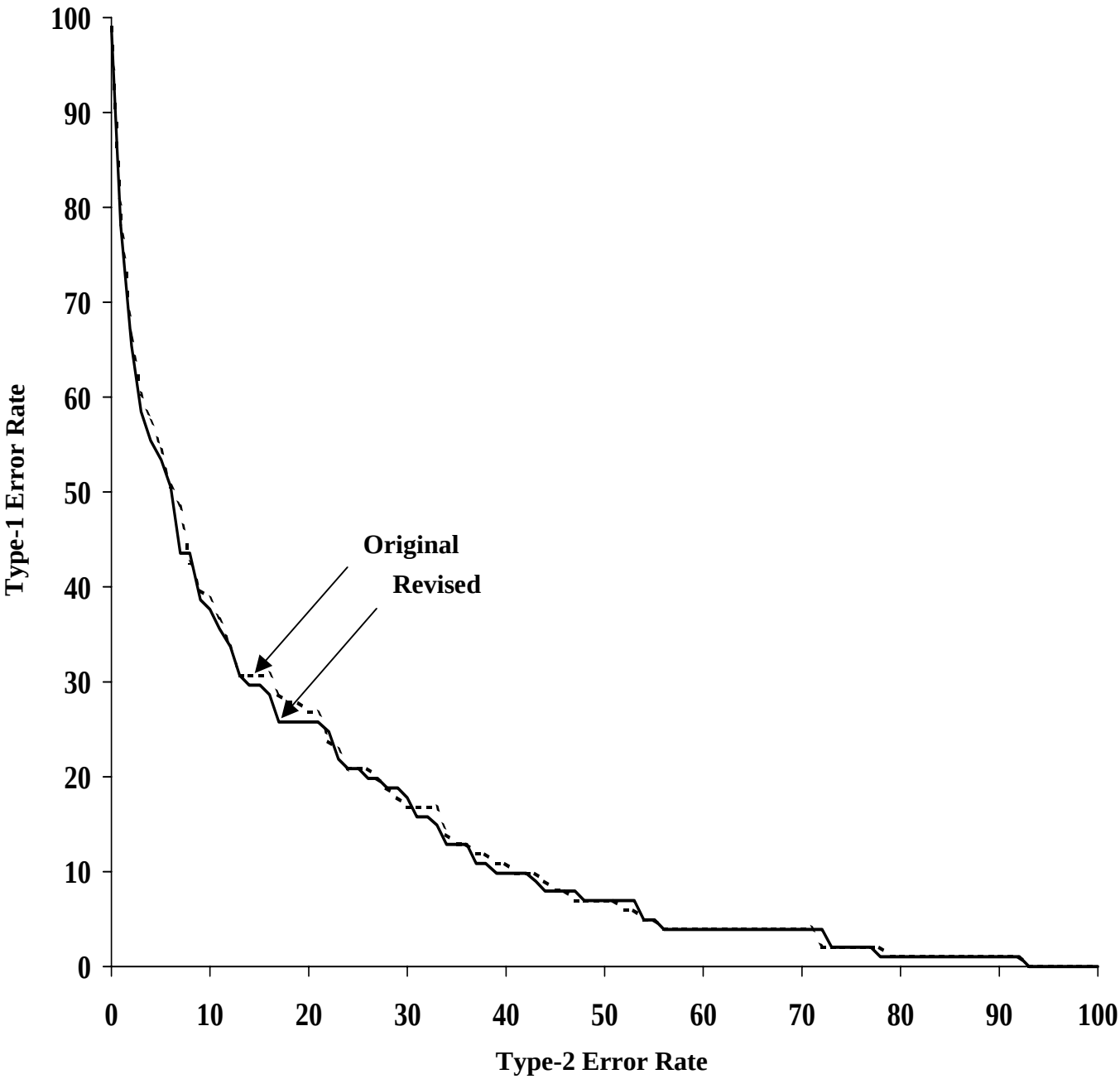
Error Rates Using Second Quarter Data to Predict Third Quarter Downgrades



Note: The type-1 error rate is the percentage of problem banks identified as nonproblem banks. The type-2 error rate is the percentage of nonproblem banks identified as problem banks. The call report data are for 1996-98. The original data are from the date on which the data were first published as "final" or closely thereafter. The revised data are from May 2000.

Figure 3

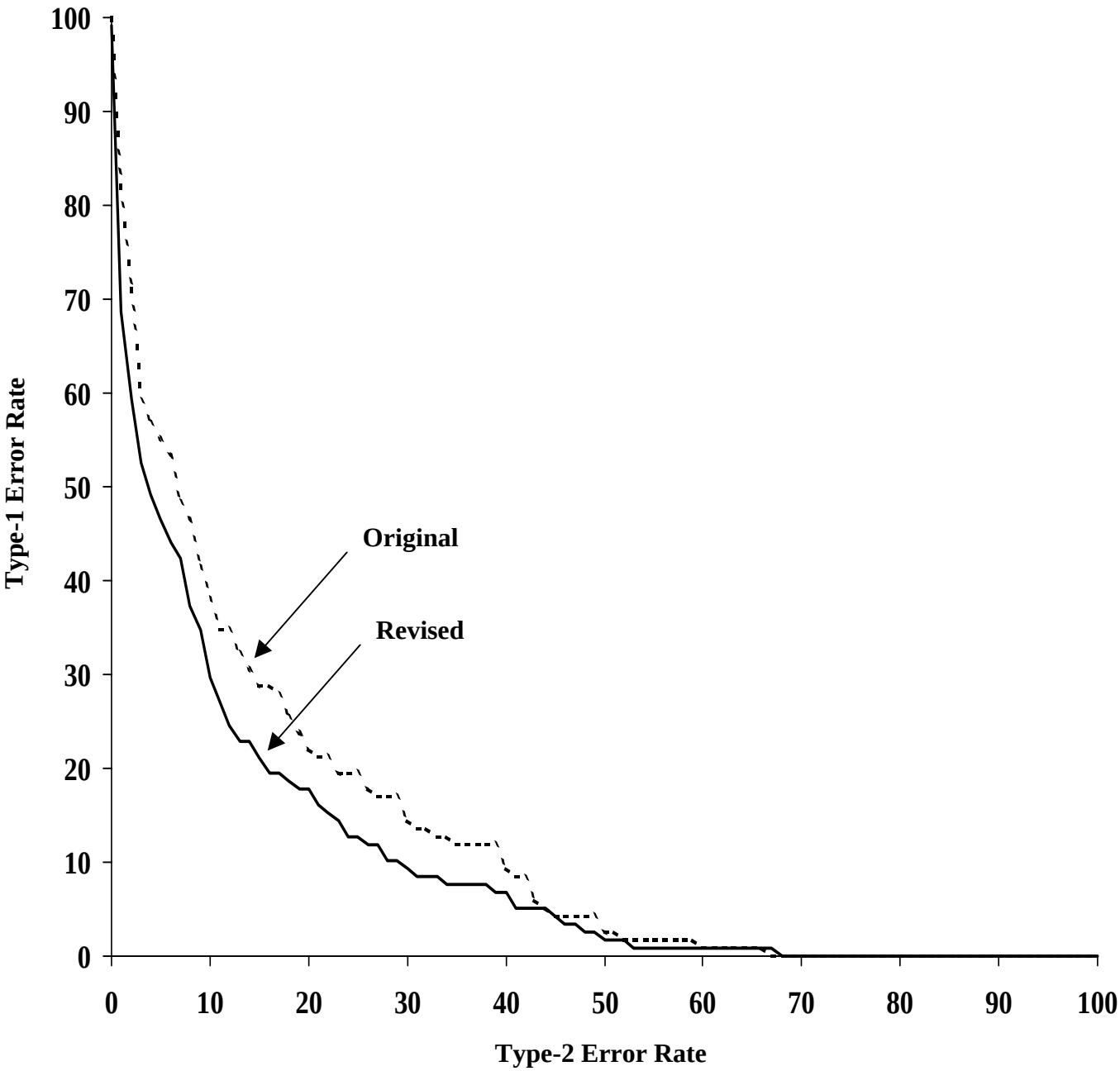
Error Rates Using Third Quarter Data to Predict Fourth Quarter Downgrades



Note: The type-1 error rate is the percentage of problem banks identified as nonproblem banks. The type-2 error rate is the percentage of nonproblem banks identified as problem banks. The call report data are for 1996-98. The original data are from the date on which the data were first published as "final" or closely thereafter. The revised data are from May 2000.

Figure 4

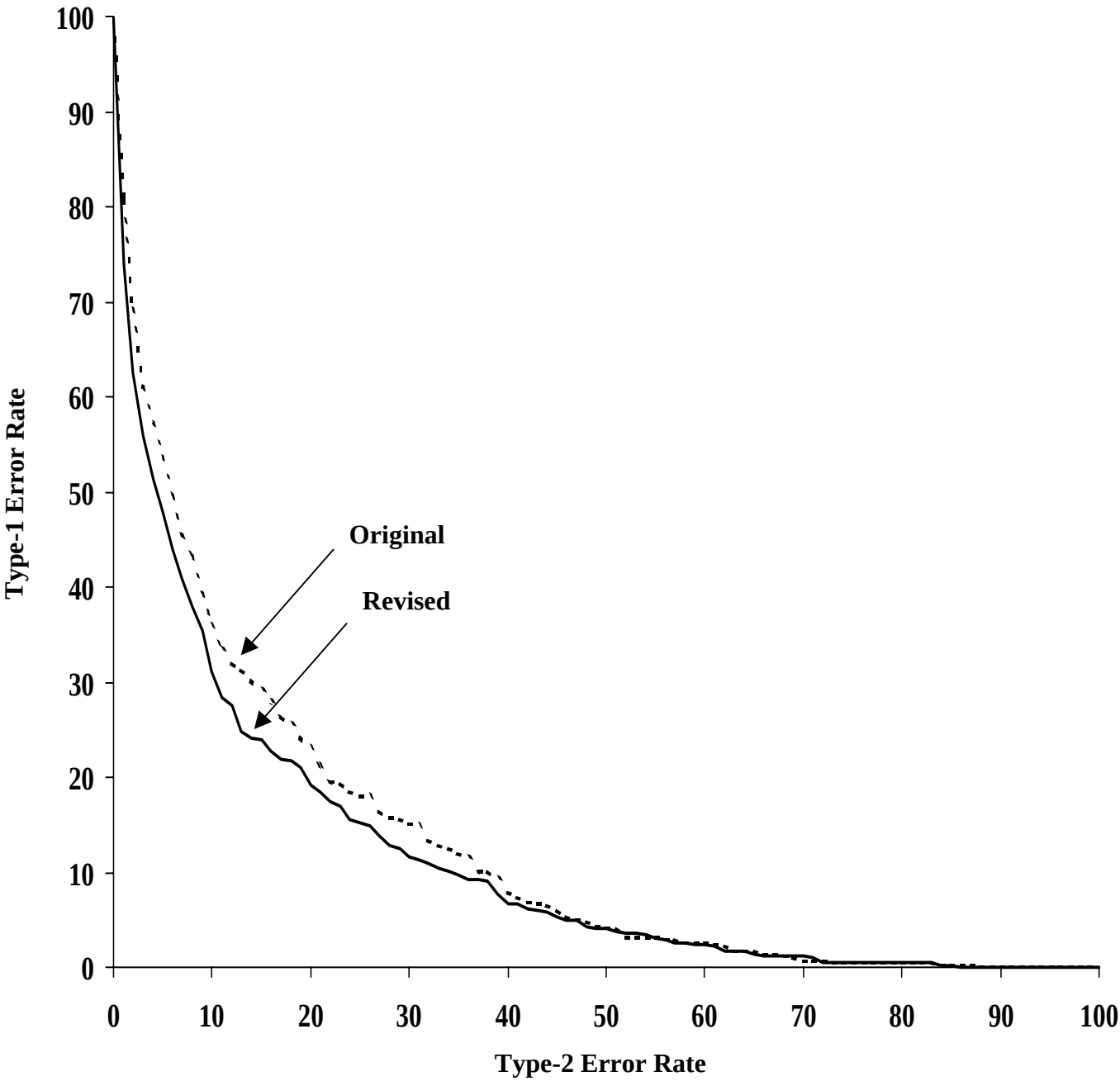
Error Rates Using Fourth Quarter Data to Predict Next Year's First Quarter Downgrades



Note: The type-1 error rate is the percentage of problem banks identified as nonproblem banks. The type-2 error rate is the percentage of nonproblem banks identified as problem banks. The call report data are for 1996-98. The original data are from the date on which the data were first published as "final" or closely thereafter. The revised data are from May 2000.

Figure 5

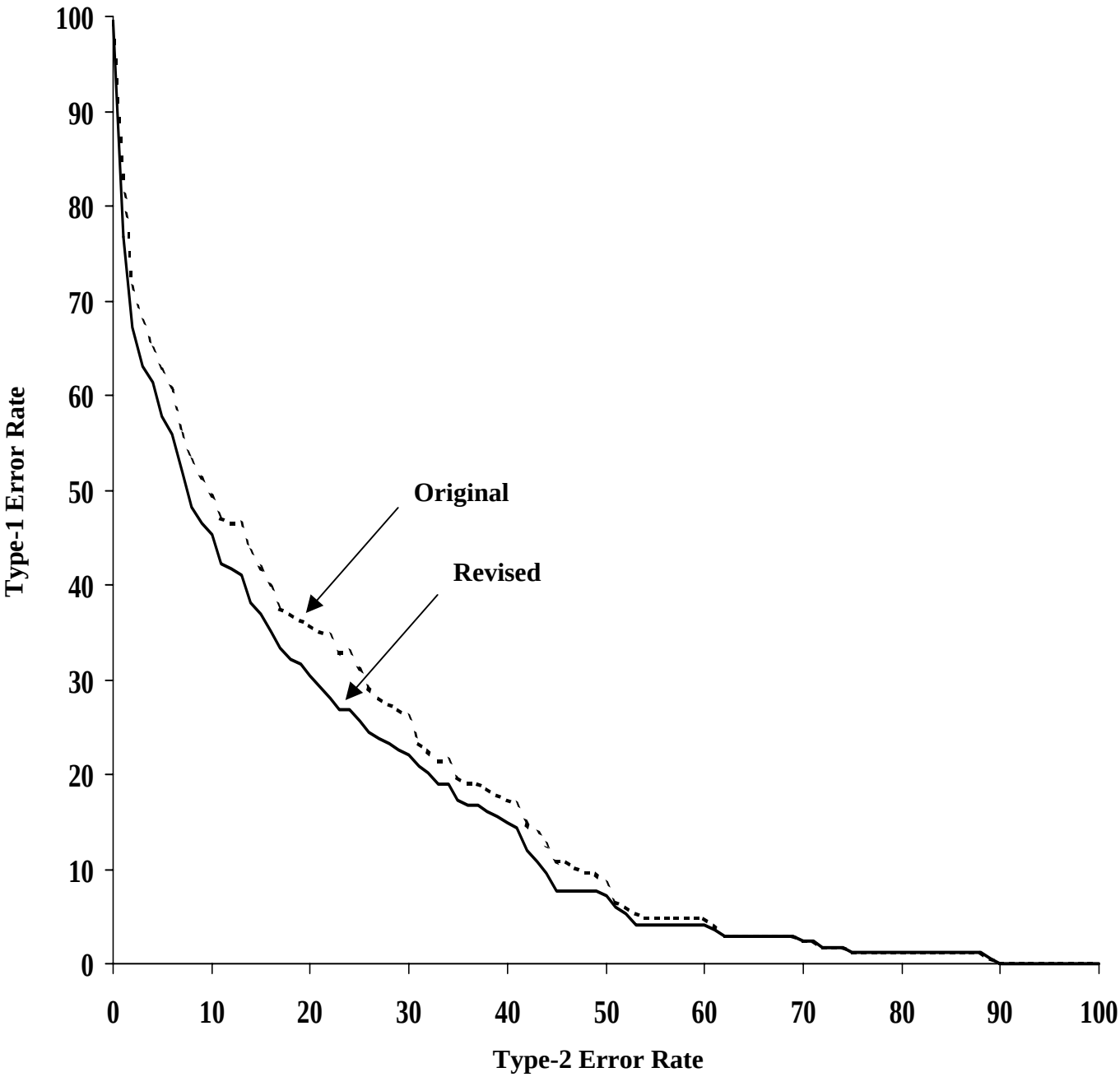
Error Rates in Predicting Next Quarter's Downgrades



Note: The type-1 error rate is the percentage of problem banks identified as nonproblem banks. The type-2 error rate is the percentage of nonproblem banks identified as problem banks. The call report data are for 1996-98. The original data are from the date on which the data were first published as "final" or closely thereafter. The revised data are from May 2000.

Figure 6

Out-of-Sample Error Rates in Forecasting Next Quarter's Downgrades



Note: The type-1 error rate is the percentage of problem banks identified as nonproblem banks. The type-2 error rate is the percentage of nonproblem banks identified as problem banks. Quarterly models estimated using revised data for 1996 and 1997 are applied to both original and revised data for 1998. The original data are from the date on which the data were first published as "final" or closely thereafter. The revised data are from May 2000.