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There is a technical distinction between a zero-inflation rule and a price-level rule. The former allows bygones to be bygones; random shocks to the price level are allowed to accumulate over time. A price-level rule would require the Federal Reserve to offset these accumulated effects eventually. This paper shows that a rule for the price level may dominate a rule for the inflation rate, even in the case where, for purely economic reasons, an inflation rule is preferred. A price-level rule constrains the current behavior of policy-makers because today's choices directly affect tomorrow's options.

This paper uses a single-equation logit model to discriminate between samples of failed and nonfailed banks over the 1984–1989 period. Previous failure prediction studies had to pool bank failures across years to obtain an adequate sample. The historically high number of failed banks over the past decade, however, allows each year in the sample period to be examined separately. The author incorporates measures of economic conditions in the failure prediction equation, along with the traditional balance-sheet risk measures, and finds that the majority of these variables are significantly related to bank failure as much as four years before an institution actually folds.

The large number of bank failures in recent years has created incentives for both regulators and providers of funds to identify high-risk banks accurately. One potentially cost-effective way to do this is through use of a statistical "early warning model." In this article, the author shows that a Cox proportional hazards model can identify both failed and healthy banks with a high degree of accuracy using a relatively small set of publicly available data.

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Why a Rule for Stable Prices May Dominate a Rule for Zero Inflation

by William T. Gavin
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Introduction

Economists have long debated the wisdom of various constitutional constraints on monetary policy. Milton Friedman argued that economists do not know enough about the complexities of the economy to make discretionary policies that would be better than rules, and that the attempt to improve economic performance through discretionary policies has led to consequences worse than those that would have resulted from rules.[1] Another, entirely different, argument in favor of rules comes from the time-consistency literature: Rules affect expectations, and committing in advance to a policy rule (typically of a state-contingent nature) leads to better outcomes than can be obtained with optimal discretionary actions.[2]

Opponents of rules typically focus on the complexity of optimal state-contingent rules, arguing that these complex rules might be better approximated by discretionary policy actions than by simple rules that could be written and enforced at reasonable cost.[3]

One implication of the time-consistency literature is that institutions and rules might be used to improve an economy's inflation performance without sacrificing output. Some of our current monetary institutions have been rationalized as attempts to achieve a lower inflation outcome than occurs in a world in which the optimal short-run policy is not time-consistent. One institution that has lowered inflation is the independent central bank.[4] Another is the practice of appointing conservative central bankers.[5]

In this paper, we show that a rule for the price level may dominate a rule for the inflation rate, even in the case where, for purely economic reasons, an inflation rule is preferred. In our model, policymakers do not have perfect control over inflation, some policymakers have a preference for more inflation than is socially desirable, and the penalty for breaking the rules

■ 1 See Friedman (1959).

■ 2 See Kydland and Prescott (1977) for an original statement of the time-consistency problem.

■ 3 See Summers (1988) for three arguments against rules.

■ 4 See Bade and Parkin (1987) and results summarized in Alesina (1988), table 9 on page 41.

■ 5 See Rogoff (1985).

is not overly severe. Under these conditions, an inflation rule will lead some policymakers to attribute policy-induced inflation to nonpolicy causes. Because nonpolicy shocks to the inflation rate can occur in any time period, a severe penalty is not optimal.

Under a price-level rule, the source of the inflation in any time period does not matter. The penalty associated with this rule provides an incentive for policymakers to offset inflation, regardless of the source. A price-level target constrains the current behavior of policymakers because today's choices directly affect tomorrow's options.

I. Stable Prices vs. Zero Inflation

We present a simple example of inflation and monetary policy in which two types of policymakers might be in charge of monetary policy. These two types want different levels of inflation. They differ because inflation has two effects: 1) a negative effect on overall social welfare and 2) uninsurable redistributive effects that benefit some people at the expense of others. We assume one type of potential policymaker receives private gains from inflation that may dominate his share of the overall social loss. The other type loses more than the aggregate social loss from inflation. We do not model the reasons for the lack of insurability of these redistributive consequences of inflation; our model simply assumes there are limits on insurance or financial markets that prevent such insurance from operating perfectly.

We assume that while inflation is observable, the behavior of policymakers is not—people observe and understand inflation, but not the monetary policy that affected it. Monetary policy cannot be perfectly inferred from either inflation or monetary growth because random factors, such as shifts in output supply and the demand for money, also affect these variables.

We interpret rules as penalties (or rewards) for policymakers based on observed outcomes of inflation: They are features of the overall compensation package of policymakers. This package could include implicit as well as explicit payments, and deferred as well as current payments (in such forms as fame, praise by the news media, and opportunities to give speeches and write books, or to take various desirable positions after the policymaker's term of office expires).

If there were no limits on the penalties that could be imposed on policymakers, a rule could specify an extreme penalty for policymakers whenever inflation deviates from zero by some threshold amount. Then any policymaker would try to achieve zero inflation. But the random forces affecting inflation would sometimes make it exceed that threshold, so the penalty would sometimes apply. To induce anyone to be a policymaker, the salary would have to compensate for the *risk* of high inflation due to random events and the subsequent penalty. With risk-averse individuals, the required salary would have to be very high to compensate for the risk of a severe penalty.

Thus, an optimal reward structure for policymakers involves a limited penalty for deviating from target inflation and a correspondingly smaller expected reward. We do *not* model the incentives to enforce the rule; we simply assume that constitutional rules are enforceable and are actually enforced.

For simplicity, we assume the socially optimal inflation rate is zero (though the optimal inflation rate is immaterial to our argument).[6] We compare two policy rules (compensation packages for policymakers)—one that penalizes policymakers whenever inflation deviates from the socially optimal rate (zero), and another that penalizes them whenever prices deviate from a stable level.

We believe that a stable price level is a better goal for monetary policy than a zero-inflation goal that allows drift in the price level. A stable price policy eliminates inflation and the associated uncertainty that interferes with efficient long-term nominal contracting and borrowing.

To avoid biasing our results in favor of the price-level rule, however, we ignore these arguments for a stable price level. Instead, we assume that society gains from a zero rate of inflation (even if this means price-level drift). The stable-price-level rule requires inflation or deflation to correct for past changes in the price level. Although this inflation or deflation causes a social loss when it occurs, the stable-price rule can generate a socially better outcome because it alters the incentives of policymakers.

■ 6 We have argued elsewhere for zero inflation (see Gavin and Stockman [1988]). Our arguments there suggest that policymakers should stabilize the price level rather than its rate of change. In our current example, we assume that the socially optimal policy is designed to achieve a zero *rate of change* of prices.

II. A Simple Model

We examine a simple two-period model in which inflation, π , results from a monetary policy variable, m, and an exogenous random disturbance, e:

(1) $\pi = m + e.$

We assume $E(e) = 0$ and is observed only after m is chosen. This random disturbance may be thought of as a combination of shocks to output supply, shifts in money demand, and errors in monetary control. This random component prevents people from observing policy actions directly.

Inflation is socially costly. We assume there is a social loss from inflation $z(\pi)$, where

(2) $Z(\pi) = z\pi^2,\ z > 0.$

The population of the economy is fixed and normalized at two. The social cost of inflation is divided equally among all households, so each bears one-half of this social cost.

There are two types of households in the economy—type-i households, who privately benefit from inflation at the level $\pi^* > 0$, and type-0 households, who privately lose from nonzero inflation. The population of each type is normalized at one.

The purely private component of the loss to each type-0 household from nonzero inflation is $H(\pi)$, where

(3) $H(\pi) = (h/2)\,\pi^2,\ h > 0.$

The total loss each period to each type-0 household is the sum of the two losses, $Z(\pi)/2 + H(\pi)$.

The purely private component of the loss to each type-i household is $G(\pi)$, where

(4) $G(\pi) = (g/2)(\pi - \pi^*)^2,\ g > 0.$

The total loss each period to each type-i household is $Z(\pi)/2 + G(\pi)$.

In our example, as inflation rises from zero to π^*, some households gain at the expense of others. In addition to this redistribution, inflation has a social cost of $Z(\pi)$.

The monetary policy variable, m, is controlled by a central bank that may be captured by either group. We do not model this capture here, as it is largely immaterial for our argument. The outcome of this process is a random variable. We assume that the same policymaker is in charge for both periods.

We consider two alternative rules for monetary policy. Each rule is a set of penalties to the group in charge of policy, for deviating from some target inflation outcome. We assume these rules can be perfectly enforced. Section III considers a rule for zero inflation—one that does *not* penalize the policymaker for failing to correct past changes in the price level. Section IV then considers a rule for a stable price level—a zero-inflation rule that penalizes policymakers for failing to correct *past* changes in the price level.

III. A Zero-Inflation Rule that Allows Price Drift

Consider a rule for zero inflation that does *not* penalize a policymaker for failing to correct past changes in prices. The rule consists of a penalty (smaller total compensation) for inflation. We assume it takes the form

(5) $K(\pi) = (k/2)\,\pi^2,\ k > 0.$

We do not derive the optimal penalty in this paper. To do so would require the explicit specification of the relationship between the cost of compensating policymakers and the level of the penalty. The optimal penalty would be chosen so that the marginal benefit from a lower inflation trend associated with a higher penalty would just offset the increased compensation required by the policymaker at the higher penalty rate.

Type-0 Policymakers

If a type-0 individual controls policy, his problem in the second period ($t = 2$) is to choose m to minimize

$$E[H(\pi) + \frac{Z(\pi)}{2} + K(\pi)]$$

subject to (1). Let $q = z + k$. The type-0 policymaker minimizes

$$E[\frac{h+q}{2}(m+e)^2],$$

which implies that he chooses $m = 0$. His minimized expected loss is then

$$\frac{h+q}{2}E(e^2).$$

The optimization problem of a type-0 policymaker in the first period is to choose m to minimize

$$(6) \qquad E[\frac{h+q}{2}(m+e)^2 + \beta \frac{h+q}{2} e_2^2],$$

where β is a discount factor and e_2 denotes the second-period realization of the random disturbance e. This obviously has the same solution as at $t = 2$, namely $m = 0$. A type-0 policymaker subject to this rule would choose monetary policy that results in zero expected inflation each period.

Type-i Policymakers

We now turn to the optimization problem of a type-i policymaker. At $t = 2$, he chooses m to minimize

$$E[\frac{g}{2}(m+e-\pi^*)^2 + \frac{q}{2}(m+e)^2].$$

This implies

$$(7) \qquad m = \frac{g}{g+q}\pi^* \equiv \mu\pi^*.$$

The minimized expected loss of the type-i policymaker at $t = 2$ is

$$(8) \qquad E\{\frac{g}{2}[(\mu-1)\pi^* + e]^2 + \frac{q}{2}(\mu\pi^* + e)^2\}.$$

In the first period, this policymaker chooses m to minimize

$$E[\frac{g}{2}(m+e-\pi^*)^2 + \frac{q}{2}(m+e)^2] + \beta E\{\frac{g}{2}[(\mu-1)\pi^* + e_2]^2 + \frac{q}{2}(\mu\pi^* + e_2)^2\},$$

which implies

$$(9) \qquad m = \frac{g}{g+q}\pi^* \equiv \mu\pi^*.$$

This is the same monetary growth rate as in the second period. So, a type-i policymaker chooses a time-invariant money growth rate that yields *positive expected inflation*.

The policy rule for zero expected inflation results in *positive* expected inflation if a type-i policymaker is in charge because he balances the penalty for higher inflation against his private gains from inflation. The limitations on penalties discussed earlier prevent the penalty from being so large that this policymaker would set $m = 0$.

IV. A Stable-Price Zero-Inflation Rule

We now turn to a *stable-price rule*, which invokes a penalty in the second period if inflation deviates from a level that would return the price level to its original position in the first period. We assume the penalty at $t = 2$ raises the per-household cost of inflation, to the households in charge of policy, from $K(\pi)$ to $K(\pi - \pi^T)$, where π^T is the *target inflation* specified by the rule. This target inflation is, in our setup, simply the negative of *actual* inflation at $t = 1$: $\pi^T = -\pi_1 = -(m_1 + e_1)$, where m_1 is the first-period money growth rate and e_1 is the first-period exogenous disturbance. This implies $K(\pi - \pi^T) = k(m + e + m_1 + e_1)^2$.

Type-0 Policymakers

A type-0 policymaker at $t = 2$ chooses m to minimize

$$E[\frac{h+z}{2}(m+e)^2 + \frac{k}{2}(m+e+m_1+e_1)^2],$$

which implies

$$(10) \qquad m = \frac{-k}{h+z+k}(m_1+e_1) \equiv -r(m_1+e_1).$$

The policymaker weighs the costs of nonzero inflation against the costs of deviating from the rule. He then chooses money growth to attempt to reverse a fraction r of the previous period's inflation. His minimized expected loss at $t = 2$ under the stable-price rule is

$$(11) \qquad E\{\frac{h+z}{2}[-r(m_1+e_1)+e]^2 + \frac{k}{2}[(1-r)(m_1+e_1)+e]^2\}.$$

Now consider the incentives of this policymaker in the first period. He chooses m_1 to minimize

$$E[\frac{h+z+k}{2}(m_1+e_1)^2]$$

$$+\beta E\{\frac{h+z}{2}[-r(m_1+e_1)+e]^2$$

$$+\frac{k}{2}[(1-r)(m_1+e_1)+e]^2\}.$$

This implies that $m_1 = 0$ in the first period and that the second-period policy simplifies to $m = -re_1$. So a type-0 policymaker would choose the policy $m = 0$ in the first period. In the second period, he would choose policy to try to reverse a fraction r of any accidental inflation in the first period resulting from the random shock e.

Type-i Policymakers

Finally, we turn to the behavior of a type-i policymaker subject to the stable-price rule. In the second period, he chooses m to minimize

$$E[\frac{z}{2}(m+e)^2+\frac{g}{2}(m+e-\pi^*)^2$$

$$+\frac{k}{2}(m+e+m_1+e_1)^2].$$

This implies

$$E[z(m+e)+g(m+e-\pi^*)$$

$$+k(m+e+m_1+e_1)]=0,$$

or

$$(12)\quad m=\frac{g\pi^*-k(m_1+e_1)}{z+g+k}$$

$$=\mu\pi^*-r(m_1+e_1).$$

In period 2, the type-i policymaker chooses an inflation rate that balances the private gain from positive inflation against the cost of the penalty for deviating from zero. Under the stable-price regime, however, the cost of deviating from zero inflation also depends on the inflation rate in the first period. The period 2 money growth will be modified to offset some of the period 1 inflation. The minimized expected loss of the policymakers is, conditional on $t = 1$ variables,

$$E\{\frac{z}{2}[\mu\pi^*-r(m_1+e_1)+e]^2$$

$$+\frac{g}{2}[\mu\pi^*-r(m_1+e_1)+e-\pi^*]^2$$

$$+\frac{k}{2}[\mu\pi^*(1-r)(m_1+e_1)+e]^2\}.$$

In the first period, a type-i policymaker knows that positive inflation will be costly in the second period and chooses m to minimize

$$E[\frac{z+k}{2}(m+e)^2+\frac{g}{2}(m+e-\pi^*)^2]$$

$$+\beta E\{\frac{z}{2}[\mu\pi^*-r(m+e)+e_2]^2$$

$$+\frac{g}{2}[\mu\pi^*-r(m+e)+e_2-\pi^*]^2$$

$$+\frac{k}{2}[\mu\pi^*(1-r)(m+e)+e_2]^2\}.$$

So,

$$(z+k)m+G(m-\pi^*)$$

$$+\beta\{z(\mu\pi^*-rm)(-r)$$

$$+G[(\mu-1)\pi^*-rm](-r)$$

$$+k[\mu\pi^*+(1-r)m](1-r)\}=0,$$

which implies

$$(13)\quad m=\frac{g\pi^*[z+g+(1-\beta)k]}{(z+g+k)^2+(z+g)\beta k}$$

$$=\mu\pi^*\frac{z+g+k-\beta k}{z+g+k+(1-\mu)\beta k}$$

$$\equiv\varphi\pi^*$$

$$\leq\mu\pi^*.$$

An important feature of this solution for money growth is that it is positive but smaller than $\mu\pi^*$, the money growth rate that the policymaker would choose in the absence of the stable-price rule.

The solution in (13) for first-period policy implies that the second-period policy choice is

$$(14)\quad m=\mu\pi^*-r(\varphi\pi^*+e_1).$$

We summarize these results in table 1. The stable-price rule has costs and benefits relative to the rule permitting price-level drift. If type-0 households control monetary policy, they choose zero-money-growth rates under the latter rule, but they choose money growth that attempts to reverse a portion of previous inflation

TABLE 1

Money-Growth Rates Under Alternative Policy Rules

	Zero-Inflation Rule Permitting Price-Level Drift	
	Type-0 households	**Type-i households**
$t = 1$	0	$\mu\pi^*$
$t = 2$	0	$\mu\pi^*$
	Stable-Price Rule	
	Type-0 households	**Type-i households**
$t = 1$	0	$\varphi\pi^*$
$t = 2$	$-re_1$	$\mu\pi^* - r(\varphi\pi^* + e_1)$

NOTE: μ, r, and φ are as defined in equations (9), (10), and (13). Recall that φ is smaller than μ, so the stable-price rule results in less inflation in *each* period if the policymaker is type-i. This is the social benefit of a stable-price rule. The cost of that rule is the nonzero expected inflation in the second period that occurs if the policymaker is type-i.
SOURCE: Authors.

under the stable-price rule. This is a cost of a stable-price rule, because it would be socially optimal, ignoring incentives, for money growth to be zero each period.

But the stable price level also has important benefits. Under this rule, if a type-i person controls monetary policy, he chooses lower money growth each period. In the second period, the stable-price rule operates directly by penalizing him for failing to return the price level to its target level. In the first period, expectations of this penalty lead him to choose less money growth.

Suppose the probability that the policymaker is type-0 is p and the probability that the policymaker is type-i is $1 - p$. Then expected inflation under a zero-inflation rule that permits price drift is $(1 - p)\, \mu\, \pi^*$ each period; expected inflation under a stable-price rule is $(1 - p)\, \varphi\pi^* < (1 - p)\, \mu\, \pi^*$ in the first period and $(1 - p)\, (\mu - r\varphi)\, \pi^* - re_1 < (1 - p)\, \mu\, \pi^*$ in the second period.

The variance of inflation under the zero-inflation rule allowing drift is $p\,(1 - p)\, \mu^2\, \pi^{*\,2} + \sigma^2$ each period. The variance under the stable-price rule is $p\,(1 - p)\, \varphi^{\,2}\, \pi^{*2} + \sigma^2$ in the first period and $p(1 - p)\,(\mu - r\varphi)^2\, \pi^{*2} + \sigma^2$ in the second period. Since $\mu > \varphi > r\varphi > 0$, the stable-price rule also reduces the variance of inflation.

V. Conclusion

We have presented an example in which a rule for monetary policy specifying a stable price level dominates a rule for zero inflation with price-level drift. This result occurs despite our assumptions that zero inflation—rather than a stable price level—is socially optimal and that policymakers cannot perfectly control inflation. Our example thereby ignores the arguments we have made elsewhere for a stable price level.

Nevertheless, a stable-price rule can be better than a rule for zero inflation that permits price drift, particularly because policy is unobservable. The stable-price rule raises the penalty on a policymaker who purposely engineers positive inflation but falsely claims that it was the unintended result of random forces. The cost of this rule is a change in incentives of policymakers who would act in the social interest without the rule. But, as in our example, this cost can be second-order, while the benefit is first-order.

In this two-period model, the policymaker always prefers the zero-inflation rule over the price-level rule. Well-intentioned policymakers know that they would deliberately aim for the social optimum without the rule. Those who would privately gain from inflation would find that the zero-inflation rule is less costly than the price-level rule.

There are several artificial features of our example. For simplicity, we assume a two-period model. There is likely to be some inflation on average over the two periods even under a constant-price-level rule. This average inflation converges to zero as the number of periods increases.

We have not explained the social costs of inflation, though we have attempted to summarize them elsewhere. We have interpreted a rule as a penalty function for failing to achieve some goal, and we have ignored the problem of incentives for enforcement. Nevertheless, there may be enforceable rules that the government can impose on the behavior of one of its agencies, such as a central bank. If so, our conclusion may be fairly general.

This paper has not addressed the question of an *optimal* rule. But it shows why a simple stable-price rule can dominate a simple zero-inflation rule by reducing the policymaker's incentive to create inflation for special interests and blame it on random events.

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Predicting Bank Failures in the 1980s

by James B. Thomson

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Introduction

From 1940 through the 1970s, few U.S. banks failed. The past decade was a different matter, however, as bank failures reached record post-Depression rates. More than 200 banks closed their doors each year from 1987 through 1989, while 1990 saw 169 banks fold. And because more than 8 percent of all banks are currently classified as problem institutions by bank regulators, failures are expected to exceed 150 per year for the next several years.[1] The recent difficulties in the commercial real estate industry, especially in the Northeast and the Southwest, will likely add to the number of problem and failed banks in the 1990s.

The increase in bank failures in the 1980s was accompanied by an increase in the cost of resolving those failures. Furthermore, the cost of failure per dollar of failed-bank assets, which is already high, may continue to rise. For banks failing in 1985 and 1986, failure resolution cost estimates averaged 33 percent of failed-bank assets, while the estimated loss to the Federal Deposit Insurance Corporation (FDIC) reached as high as 64 percent of bank assets (see Bovenzi and Murton [1988]).

One characteristic that is different for some of the recent failures is bank size, as large-bank failures became more common in the 1980s. In 1984, for example, the FDIC committed $4.5 billion to rescue the Continental Illinois National Bank and Trust Company of Chicago, which at that time had $33.6 billion in assets. In 1987, BancTexas and First City Bancorporation of Dallas were bailed out by the FDIC at a cost of $150 million and $970 million, respectively. The $32.5 billion-asset First Republic Bancorp of Dallas collapsed in 1988, costing the FDIC approximately $4 billion, while 20 bank subsidiaries of MCorp of Houston, with a total of $15.6 billion in assets, were taken over by the FDIC in 1989 at an estimated cost of $2 billion.[2] Most recently, the Bank of New England, with $22 billion in assets, was rescued by the FDIC at an estimated cost of $2.3 billion.

1 Examiners rate banks by assessing five areas of risk: capital adequacy, asset quality, management, earnings, and liquidity. This is called the CAMEL rating. For an in-depth discussion of the CAMEL rating system, see Whalen and Thomson (1988).

2 In the 1980s, other large banks such as Texas American Bankshares, National Bank of Texas, First Oklahoma, and National of Oklahoma were either merged or sold with FDIC assistance. In addition, Seafirst of Seattle, Texas Commerce Bankshares, and Allied Bankshares had to seek merger partners to stave off insolvency.

The study of bank failures is interesting for two reasons. First, an understanding of the factors related to an institution's failure will enable us to manage and regulate banks more efficiently. Second, the ability to differentiate between sound banks and troubled ones will reduce the expected cost of bank failures. In other words, if examiners can detect problems early enough, regulatory actions can be taken either to prevent a bank from failing or to minimize the cost to the FDIC and thus to taxpayers. The ability to detect a deterioration in bank condition from accounting data will reduce the cost of monitoring banks by lessening the need for on-site examinations (see Benston et al. [1986, chapter 10] and Whalen and Thomson [1988]).

An extensive literature on bank failures exists.[3] Statistical techniques used to predict or to classify failed banks include multivariate discriminate analysis (Sinkey [1975]), factor analysis and logit regression (West [1985]), event-history analysis (Lane, Looney, and Wansley [1986, 1987] and Whalen [1991]), and a two-step logit regression procedure suggested by Maddala (1986) to classify banks as failed and nonfailed (Gajewski [1990] and Thomson [1989]). Recently, Demirgüç-Kunt (1989a, 1991, and forthcoming) has extended this work to include market data and a model of the failure decision. Unfortunately, market data are available only for the largest banking institutions, while the majority of banks that fail are small.

This study uses 1983–1988 book data from the June and December Federal Financial Institutions Examination Council's Reports of Condition and Income (call reports) in statistical models of bank failure. In addition to traditional balance-sheet and income-statement measures of risk, the failure equation incorporates measures of local economic conditions.

The historically high number of failures for every year in the sample period allows each year to be investigated separately. Previous studies had to pool the failures across years to obtain a sufficiently large failed-bank sample, making it difficult to construct holdout samples and to do out-of-sample forecasting. This was especially true for tests across years. The sample in this study is not limited in this way, however. Once failures for a particular year are classified by the model, failures in subsequent years can be used to determine the model's out-of-sample predictive ability. For example, the failure prediction model used to classify failures in 1985 can be applied to the 1984 data for banks that failed in 1986 and 1987.

I. Modeling Bank Failures

The economic failure of a bank occurs when it becomes insolvent. The official failure of a bank occurs when a bank regulator declares that the institution is no longer viable and closes it.[4] Insolvency is a necessary condition for regulators to close a bank, but not, Kane (1986) argues, a sufficient one. He suggests that the FDIC faces a set of four constraints on its ability to close insolvent banks. These constraints, which arise because of imperfect information, budget limitations, and principal–agent conflicts, include information constraints, legal and political constraints, implicit and explicit funding constraints, and administrative and staff constraints (see Kane [1989]). Both Thomson (1989, 1991) and Demirgüç-Kunt (1991) formally incorporate Kane's constraints on the FDIC's ability to close banks into models of the closure decision. These authors, along with Gajewski (1990), estimate two-equation models that formally separate economic insolvency and closure.

The model in this paper is a variant of those in the traditional bank failure prediction literature in that it is a single-equation model, the primary goal of which is to predict bank failures; therefore, it does not formally distinguish between insolvency and failure. Thus, unlike the models in Thomson (1991) and Demirgüç-Kunt (1991), the one presented here does not allow for the study of bank closure policy. On the other hand, unlike the traditional failure prediction literature, this study includes proxy variables to control for the effects of Kane's four constraints on the probability of failure. Finally, the model is an extension of the previous failure prediction models in that it incorporates general measures of local economic conditions into the analysis.

The purpose of this study is to model bank failures of all sizes. This precludes the use of market data, which are available only for a limited number of large banking organizations. Therefore, I use proxy variables based on balance-sheet and income data from the call reports. These variables, defined in box 1, are drawn from the extensive literature on bank failures.

3 For a review of this literature, see Demirgüç-Kunt (1989b).

4 I consider a bank as failed if it is closed or requires FDIC assistance to remain open. For a discussion of the different failure resolution techniques available to the FDIC, see Caliguire and Thomson (1987).

BOX 1

Definitions of Proxy Variables

Dependent variable

DFAIL	Dummy variable: equals one for a failed bank, zero otherwise.

Regressors

NCAPTA	Book equity capital plus the reserve for loan and lease losses minus the sum of loans 90 days past due but still accruing and nonaccruing loans/total assets.
NCLNG	Net chargeoffs/total loans.
LOANHER	Loan portfolio Herfindahl index constructed from the following loan classifications: real estate loans, loans to depository institutions, loans to individuals, commercial and industrial loans, foreign loans, and agricultural loans.
LOANTA	Net loans and leases/total assets.
LIQ	Nondeposit liabilities/cash and investment securities.
OVRHDTA	Overhead/total assets.
ROA	Net income after taxes/total assets.
INSIDELN	Loans to insiders/total assets.
BRANCHU	Dummy variable: equals one if the state is a unit banking state, zero otherwise.
DBHC	Dummy variable: equals one if the bank is in a bank holding company, zero otherwise.
SIZE	Natural logarithm of total assets.
AVGDEP	Natural logarithm of average deposits per banking office.
BOUTDVH	Output Herfindahl index constructed using state-level gross domestic output by one-digit SIC codes.
UMPRTC	Unemployment rate in the county where the bank is headquartered.
CPINC	Percent change in state-level personal income.
BFAILR	Dun and Bradstreet's state-level small-business failure rate per 10,000 concerns.

The dependent variable, *DFAIL,* is the dummy variable for failure. The first eight regressors in the model are motivated by the early warning system literature. Early warning systems are statistical models for off-site monitoring of bank condition used by bank regulators to complement on-site examination. These models seek to determine the condition of a bank through the use of financial data.[5] The proxy variables used in the statistical monitoring models are motivated by the CAMEL rating categories, which regulators use during on-site examinations to determine a bank's condition. *NCAPTA,* the ratio of book equity capital less bad loans to total assets, is the proxy for capital adequacy (CAMEL). This variable is similar to Sinkey's (1977) net-capital-ratio variable, which is the ratio of primary capital less classified assets to total assets.[6] Both Sinkey and Whalen and Thomson (1988) show that similar proxy variables are better indicators of a bank's true condition than is a primary capital-to-assets ratio.

The next three early warning system variables are proxies for asset quality and portfolio risk (CAMEL). *NCLNG* measures net losses per dollar of loans and, hence, the credit quality of the loan portfolio. *LOANHER* is a measure of the diversification of the risky asset or loan portfolio and is therefore a measure of portfolio risk. *LOANTA* is the weight of risky assets in the total asset portfolio and, hence, a proxy for portfolio risk.

OVRHDTA and *INSIDELN* are proxies for management risk (CAMEL). *OVRHDTA* is a measure of operating efficiency, while *INSIDELN* is the proxy for another form of management risk: fraud or insider abuse. Graham and Horner (1988) find that for national banks that failed between 1979 and 1987, insider abuse was a significant factor, contributing to the failure of 35 percent of the closed institutions; material fraud was present in 11 percent of these failures. *ROA,* the return on assets, is the proxy for the earnings component of the CAMEL rating (CAMEL), and *LIQ* is included to proxy for liquidity risk (CAMEL).

5 The purpose of early warning systems is to detect the deterioration of a depository institution's condition between scheduled examinations so that the FDIC can move that institution up in the on-site examination queue. For further information, see Korobow and Stuhr (1983), Korobow, Stuhr, and Martin (1977), Pettway and Sinkey (1980), Rose and Kolari (1985), Sinkey (1975, 1977, 1978), Sinkey and Walker (1975), Stuhr and Van Wicklen (1974), Wang and Sauerhaft (1989), and Whalen and Thomson (1988).

6 Classified assets is a measure of bad loans and other problem assets on a bank's confidential examination report; consequently, it is measured infrequently and is often unavailable to researchers.

In another study (Thomson [1991]), I show that *LOANTA, LIQ, OVRHDTA,* and *ROA* may also proxy for the non-solvency-related factors that contribute to the decision to close insolvent banks, providing additional justification for the inclusion of these variables in the failure prediction equation. I include the remainder of the variables listed in box 1 in the failure prediction equation either because the aforementioned study has shown them to be related to the closure decision (*BRANCHU, DBHC, SIZE, AVGDEP*), or because they serve as proxies for the economic conditions in the bank's home market (*BOUTDVH, UMPRTC, CPINC, BFAILR*).

BRANCHU is included in the regression to control for intrastate branching restrictions. Branching restrictions effectively limit both the opportunities for geographic diversification of a bank's portfolio and the FDIC's options for resolving an insolvency.

DBHC is a dummy variable for holding company affiliation, motivated by the source-of-strength doctrine. Source of strength is the regulatory philosophy, espoused by the Federal Reserve, that the parent holding company should exhaust its own resources in an attempt to make its banking subsidiaries solvent before asking the FDIC to intercede.

I include *SIZE,* the natural logarithm of total assets, in the failure prediction equation to control for the "too big to let fail doctrine" (TBLF). Bank regulators adopted TBLF in the 1980s as a result of the administrative difficulties, the implications for the FDIC insurance fund, and the political fallout associated with the failure of a large bank.

The average deposits per banking office, *AVGDEP,* is used as the proxy for franchise or charter value. Buser, Chen, and Kane (1981) argue that the FDIC uses charter values as a restraint on risk-taking by banks, and that bank closure policy is aimed at preserving charter value in order to minimize FDIC losses. Because the primary source of a bank's charter value is its access to low-cost insured deposits, the level of deposits per banking office should be positively correlated with the value of the banking franchise.

Finally, I include four measures of economic conditions in the bank's markets in order to incorporate the effects of local economic conditions on the bank's solvency: unemployment *(UMPRTC),* growth in personal income *(CPINC),* the business failure rate *(BFAILR),* and a measure of economic diversification *(BOUTDVH).* Unlike Gajewski (1989, 1990), who includes proxies for energy and agricultural shocks in his failure prediction models, I have included economic condition proxies that do not require knowledge of which economically important sectors will experience problems in the future.

II. The Data

Bank failures from July 1984 through June 1989 comprise the failed-bank sample and are taken from the FDIC's Annual Reports from 1984 through 1987 and from FDIC press releases for 1988 and 1989. Only FDIC-insured commercial banks in the United States (excluding territories and possessions) are included.

The nonfailed sample includes U.S. banks operating from June 1982 through June 1989 that filed complete call reports. I have drawn this sample randomly from the call reports and have checked the nonfailed sample to ensure that it is representative of the population of nonfailed banks. For instance, the majority of banks in the population are small; therefore, the nonfailed sample is drawn in a manner that ensures that small banks are adequately represented.

Data for the failed banks are drawn from the June and December call reports for 1982 through 1988 and are collected for up to nine semiannual reports prior to the date the bank was closed. I do not collect data for failed banks from call reports within six months of the failure date, because call reports are unavailable to regulators for up to 70 days after a report is issued. Furthermore, window dressing on the call reports of distressed banks just prior to their failure makes that data unreliable. In the cases where all or the majority of bank subsidiaries of a bank holding company are closed at once (for example, BancTexas Group, First City Bancorp of Houston, First Republic Bancorp of Dallas, and MCorp of Houston), the closed institutions are aggregated at the holding company level and treated as a single failure decision. I include a total of 1,736 banks in the nonfailed sample. The number of failed banks in the sample in each year appears in table 1.[7]

I obtain data on economic condition from several sources. State-level gross domestic output data are obtained from the Bureau of Economic Analysis for the years 1980 through

■ 7 Call report data are screened for errors. I deleted from the sample those failed and nonfailed bank samples that were found to have missing or inconsistent loan data or negative values for expense items such as operating and income expense. Roughly 2 percent of the failed sample and 4 percent of the nonfailed sample were eliminated for these reasons. In addition, I eliminated banks in the nonfailed sample that were missing a June or December call report between 1982 and 1988.

TABLE 1

Number of Failed Banks in the Sample

Year	Number of banks
1984	78
1985	115
1986	133
1987	193
1988	174
1989[a]	77

a. 1989 failure number is for banks closed during the first six months of the year.
NOTE: Number of banks in the nonfailed sample in each year is 1,736.
SOURCES: Author's calculations and FDIC Annual Reports.

1986. County-level employment data are taken from the Bureau of Labor Statistics' *Employment and Earnings* for the years 1980 through 1986. State-level personal income data are from the Bureau of Economic Analysis' annual personal income files for the years 1981 through 1988, and business failure data are from Dun and Bradstreet's *Business Failure Record* for the years 1982 through 1988. Because all of the economic condition data are annual, I match the business failure and personal income data with the December call report data of the same year and the following June. The gross domestic output and employment data are matched with the December and June call report data in a similar manner, but with a two-year lag.[8]

III. Empirical Results

I estimate the model by logit regression using the logist regression procedure in SAS. I have chosen logit estimation rather than ordinary least squares (OLS) because of the undesirable properties of the OLS estimator when the dependent variable in the model is a binary (Amemiya [1981]). The unequal frequency of the failed and nonfailed samples suggests the use of logit rather than probit estimation because logit is not sensitive to the uneven sampling frequency problem (Maddala [1983]). The panel nature of the data allows two types of tests to be performed. First, I pool the data over time (using the June 1983 through December 1988 call reports) and assess the predictive accuracy of the model for up to 48 months before failure. Then, using the June call reports for 1983 through 1986, I ascertain the model's in-sample and out-of-sample accuracy.

Overall, the results indicate that up to 30 months before failure, solvency and liquidity are the most important predictors of failure. As the time to failure increases, however, asset quality, earnings, and management gain in importance as predictors of failure. The performance of the FDIC closure constraint proxies in table 2 demonstrates that the distinction between official failure and insolvency is significant and should be accounted for in studies of bank failures. Although the performance of the economic condition variables is mixed, their inclusion increases the predictive accuracy of the model.

Table 2 shows that the coefficient on *NCAPTA* is negative and significant for banks failing within 30 months of the call date and positive for banks failing within 30 to 48 months of the call date. However, the coefficient is only positive and significant for the 36- to 42-month subsample. The positive sign on *NCAPTA* for banks failing after 30 months is paradoxical, because it suggests that book solvency is positively related to failure. This, however, is not a new result (see Thomson [1991] and Seballos and Thomson [1990]). One possible explanation is that banks beginning to experience difficulties improve their capital positions cosmetically by selling assets on which they have capital gains and by deferring sales of assets on which they have capital losses. Another explanation, although not a mutually exclusive one, is that strong banks are more aggressive in recognizing and reserving against emerging problems in their loan portfolios than are weak banks.

The probability of failure is a negative function of asset quality, as the coefficient on *NCLNG* is negative and significant in all of the regressions except the six- to 12-month subsample. In addition, portfolio risk is positively related to the probability of failure, as evidenced by the positive and significant coefficient on *LOANTA* for all subsamples.

The positive and significant coefficients on *OVRHDTA* and *INSIDELN* for all subsamples indicate that management risk and insider

8 The output and employment data are matched with the sample having a two-year lag, because at the time this study was conducted I had access to these data only through the end of 1986; therefore, I could not match the employment and output data to the call data through 1988 without lagging them. Because a state's output mix is unlikely to change much in two years, this data-matching procedure should not affect the performance of *BOUTDVH*. However, while the decline of the financial sector is likely to follow a decline in the real sector, as measured by unemployment, the choice of a two-year lag is clearly ad hoc.

TABLE 2

Logit Regression Results from the Pooled Sample

	Months to failure after call report issued						
	6 to 12	12 to 18	18 to 24	24 to 30	30 to 36	36 to 42	42 to 48
φ_0	2.39	–0.16	–1.42	–3.27	–4.70	–4.52	–5.87
	(1.05)[a]	(0.95)	(0.93)	(0.95)[b]	(1.03)[b]	(1.12)[b]	(1.27)[b]
NCAPTA	–41.94	–30.71	–18.28	–11.08	1.06	4.72	7.21
	(1.73)[b]	(1.66)[b]	(1.56)[b]	(1.61)[b]	(1.73)	(1.68)[b]	(1.96)[b]
NCLNG	–5.08	–8.61	–14.63	–17.25	–23.92	–19.15	–19.10
	(3.72)	(4.13)[a]	(4.57)[b]	(5.07)[b]	(6.02)[b]	(6.52)[b]	(8.60)[b]
LOANHER	0.89	0.32	0.75	0.22	0.58	0.63	0.57
	(0.61)	(0.54)	(0.52)	(0.55)	(0.56)	(0.59)	(0.69)
LOANTA	6.84	8.25	8.96	9.36	9.47	8.60	8.34
	(0.60)[b]	(0.55)[b]	(0.53)[b]	(0.55)[b]	(0.58)[b]	(0.61)[b]	(0.70)[b]
OVRHDTA	193.37	192.71	234.77	261.39	229.73	242.42	282.60
	(28.04)[b]	(26.40)[b]	(25.55)[b]	(26.11)[b]	(27.79)[b]	(29.43)[b]	(34.27)[b]
INSIDELN	28.44	30.08	30.86	31.40	29.50	30.45	30.62
	(4.20)[b]	(3.67)[b]	(3.48)[b]	(3.52)[b]	(3.65)[b]	(3.85)[b]	(4.32)[b]
ROA	–43.87	–52.74	–62.87	–65.97	–82.64	–72.64	–78.57
	(5.69)[b]	(5.94)[b]	(6.55)[b]	(6.95)[b]	(8.11)[b]	(8.81)[a]	(10.81)[b]
LIQ	0.49	0.48	0.42	0.35	0.19	0.40	0.23
	(0.13)[b]	(0.13)[b]	(0.12)[b]	(0.12)[b]	(0.18)	(0.22)[c]	(0.36)
BRANCHU	0.05	0.14	0.10	–0.04	0.06	–0.03	0.30
	(0.14)	(0.13)	(0.12)	(0.12)	(0.13)	(0.14)	(0.15)[a]
DBHC	–0.66	–0.65	–0.66	–0.57	–0.50	–0.59	–0.59
	(0.13)[b]	(0.12)[b]	(0.11)[b]	(0.11)[b]	(0.12)[b]	(0.12)[b]	(0.15)[b]
SIZE	–0.79	–0.72	–0.68	–0.57	–0.45	–0.42	–0.18
	(0.11)[b]	(0.10)[b]	(0.09)[b]	(0.09)[b]	(0.10)[b]	(0.11)[b]	(0.12)
AVGDEP	0.23	0.37	0.43	0.49	0.45	0.45	0.29
	(0.14)[c]	(0.12)[b]	(0.11)[b]	(0.12)[b]	(0.12)[b]	(0.13)[b]	(0.15)[a]
BOUTDVH	–11.12	–12.88	–20.62	–20.70	–21.40	–22.08	–18.68
	(3.70)[b]	(3.27)[b]	(3.43)[b]	(3.53)[b]	(4.04)[b]	(4.38)[b]	(4.77)[b]
UMPRTC	–0.06	–0.04	–0.03	–0.04	–0.05	–0.07	–0.09
	(0.02)	(0.02)[a]	(0.02)[c]	(0.09)[a]	(0.02)[b]	(0.02)[b]	(0.03)[b]
CPINC	–12.19	–15.12	–13.95	–15.01	–14.19	–16.12	–19.33
	(2.58)[b]	(2.24)[b]	(2.07)[b]	(2.12)[b]	(2.23)[b]	(2.29)[b]	(2.66)[b]
BFAILR	–0.00	–0.00	–0.00	–0.00	–0.00	0.00	–0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.15)
χ^2[d]	3884.46[b]	2937.13[b]	2174.88[b]	1709.46[b]	1374.68[b]	1063.92[b]	854.93[b]
Type I	7.99	11.99	16.04	17.90	20.36	19.95	20.19
Type II	6.81	11.04	14.57	16.29	17.72	18.49	17.63
Class[e]	6.86	11.08	14.64	16.36	17.85	18.56	17.74
PPROB	0.04	0.04	0.05	0.05	0.05	0.05	0.05

a. Significant at the 5 percent level.
b. Significant at the 1 percent level.
c. Significant at the 10 percent level.
d. Model chi-square with 16 degrees of freedom.
e. Percentage of all banks misclassified.
NOTE: Dependent variable = *DFAIL*. Standard errors are in parentheses.
SOURCE: Author's calculations.

TABLE 3

Cross-Sectional Logit Regression Results

Call Date: Year Failed:	June 1984 1985	June 1985 1986	June 1986 1987
φ_0	0.41	0.54	1.38
	(2.85)	(2.88)	(2.34)
NCAPTA	–31.53	–29.90	–43.51
	(5.82)[a]	(4.75)[a]	(5.22)[a]
NCLNG	21.93	–1.21	7.20
	(20.01)	(13.72)	(8.77)
LOANHER	2.57	0.41	–0.92
	(1.39)[b]	(1.63)	(1.61)
LOANTA	10.13	9.49	7.37
	(1.74)[a]	(1.80)[a]	(1.52)[a]
OVRHDTA	301.45	242.80	489.16
	(86.83)[a]	(96.12)[c]	(86.14)[a]
INSIDELN	39.58	30.84	50.00
	(12.15)[a]	(10.75)[a]	(13.20)[a]
ROA	–49.91	–69.79	–0.41
	(27.18)[b]	(20.67)[a]	(17.66)
LIQ	2.71	1.53	0.95
	(1.22)[c]	(0.81)	(0.40)[c]
BRANCHU	0.11	–0.17	0.03
	(0.34)	(0.35)	(0.36)
DBHC	–0.79	–0.16	–0.99
	(0.34)[c]	(0.37)[a]	(0.33)[a]
SIZE	–1.13	–0.67	–0.91
	(0.32)[a]	(0.25)	(0.26)[a]
AVGDEP	0.58	0.42	0.50
	(0.38)	(0.32)	(0.32)
BOUTDVH	–10.22	–16.36	1.87
	(9.42)	(9.32)[b]	(8.24)
UMPRTC	–0.07	–0.03	–0.09
	(0.07)	(0.05)	(0.05)[c]
CPINC	–22.91	–30.19	–28.02
	(7.74)[a]	(8.81)[a]	(14.32)[b]
BFAILR	–0.00	–0.00	0.00
	(0.00)	(0.00)	(0.00)
χ^2[d]	402.59[a]	462.30[a]	667.31[a]
Type I	11.30	11.28	9.38
Type II	10.48	9.56	7.03
Class[e]	10.58	9.79	7.45
PPROB	0.13	0.15	0.22

a. Significant at the 1 percent level.
b. Significant at the 10 percent level.
c. Significant at the 5 percent level.
d. Model chi-square with 16 degrees of freedom.
e. Percentage of all banks misclassified.
NOTE: Dependent variable = *DFAIL*. Standard errors are in parentheses.
SOURCE: Author's calculations.

abuse are positively related to failure. In addition, the negative and significant coefficient on *ROA* in all subsamples and the positive and significant coefficient on *LIQ* for all regressions (except the 30- to 36-month and 42- to 48-month subsamples, for which the coefficient is positive and insignificant) indicate that the probability of failing is a negative function of earnings and liquidity.

With the exception of *BRANCHU* (all subsamples) and *SIZE* in the 42- to 48-month *SIZE* subsample, the coefficients on Thomson's (1991) closure constraint proxies are all significant, with the sign predicted by the author's call-option closure model in all the regressions.

The results for the economic condition variables are somewhat mixed. The coefficients on *BOUTDVH, UMPRTC,* and *CPINC* are negative and significant for all subperiods. In other words, the probability of failure is negatively related to state-level economic concentration *(BOUTDVH),* to county-level unemployment *(UMPRTC),* and to changes in state-level personal income *(CPINC).*

The negative sign on *CPINC* is consistent with its use as a proxy for differences between market and book solvency across regions. The significant negative relationship between the probability of failure and both *BOUTDVH* and *UMPRTC* is counterintuitive. If the condition of the banking industry were affected by the health of the economy, then I would expect the coefficients on both *BOUTDVH* and *UMPRTC* to be positive. *BOUTDVH* is a measure of economic diversity in the state where a bank does business. The more diversified a state's or region's economy, the more stable that economy should be and the lower *BOUTDVH* should be. It could be that *BOUTDVH* and *UMPRTC* are picking up the increased political constraints associated with the closing of banks in depressed regions like the Southwest. These political constraints increase as the number of insolvencies in a region grows. Finally, the coefficient on *BFAILR* is negative and insignificant for all subsamples.

Table 3 gives the results when the model is estimated using cross-sectional data from the June 1984, 1985, and 1986 call reports and from failures occurring in the subsequent calendar year. I use cross-sectional estimation for two reasons: 1) to test indirectly the pooling restriction imposed in the earlier tests and 2) to investigate the model's ability to predict failures outside the sample. To facilitate out-of-sample forecasting, I also split the nonfailed sample into two random samples of 868 banks. One is for use in in-sample forecasting, and the second is for use in out-of-sample forecasting. As seen in table 3, with the exception of the coefficients on *ROA* and *DBHC,* no significant difference seems to exist between the coefficients of each model across years. Therefore, the results reported in table 2 do not appear to be sensitive to the pooling restriction.

In-Sample Classification Accuracy

The second criterion for judging bank failure models is the classification accuracy of the model. In other words, how precise is the model in discriminating between failed and nonfailed banks within the sample, and how effective is it in discriminating between failed and nonfailed banks outside the sample?

For the pooled data, I perform only in-sample forecasting. Tables 2 and 3 report the overall classification accuracy of the three models, along with each model's type I and type II error. Type I error occurs when a failed bank is incorrectly classified as a nonfailed bank, and type II error occurs when a nonfailed bank is incorrectly classified as a failed bank. The overall classification error is the weighted sum of both types of errors. Typically, there is a trade-off between type I error and overall classification accuracy.

The logit model classifies a bank as failed if the predicted value of the dependent variable exceeds an exogenously set probability cutoff point (PPROB). The PPROB is set according to the prior probabilities of being in each group — typically, at 0.5. However, for studies such as this one, where closed banks are sampled at a higher rate than nonclosed banks, Maddala (1986) argues that the use of logit leads to a biased constant term that reduces the predictive power of the model. To correct for this, he suggests that one should assume that the prior probabilities are the sampling rates for the two groups. In addition, if type I error is seen to be more costly than type II error, a lower value for the PPROB is justified.

Overall, the model's in-sample classification accuracy is excellent (see table 2). Using the ratio of failed to nonfailed observations in the sample as the PPROB, I find that type I error ranges from 7.99 percent in the six- to 12-month subsample to 20.19 percent in the 42- to 48-month subsample. Overall classification error ranges from 6.86 percent in the six- to 12-month subsample to 18.56 percent in the 36- to 42-month subsample. As expected, type I errors and overall classification errors increase with time to failure.

Out-of-Sample Forecasting

One reason for studying bank failures is so that statistical models can be constructed to identify banks that may fail in the future. Such models are referred to as off-site monitoring or early warning systems in the literature and are used by bank regulators as a complement to on-site examinations. Out-of-sample forecasting not only yields information on the usefulness of the bank failure model as an examination tool, but also provides data on the stability of the failure equation over time.

For the out-of-sample forecasts, I use the estimated coefficients from the cross-sectional logit regressions, employing data from the June call reports of 1984 through 1986 and half of the nonfailed sample. The failed sample consists of all banks that failed in the year following the one from which the call report data were drawn. The coefficients for the model estimated over this sample appear in table 3. I use the second half of the nonfailed sample as the holdout sample for forecasting. I also construct three failed holdout samples using data from the June 1984 and June 1985 call reports. Only two holdout samples could be constructed for the June 1986 call date, because the failed-bank sample only runs through June 1989. The first failed holdout sample consists of banks failing in the second calendar year following the call report, and the second consists of banks failing in the third calendar year following the call report. The third holdout sample (unavailable for forecasting when the June 1986 call report is used) is comprised of banks failing in the fourth calendar year following the call report.

The results for this out-of-sample forecasting experiment appear in table 4. The PPROB cutoff point for classifying banks as failed or nonfailed is the ratio of failed to nonfailed banks from the in-sample regressions. Other cutoff points yield similar results. When PPROB = 0.132, the model misclassifies 10.19 percent of the banks in the holdout sample using 1986 failures. The type I error rate indicates that the model misclassifies nearly two-thirds of the failures, while roughly 2 percent of the nonfailed sample (type II error rate) is misclassified. Looking at the results for the 1987 and 1988 failure holdout samples, one can see that the type I errors and overall classification errors for all

TABLE 4

Out-of-Sample Forecasts

Date of call report	Failure date		
	1986	1987	1988
June 1984 (PPROB = 0.132)			
Type I	64.66	67.21	74.83
Type II	1.84	1.84	1.84
Class[a]	10.19	13.23	12.66
June 1985 (PPROB = 0.153)	1987	1988	1989[b]
Type I	63.73	71.93	75.34
Type II	1.73	1.73	1.73
Class[a]	13.01	13.28	7.44
June 1986 (PPROB = 0.221)	1988	1989[b]	
Type I	52.87	62.67	
Type II	3.23	3.23	
Class[a]	11.52	7.95	

a. Percentage of all banks misclassified.
b. 1989 sample of failed banks consists of banks closed during the first six months of the year.
NOTE: Forecasts employ the half of the nonfailed sample not used for the logit regressions in table 3.
SOURCE: Author's calculations.

TABLE 5

Additional Out-of-Sample Forecasts

Call date	Year failed	Type I	Type II	Class[a]
June 1985	1986	52.63	0.86	4.55
June 1986	1987	39.58	1.73	5.50
June 1987	1988	27.59	2.07	4.40
June 1988	1989[b]	22.08	1.67	2.54
In-sample forecast	—	12.48	10.21	10.91

a. Percentage of all banks misclassified.
b. 1989 sample of failed banks consists of banks closed during the first six months of the year.
NOTE: Out-of-sample forecasting is done with PPROB equal to 0.066 (the ratio of failed to nonfailed banks for the in-sample logit regressions) and using coefficients estimated from logit regressions on 1985 failures and the nonfailed sample from the June 1984 call report.
SOURCE: Author's calculations.

three models increase as we attempt to forecast further into the future. Note that the results for the June 1985 and June 1986 call reports are similar to those obtained using June 1984 data.

Given the high type I error rates, one might question the usefulness of the model for off-site monitoring of bank condition. However, the type I error rate could be lowered by decreasing PPROB enough so that the percentage of failed banks classified as nonfailed becomes acceptable. What is interesting from the standpoint of an early warning application is the low classification error and the low type II error. If one wanted to use this model to determine which banks should be examined next, low type II error would be an extremely important consideration, since the FDIC has limited examination resources.

In practice, the first out-of-sample experiment is of little use for designing early warning models because it requires the ability to identify failures in subsequent years in order to apply it. Therefore, I perform a second out-of-sample experiment that is able to mimic an early warning model in practice. Employing the June 1984 call report data, I estimate the three models using the entire nonfailed sample and the failures occurring in the next calendar year. I then use the coefficients to perform out-of-sample forecasting using 1) June call data for 1985 through 1988 on the nonfailed sample and 2) failures in the calendar year following the call report as the holdout samples. The PPROB is again set equal to the ratio of failed banks to nonfailed banks used in the in-sample logit regressions.

The results in table 5 show that using the 1984 version of the failure model, the out-of-sample classification error ranges from 5.50 percent in June 1986 to 2.54 percent in June 1988, and type I error ranges from 52.63 percent in June 1985 to 22.08 percent in June 1988. It is somewhat curious that the out-of-sample classification accuracy of all three models increases as we move further from the call date of the in-sample experiment. Again, note that the type I error for the out-of-sample regressions could be lowered at the expense of the type II error (and the overall classification error) by decreasing PPROB. The performance of all the models in the second out-of-sample forecasting experiment suggests that they could be used as part of an early warning system of failure.

IV. Conclusion

This study shows that the probability that a bank will fail is a function of variables related to its solvency, including capital adequacy, asset quality, management quality, earnings performance, and the relative liquidity of the portfolio. In fact, the CAMEL-motivated proxy variables for bank condition demonstrate that the majority of these factors are significantly related to the probability of failure as much as four years before a bank fails.

Overall, the model demonstrates good classification accuracy in both the in-sample and out-of-sample tests. For the in-sample tests, it is able to classify correctly more than 93 percent of the banks in the six- to 12-month subsamples and more than 82 percent of the banks in the 42- to 48-month subsamples. In addition, the model correctly classifies more than 94 percent of those banks that fail between six and 12 months of the call date and almost 80 percent of those that fail between 42 and 48 months of the call date. Out-of-sample classification accuracy is also excellent, indicating that the model could be modified for use as an early warning model of bank failure.

Economic conditions in the markets where a bank operates also appear to affect the probability of bank failure as much as four years before the failure date. However, given that regional economic risk is diversifiable, the sensitivity of the banking system to regional economic conditions suggests that policymakers should revise the laws and regulations that limit banks' ability to diversify their portfolios geographically (especially in light of the fact that the national economy was relatively strong during the years covered in this study).

Finally, the performance of the closure-constraint proxy variables indicates that the probability of failure is not simply the probability that a bank will become insolvent, but that it will be closed when it becomes insolvent. In other words, the results show that the distinction between official failure and economic insolvency is an important one, suggesting the need for further research on the determinants of the incentive systems faced by bank regulators (see Kane [1986, 1989]).

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A Proportional Hazards Model of Bank Failure: An Examination of Its Usefulness as an Early Warning Tool

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Introduction

The number of U.S. bank failures jumped sharply in the mid-1980s and has remained disturbingly high, averaging roughly 170 banks a year over the 1985–1990 period. Furthermore, large-bank failures have become increasingly common. For a variety of reasons, the timing of closures and the resolution techniques used have severely strained the resources of the Federal Deposit Insurance Corporation (FDIC). These developments have stimulated a great deal of debate about the causes of costly bank closures and about alternative ways to prevent them. One focus of this debate has been on the appropriate roles of market versus regulatory discipline. A necessary condition for effective discipline by either force is the ability to identify high-risk banks accurately at a reasonable length of time prior to failure without the use of expensive and time-consuming on-site examinations. This requires the use of some sort of statistical model, conventionally labeled an "early warning model," to translate bank characteristics into estimates of risk. There is considerable debate about whether models of sufficient accuracy can be built using only currently available accounting data.[1]

This study examines a particular type of early warning model called a Cox proportional hazards model, which basically produces estimates of the probability that a bank with a given set of characteristics will survive longer than some specified length of time into the future. The sample consists of all banks that failed between January 1, 1987 and October 31, 1990 and a randomly selected group of roughly 1,500 nonfailed banks. Using a relatively small set of publicly available explanatory variables, the model identifies both failed and healthy banks with a high degree of accuracy. Furthermore, a large proportion of banks that subsequently failed are flagged as potential failures in periods prior to their actual demise. The classification accuracy of the model over time is impressive, since the coefficients are based on 1986 data and are not updated over time. In short, the results demonstrate that reasonably accurate early warning models can be built and maintained at relatively low cost.

The following section describes the proportional hazards model (PHM) in general terms and compares it to alternative statistical early

1 This is the opinion reflected in Randall (1989), for example.

warning models. A short discussion of sampling issues follows. Section III contains a more detailed discussion about the specification of the model estimated in this paper, and section IV presents the model's estimation results and classification accuracy. The final section contains a brief summary and conclusions.

I. The Proportional Hazards Model

Of the large number of early warning/failure prediction studies that have been done, most have employed discriminant analysis or probit/logit techniques to construct the models. These models are designed to generate the probability that a bank with a given set of characteristics will fall into one of two or more classes, most often failure/nonfailure.[2] Further, the predicted probabilities are of failure/nonfailure at some unspecified point in time over an interval implied by the study design.

Like these statistical techniques, a PHM can be used to generate estimates of the probability of bank failure or, alternatively, of survival. However, a PHM has several advantages relative to these other types of models, including the ability to produce estimates of probable time to failure. In fact, it can be used to generate a survival profile for any commercial bank (the estimated probability of survival longer than specified times as a function of time). The other types of models yield only the probability that a bank will fail at some point in time over some specified period, but provide no insight on when the failure will occur over this period. Additionally, a PHM does not require the user to make assumptions about the distributional properties of the data (for example, multivariate normality) that may be violated. In the one somewhat dated study of bank failures in which a PHM is estimated and used, the model is also found to be slightly more accurate than alternative models (see Lane, Looney, and Wansley [1986, p. 525]).

The dependent variable in a PHM is time until failure, T. The survivor function, which represents the probability of surviving longer than t periods, has the following general form:

$$(1) \qquad S(t) = \text{Prob}\,(T > t) = 1 - F(t)\,,$$

where $F(t)$ is the cumulative distribution function for the random variable, time to failure. The probability density function of t is equal to $f(t) = -S'(t)$. Given these definitions, the general form of the so-called hazard function is then

$$(2) \qquad h(t) = \lim_{dt \to 0} \frac{P(t < T < t + dt \mid T > t)}{dt} = \frac{-S'(t)}{S(t)}.$$

The hazard function specifies the instantaneous probability of failure given survival up to time t.

A number of different types of hazard models can be specified, depending on the assumptions made about the nature of the failure time distribution.[3] In the PHM, the hazard function is assumed to have the following rather simple form:

$$(3) \qquad h(t \mid X, B) = h_0(t)\, g(X, B)\,,$$

where X represents a collection of characteristic variables assumed to affect the probability of failure (or, alternatively, of survival) and B stands for the model coefficients to be estimated that describe how each characteristic variable affects the likelihood of failure. The first part of this expression, $h_0(t)$, is a nonparametric term labeled the baseline hazard probability. This probability depends only on time. To obtain the failure probability in a particular case, the baseline hazard probability is shifted proportionally by the parametric function that is the second part of the expression. In the Cox variant used in this paper, the second function is assumed to have an exponential form. That is, the Cox PHM has the following form:

$$(4) \qquad h(t \mid X, B) = h_0(t)\, e^{X'B}.$$

The related survivor function for the Cox PHM, which is used to calculate the probability that a commercial bank with a given set of characteristics will survive longer than some given amount of time into the future, is as follows:

$$(5) \qquad S(t \mid X, B) = S_0(t)^{q}\,,$$

where $q = e^{X'B}$ and

$$S_0(t) = \exp\left[-\int_0^t h_0(u)\; du\right].$$

2 In some studies, the categorization of banks into risk classes is made on the basis of confidential CAMEL ratings.

3 See, for example, the excellent review of a number of hazard models in Kiefer (1988) or Kalbfleisch and Prentice (1980).

As in the hazard function, the first part of this expression, $S_0(t)$, is called the baseline survival probability and depends only on time. It is the same for every bank. To calculate survival probabilities for any bank, it is necessary to choose the relevant time horizon that determines the relevant baseline probability and then plug the values of its characteristic variables into the formula.

The PHM does have several disadvantages, although some of these are shared by competing failure prediction models. Perhaps the most important drawback is that estimation of the PHM requires data on the time to failure. As many others have noted, there is a distinction in banking between insolvency (an economic event) and failure (a regulatory event). That is, bank failure represents a regulatory decision. So whether one uses a PHM or a logit model, it is actually the regulatory closure rule that is being modeled. This can be problematic when one is analyzing bank failures over the late 1980s. During this time, regulators had to resolve a number of large distressed holding companies in Texas, where financial problems were concentrated in some but not all of a holding company's banks (generally, the lead or large subsidiary banks). Typically, closure of the insolvent units was delayed while attempts were made to dispose of the entire organization. Thus, in some cases, the reported financial condition of the larger subsidiaries of these holding companies suggests that they were probably insolvent prior to resolution, while smaller, sometimes numerous coaffiliate banks exhibited relatively healthy financials even shortly before closure. Failure to control for these circumstances in some way could significantly affect the coefficients and classification accuracy of any type of estimated early warning model, but the nature of the adjustment is critically important for PHMs given the nature of the dependent variable.

Empirically, this problem can be dealt with in a number of ways. Some researchers have added a consolidated holding-company size variable to estimated bank failure equations (see Gajewski [1989]). Others have estimated two-equation systems: a solvency equation and a failure equation, adding holding company variables to the latter (see Thomson [1989]). Alternatively, one could take the view that smaller bank affiliates in unit banking states are the functional equivalent of branches and so should be consolidated into one or more of the larger subsidiary banks in failure prediction studies.[4] Another, somewhat cruder, solution that is generally equivalent to consolidation is simply to exclude some or all of the smaller bank subsidiaries of the holding companies in question. This is the approach taken here. I include in the estimation sample only the larger subsidiaries (more than $500 million in total assets) of the large Texas holding companies that failed.[5]

One is still left with the problem of somewhat ambiguous dates of failure for some of the large Texas holding companies. For example, in several cases, resolution transactions that were announced (indicating that the company was judged to be failing as of a specific date) ultimately collapsed, and the institutions were not closed until some later date. Here, following standard practice, I use the failure date designated by the FDIC (typically the date that FDIC funds are disbursed).

Another possible disadvantage of the simple PHM is the assumption that the values of the explanatory variables remain constant over the time horizon implicit in the specification. Obviously, this may not be the case, and if this assumption is violated, classification accuracy of estimated PHMs could suffer. It is possible to estimate PHMs that relax this assumption (with so-called time-varying covariates).[6] However, this complicates the analysis and is not undertaken here.

II. Sampling

Using the entire population of banks to generate early warning models is typically not done, since this method is costly and requires substantial computer time and suitable hardware and software. Practically, models of comparable accuracy can be built and maintained much more easily and cheaply using a sample of banks. This is the approach taken here.

In bank failure studies, sampling is an important issue, since it can significantly affect the reported results. One common approach — the one used in the only PHM study done to date — is the use of a matched sample. In this type of approach, the sample initially consists of some collection of failed banks. Then, for each failed

4 In fact, limited consolidation was authorized under a change in Texas branching laws in 1987, and was done in varying degrees by several of the state's multibank holding companies.

5 However, I include *all* bank affiliates of failed holding companies in the holdout sample.

6 For a discussion of time-varying covariates, see Kalbfleisch and Prentice (1980).

bank included in the sample, the researcher adds one or more nonfailed banks determined to be peers. This method is tedious and costly and requires numerous subjective judgments on the part of the researcher. It also is infeasible to use when analyzing relatively recent failures, since close matching is simply not possible. Furthermore, it is not clear that models developed using matched samples could be easily updated/ reestimated, and updating may be necessary to preserve model accuracy.

I rejected relying solely on random sampling because of the danger of too few failed banks and because of cost considerations. Instead, I employed a choice-based sampling approach similar to that used in numerous other failure prediction studies. Specifically, the data set includes all banks that failed between January 1, 1987 and October 31, 1990 for which complete data could be obtained and that were in operation for at least three full years prior to failure. The nonfailed portion of the sample consists of roughly 1,500 randomly selected banks. The estimation sample is comprised of the 1987 and 1988 failures and approximately 1,000 of the nonfailed banks. The remainder of the failed and nonfailed banks comprise the holdout sample.

III. The Specific Form of the Model

The Approach of Lane, Looney, and Wansley

Lane, Looney, and Wansley (1986), hereafter referred to as LLW, estimate two different versions of PHMs using a relatively small sample of banks that failed over the 1979–1983 period and a matched sample of nonfailed banks. One version, labeled a one-year model, is designed to generate a survivor function that permits the user to predict the probability that a bank with a given set of characteristics will survive longer than times ranging from roughly zero to 12 months into the future. Another version, the two-year model, allows the user to predict survival probabilities ranging from roughly 12 to 24 months into the future. In their sample, LLW pool failures from all the years examined and use stepwise methods to select a relatively small subset of 21 financial condition variables for use as explanatory variables. They do not employ any local economic condition variables.

In the one-year model, LLW find the following ratios to be significant and include them in the final form of the estimated equation: the log of the commercial loans to total loans ratio, the total loans to total deposits ratio, the log of the total capital to total assets ratio, and the log of the operating expense to operating income ratio. In the two-year model, the ratios included are the total loans to total assets ratio, the log of the commercial loans to total loans ratio, the log of the total capital to total assets ratio, the log of the operating expense to operating income ratio, the log of the municipal securities to total assets ratio, and the rate of return on equity.[7] It is interesting that none of the loan quality variables that LLW examine is found to be significant in either model. However, their set of loan quality variables does not include a measure of nonperforming loans, since such data were not reported by banks over the period examined. This may have lowered the classification accuracy of LLW's models, because nonperforming loan data are probably a better leading indicator of incipient asset quality problems than variables such as loan loss provisions or net chargeoffs, and asset quality problems are a primary cause of bank failure. The out-of-sample classification accuracy of these relatively simple models is good, although the holdout sample is relatively small and the time period examined is quite short.

The Current Model

I designed the model used here to produce estimates of the probability that a bank with some given set of characteristics will survive longer than times ranging from roughly zero to 24 months into the future. To accomplish this, I measure the dependent variable, the time to failure, as the time in months from the end of 1986 to the failure date for each failed bank in the estimation sample. For all nonfailed banks in the estimation sample, I censor the time to failure at 24 months, since these banks are known to have survived at least this amount of time into the future.[8] I measure all of the explanatory variables for both failed and nonfailed banks as of year-end 1986. This approach

■ 7 LLW use log values in some cases to transform explanatory variables that appear to be non-normally distributed. This is done because the authors estimate competing discriminant models that require the explanatory variables to be multivariate normal.

■ 8 An additional advantage of the PHM is that it can accommodate censored failure times.

is feasible given the relatively large number of failed banks over the 1987–1988 period and the sampling method used. So, unlike LLW, I do not pool failures from different years. Furthermore, by estimating a single model with a 24-month time horizon, I incorporate the implicit assumption that these survival probabilities depend only on a single set of explanatory variables.

The Explanatory Variables

In general, I employ subsets of a relatively small number of "typical" financial ratios used in previous bank failure prediction studies as explanatory variables in this study. All of these are publicly available numbers drawn from the year-end reports of the Federal Financial Institutions Examination Council's Reports on Condition and Income, known as call reports. The variable names and definitions, along with the 1986 mean values for banks in the estimation sample, appear in the appendix. I do not use loan classification data drawn from examination reports for a variety of reasons, the most important of which is that such data are available only at irregular intervals.[9]

The only other type of explanatory variable used in this study is a single indicator of "local" economic conditions. Recently, a consensus has emerged that such variables have a significant impact on the probability of bank failure and should somehow be incorporated into the analysis. However, an examination of previous research reveals that this has not typically been done in the past. In those studies that use local economic variables, the standard approach is to add one or more as explanatory variables in the estimated failure equation. The identity of the variables and the precise forms of these relationships differ considerably. Some researchers have found that such variables are significant and aid classification accuracy.

More recent studies have used state-level economic variables such as the change in personal income, unemployment, or real estate construction. Some employ a form of state economic diversification variable, while others simply add variables designed to capture the importance of the energy or farm sector in a given state. In a few studies, economic data from the county level or the metropolitan statistical area are employed.

It seems inappropriate to simply add farm- or energy-sector variables to failure prediction equations. Although it is true that downturns in these industries appear to be highly correlated with bank failures in the recent past, there is no reason to believe that this pattern will repeat itself in the future (in the Northeast or the Southeast in the early 1990s, for example). If one deems it desirable to add local economic variables to a bank failure model (and this may not be the best way to proceed), a preferable approach would be to use local variables such as unemployment, employment, or some construction series that reflect local economic shocks regardless of their source.

I employ a state-level variable rather than a more local variable for several reasons. Incorporating more local variables into the analysis is much more tedious and costly. It would also be more difficult to update such variables over time. Furthermore, it is not clear that using more local variables would produce more accurate failure probabilities than state-level data. Previous research indicates that two of the most useful leading indicators of economic conditions at the state level are movements in building permits and initial unemployment claims.[10] Here, only one state variable is used: the percentage change in state residential housing permits issued over the three-year period ending in the year in which the other explanatory variables are measured.

Realistically, the response of the financial condition of any individual bank to local economic conditions varies across banks and changes over time as managers react to anticipated movements in relevant local and national economic variables. This view suggests that perhaps a more correct approach (and a much more ambitious one) would be to use only forecasted bank financial condition variables in the failure prediction equation. The values of these variables would be based on forecasts of local or regional economic conditions generated using separate models (see Goudie [1987], for example). Alternatively, one might develop state-level leading economic index series and sequential probability models, which can be used to generate the probability of a local recession, and then use these probabilities in a failure prediction model (see Phillips [1990]). Neither of these approaches is attempted here.

■ **9** It would be interesting to add the currently confidential data on 30- to 89-day nonperforming loans to the model to see if this resulted in a substantial increase in explanatory power. Such data are likely to be highly correlated with classified loans and are available at regular intervals.

■ **10** See Whalen (1990). The leading-indicator variables could also reflect the divergence between actual and anticipated local economic conditions, which should be an important determinant of bank asset quality and therefore of the probability of failure.

TABLE 1

PHM Estimation Results

Covariate	Coefficient	Standard error	*t* statistic
LAR	0.0242	0.0055	4.39
OHR	0.1766	0.0339	5.21
ROA	–0.0499	0.0193	–2.58
CD100R	0.0105	0.0050	2.07
NPCR	–0.1419	0.0086	–16.56
PCHP64	–0.0120	0.0019	–6.26

NOTE: Model chi square with six degrees of freedom: 1490.75. See appendix for variable definitions.
SOURCE: Author's calculations.

IV. Model Estimation and Results

I derive the survivor function from the underlying hazard function that is actually estimated.[11] Although the focus in this study is on the former, it should be noted that the coefficients from the hazard function appear in the survivor function unchanged. As a result, in a survivor function, coefficients can be expected to exhibit counterintuitive signs. Variables that are expected to be positively associated with the probability of survival, like return on assets (*ROA*), will exhibit negative coefficients. Similarly, variables that are expected to be negatively associated with the probability of survival, such as the overhead expense ratio (*OHR*), will have positive coefficients.

The survivor function consists of estimated baseline survival probabilities ($S_0[t]$ for various t's) and a vector of estimated model coefficients (the B vector), which I use to generate survival probabilities for banks, given their particular set of characteristics. I estimate a number of alternative models with differing sets of explanatory variables. The estimation results for one of these model specifications appear in table 1. I focus only on a single model because this allows the classification results to be examined in detail. However, I obtain similar classification results using the other specifications.

All of the estimated coefficients exhibit the correct sign and are highly significant. However, it should be noted that, as in multiple regression, collinearity among explanatory variables can be and is a problem. Therefore, this specification, like the others examined, is necessarily parsimonious. The variables that consistently exhibit the strongest statistical relationships to the probability of bank survival are *OHR*, the large certificate of deposit dependence ratio, the loan to asset ratio, the primary capital ratio, the nonperforming loan ratio, the net primary capital ratio, and the change in housing permits variable. It is interesting to note that the commercial real estate loan variable is never found to be significant in any version of the equation estimated, possibly reflecting the somewhat aggregated form of the variable used. A construction loan variable was not employed, and this type of activity is generally viewed as the riskiest form of commercial real estate lending.

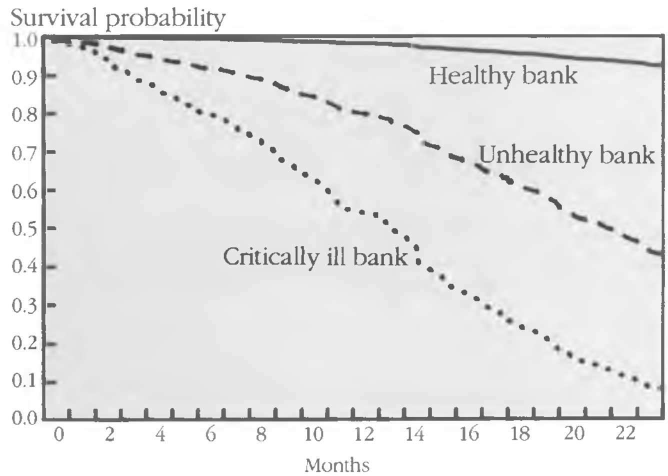
As noted above, the models estimated here can be used to generate the probability that a bank will survive longer than t units, where t can take on any value from roughly zero to 24 months. This is done by substituting the relevant X, B, and baseline survival probabilities into equation (5). Allowing t to vary over the entire permissible range for a bank with some given set of characteristics results in the survival profile for that bank. Thus, this profile shows the probability that some particular bank will survive longer than each possible t value, and vividly portrays the model's estimate of the health of a particular institution. Three illustrative profiles are presented in figure 1.

The top curve depicts the survival profile for a typical "healthy" bank. This profile is derived by inserting the 1986 mean values of the explanatory variables for the nonfailed banks in the estimation sample into the estimated survivor function. Thus, the curve shows that the estimated probability of a healthy bank surviving longer than any number of months ranging from roughly zero to 24 is high — above 0.9. The intermediate profile is for a hypothetical "unhealthy" bank. In this case, the explanatory variable values are set at the 1986 mean value for the banks in the estimation sample that failed in 1988 (that is, those that survived roughly 12 to 24 months into the future). The vertical distance between the two curves represents the estimated reduction in survival probability for the unhealthy bank relative to the healthy bank at every time horizon. The estimated probability

11 I used the Survival Module of SYSTAT to estimate the model, a routine that employs the partial likelihood approach to estimate the B coefficients. This approach does not require that the form of the baseline hazard be specified. For tied failure times, I use Breslow's generalization of the Cox likelihood function. For details, see Steinberg and Colla (1988), appendix C.

FIGURE 1

Survivor Profiles for Three Hypothetical Banks



SOURCE: Author's calculations.

TABLE 2

In-Sample Classification Accuracy

Time horizon (months)	Type I	Type II
12	23 (14.0)	139 (11.8)[a]
18	34 (13.5)	115 (10.6)[b]
24	36 (10.8)	94 (9.3)

a. Of the 139 banks, 107 subsequently failed within 12 to 24 months. Thus, only 32 type II errors occurred for nonfailed banks (3.2 percent).
b. Of the 115 banks, 60 subsequently failed after 18 months. Thus, only 55 type II errors occurred for nonfailed banks (5.5 percent).
NOTE: In the estimation sample, 164 banks failed within 12 months, 252 failed within 18 months, and 333 failed within 24 months. The number of nonfailed banks used in the estimation sample is 1,008. Thus, the type II error rates at the 12-month, 18-month, and 24-month horizons are based on 1,177 banks, 1,089 banks, and 1,008 banks, respectively. The percentage of banks misclassified is in parentheses.
SOURCE: Author's calculations.

of the unhealthy bank surviving longer than 24 months is roughly 0.46. The bottom curve is the survival profile for a hypothetical "critically ill" bank: The values of all the explanatory variables are set at the 1986 mean values for those banks in the estimation sample that failed within 12 months (that is, 1987 failures). Because the values of the explanatory variables for this group of banks are indicative of very high risk and greater likelihood of failure, the survival profile lies well below that of both of the other groups. The estimated 24-month survival probability for the critically ill bank is just 0.11.

Tables 2 through 8 present the classification results produced using the estimated model. The analysis of classification accuracy and the types of classification errors made using an estimated model are the acid tests of the worth of a potential early warning model.

In the analysis presented here, I focus only on predicted 12-, 18-, and 24-month survival probabilities. In order to use the estimated models to classify banks as failures or nonfailures at each of these time horizons in and out of sample, the generated survival probabilities must be compared to some critical probability cutoff value. Typically, the proportions of failed and nonfailed banks in the estimation sample are used to determine the cutoff values. This is the approach taken here. In the estimation sample used in this study, the probabilities of a bank surviving beyond 12, 18, and 24 months are roughly 0.88, 0.81, and 0.75, respectively. These are the cutoff values used in the analysis. Thus, if a bank's estimated 24-month survival probability is less than 0.75, it is predicted to fail within two years. If its estimated survival probability is greater than 0.75, it is predicted to survive longer than 24 months.

Type I and type II errors are defined in the typical fashion: The former is a bank that failed over some specified time horizon during which it was predicted to survive, and the latter is a bank that survived beyond some specified time horizon during which it was predicted to fail. Both types of errors are important in evaluating the potential usefulness of an early warning model. Obviously, a good model should exhibit low type I error rates. Missing failures typically implies delayed resolution, higher resolution costs, or both. However, if an early warning model is to be useful in allocating scarce examination resources, type II error rates should also be relatively low. One exception to this general rule is illustrated below. In particular, the categorization of a prediction as a type II error depends on the time period and the time horizon examined. Some type II errors could actually represent banks that ultimately fail in some future period. In evaluating the accuracy of any early warning model, it is useful to identify how many banks fall into this category of type II error, since they actually represent a success.

The estimated models are quite accurate in-sample (see table 2). The type I and type II error rates are typically in the 10 to 15 percent range, and the overall classification accuracy is

TABLE 3

Out-of-Sample Classification Accuracy: 1988 Failed Banks

Time horizon (months)	Type I	Type II
	1987 Data	
12	21 (12.4)	—
18	18 (10.7)	—
24	11 (6.5)	—

NOTE: Total number of failed banks in the sample is 169. Percentage of banks misclassified is in parentheses.
SOURCE: Author's calculations.

TABLE 4

Out-of-Sample Classification Accuracy: 1989 Failed Banks

Time horizon (months)	Type I	Type II
	1987 Data	
12	—	121 (73.3)
18	13 (15.5)	67 (40.6)
24	12 (7.3)	—
	1988 Data	
12	20 (12.1)	—
18	14 (8.5)	—
24	7 (4.2)	—

NOTE: Total number of failed banks is 165. Of these, 84 failed in the first six months of 1989. Percentage of banks misclassified is in parentheses.
SOURCE: Author's calculations.

above 85 percent for the 12- and 18-month time horizons. The results for the 24-month time horizon are slightly better. Furthermore, a relatively large proportion of the type II errors at the 12- and 18-month time horizons are banks that ultimately failed before 24 months elapsed. Thus, the model was signaling that these banks were potential failures prior to their actual closure.

However, the important yardstick of success for a failure prediction or early warning model is its out-of-sample forecasting accuracy. To obtain insight on this issue, I use the estimated model to generate survival probabilities for all banks in the estimation and holdout samples using data for 1987, 1988, and 1989. Obviously, data are not available for all banks for all years. For example, only 1987 data exist for the 1988 failures. I never reestimate the model coefficients, and use the same cutoff values detailed above. The results for every year are presented for each of the various subsamples in tables 3 to 8.

Turning first to table 3, it is apparent that the model does a relatively good job of identifying the 1988 failed banks. The type I error rate declines from 12.4 percent at the 12- month horizon to 6.5 percent at the 24-month horizon. No type II errors are possible for this subsample.

Table 4 shows the results for the 1989 failures using 1987 and 1988 data. Note that the type I error rates remain relatively low. A look at the type II errors again demonstrates that the model does a reasonably good job of providing an early warning of high-risk banks. For example, using 1987 data, 73.3 percent of the 1989 failures were predicted to fail within 12 months (that is, by year-end 1988).

Results for the 1990 failures (table 5) are similar. The type I error rates are virtually the same as those for the banks that failed in previous years. And again, relatively high proportions of the banks that ultimately failed in 1990 are identified as potential problems in 1987 and 1988.

Table 6 contains the 1987–1989 results for the nonfailed banks used in the estimation sample. Because none of these banks failed, no type I errors are possible. The number and rate of type II errors for this nonfailed subsample are quite low. Table 7 contains virtually identical results for a holdout sample of nonfailed banks.

Finally, table 8 presents results for the largest possible sample. The total number of banks and the numbers classified as failures and nonfailures necessarily change through time. For the 1987 data, for example, the total number of failed banks at the 12-month time horizon consists of all the 1988 failures. The total number of nonfailed banks consists of the 1989 and 1990 failures and the roughly 1,500 nonfailed banks in the estimation and holdout samples. At the 18-month time horizon, those banks that failed in the first six months of 1989 are removed from the nonfailed subsample and considered to be failures. At the 24-month time horizon, all of the 1989 failures are removed from the nonfailed subsample and counted as failures. I use the same procedure to define the subsamples in subsequent years. This exercise perhaps gives the best idea of the potential usefulness of a PHM as an early warning model.

TABLE 5

Out-of-Sample Classification Accuracy: 1990 Failed Banks

Time horizon (months)	Type I	Type II
	1987 Data	
12	—	69 (56.7)
18	—	87 (71.3)
24	—	97 (79.5)
	1988 Data	
12	—	92 (75.4)
18	9 (10.1)	25 (20.5)
24	9 (7.4)	—
	1989 Data	
12	15 (12.3)	—
18	8 (6.6)	—
24	2 (1.6)	—

NOTE: 1990 failed-bank data through October 31. Total number of failed banks is 122. Of these, 89 failed in the first six months of 1989. Percentage of banks misclassified is in parentheses.
SOURCE: Author's calculations.

TABLE 6

Out-of-Sample Classification Accuracy: Nonfailed Estimation Sample

Time horizon (months)	Type I	Type II
	1987 Data	
12	—	29 (2.9)
18	—	58 (5.8)
24	—	101 (10.1)
	1988 Data	
12	—	33 (3.3)
18	—	68 (6.7)
24	—	116 (11.5)
	1989 Data	
12	—	20 (2.0)
18	—	41 (4.1)
24	—	78 (7.7)

NOTE: Total number of nonfailed banks in the estimation sample is 1,008. Percentage of banks misclassified is in parentheses.
SOURCE: Author's calculations.

The model appears to perform quite well. In each year, type I error rates are relatively low for all three time horizons. Similarly, type II error rates are also quite low, particularly if the impact of misclassification of subsequent failures is considered. For example, when 1987 data are used and subsequent failures are excluded, the type II error rates for the 12-, 18-, and 24-month horizons fall to 2.7 percent, 5.6 percent, and 9.4 percent, respectively. As noted above, type II errors attributable to misclassification of banks that ultimately fail are not undesirable but rather indicate the ability of the model to identify subsequent failures early. The model appears to perform this task quite well.

The fact that the classification accuracy does not decline over time even though the model coefficients are not reestimated is encouraging. It indicates that the relationship between the explanatory variables and bank survival probabilities represented by the estimated model is relatively stable. This is a desirable characteristic of an early warning model, since it obviates the need to update the model coefficients or to change the specification frequently.[12]

V. Summary and Conclusions

The results strongly suggest that a PHM with a relatively small number of explanatory variables constructed only from publicly available data could be an effective early warning tool. The overall classification accuracy of the estimated model is high, while both type I and type II error rates are relatively low. Furthermore, the model flags a considerable proportion of failures early.

Many further refinements (in variables or in specification, for example) are possible. In particular, it would be interesting to determine if the currently confidential data on 30- to 89-day nonperforming loans would have a significant impact on the explanatory power of this type of equation. It would also be interesting to investigate the relationship between the model's predictions and CAMEL ratings, which reflect additional nonpublic information generated at considerable cost.

■ 12 Although the errors are not examined in detail, a cursory review reveals that a considerable number of the type II out-of-sample errors involved Texas banks. This is an important consideration given the earlier discussion of insolvency versus failure, and may imply that the accuracy of the model is even slightly higher than indicated by the classification results reported in the tables.

TABLE 7

Out-of-Sample Classification Accuracy: Nonfailed Holdout Sample

Time horizon (months)	Type I	Type II
	1987 Data	
12	—	12 (2.4)
18	—	26 (5.1)
24	—	40 (7.8)
	1988 Data	
12	—	8 (1.6)
18	—	26 (5.1)
24	—	43 (8.4)
	1989 Data	
12	—	8 (1.6)
18	—	17 (3.3)
24	—	36 (7.1)

NOTE: Total number of nonfailed banks in the holdout sample is 510. Percentage of banks misclassified is in parentheses.
SOURCE: Author's calculations.

TABLE 8

Out-of-Sample Classification Accuracy: Maximum Sample

Time horizon (months)	Type I	Type II
	1987 Data	
12	21 (12.4)	231 (12.8)[a]
18	31 (12.3)	238 (13.8)[b]
24	23 (6.9)	238 (14.5)[c]
	1988 Data	
12	20 (12.1)	133 (8.1)[d]
18	23 (9.1)	119 (7.7)[e]
24	22 (7.7)	159 (10.5)
	1989 Data	
12	15 (12.3)	28 (1.8)
18	8 (6.6)	58 (3.8)
24	2 (1.6)	114 (7.5)

a. 190 of these subsequently failed.
b. 154 of these subsequently failed.
c. 97 of these subsequently failed.
d. 92 of these subsequently failed.
e. 25 of these subsequently failed.
NOTE: When year-end 1987 data are used, the sample consists of the 1988, 1989, and 1990 failures and the nonfailed estimation and holdout samples. The number of failed and nonfailed banks at each time horizon depends on the year and time horizon examined. The percentage of banks misclassified is in parentheses.
SOURCE: Author's calculations.

Finally, it will be interesting to see how accurately the model forecasts failures in 1991 and beyond. Some believe that the reasons why banks are encountering financial difficulties at present are somehow different than those faced during the 1980s by southwestern banks, which make up a large part of the sample used to estimate this model. Many argue that effective monitoring of bank financial conditions requires disclosure of additional detailed information on the market value of assets and liabilities. If the estimated PHM exhibits the same degree of accuracy reported here over the next several years, it suggests that neither of these views is correct.

APPENDIX

Estimation Sample: 1986 Mean Values[a]

	1987 failures	1988 failures	Nonfailures
LAR	63.28	64.41	50.82
COMLR	19.33	21.03	11.25
CRELR	9.39	13.14	8.92
CD100R	18.19	22.59	8.44
ROA	–4.57	–2.03	0.59
OHR	5.04	4.68	3.34
PCR	4.31	7.26	9.20
NPCR	–5.62	1.52	7.64
NCOR	6.71	3.13	1.53
NPLR	16.01	9.26	3.10
PCHPxy	–32.53	–39.06	6.09
ASSETS	37.36	271.72	238.38

a. Assets measured in millions of dollars. All other variables are measured in percentages.
SOURCE: Author's calculations.

Variable Definitions

LAR: Total loans/total assets
COMLR: Commercial and industrial loans/total assets
CRELR: Commercial real estate loans/total assets
CD100R: Total domestic time deposits in denominations of $100,000 or more/total assets
ROA: Consolidated net income/average total assets
OHR: Operating expenses/average total assets
PCR: Primary capital/average total assets
NPCR: *PCR* less (total nonperforming loans/average total assets)
NCOR: Total net chargeoffs/average net loans plus leases
NPLR: Total nonperforming loans/total loans plus leases
PCHPxy: Percent change in state's residential housing permits measured over the 198*x* to 198*y* period

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