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Is hazard or probit more accurate in predicting financial distress? Evidence from U.S. bank failures

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Abstract:

We compare the out-of-sample forecasting accuracy of the time-varying hazard model developed by Shumway (2001) and the one-period probit model used by Cole and Gunther (1998). Using data on U.S. bank failures from 1985 – 1992, we find that, from an econometric perspective, the hazard model is more accurate than the probit model in predicting bank failures, but this improvement in accuracy results from incorporating more recent information into the hazard, but not the probit, model. When we limit both models to the same information set, we find that the one-period probit model is slightly more accurate than the time-varying hazard model. We also find that a parsimonious specification of the one-period probit model fit to data from the 1980s performs surprisingly well in forecasting bank failures during 2009 – 2010.

Keywords: bank, bank failure, failure prediction, financial crisis, forecasting, hazard model, probit model, static model, time-varying covariates

JEL Classifications: G17, G21, G28,

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Is hazard or probit more accurate in predicting financial distress?

Evidence from U.S. bank failures

1. Introduction

Recent empirical research strongly supports the theoretical view that a well-functioning banking system is a critically important determinant of a country's economic growth (Levine 2005). Because the banking system plays such an important role in a country's economic development, a banking crisis would generate an independent negative real effect (Dell' Ariccia *et al* 2008; Campello *et al* 2010), and cause serious disruptions of a country's economic activities (Hoggarth *et al.* 2002; Boyd *et al.* 2005; Hutchison and Noy 2005; and Serwa 2010).

During the past decade, a housing boom-and-bust in the U.S. led to massive losses on mortgages and mortgage-backed securities, which were magnified by leverage from derivatives—primarily credit default swaps—tied to those securities. These losses forced regulators to seize a large number of banks and other financial institutions, both in the U.S. and in other countries around the world. These seizures, in turn, led to a international freeze-up in credit markets and a serious global recession (see, e.g., Ivashina and Scharfstein, 2009).

How to differentiate sound banks from troubled banks in order to ensure that the banking sector continues to provide credit to the private sector is a primary concern of both policy makers and bank regulators around the world, and has risen to the top of the agenda at the recent world government summits¹. Consequently, development of more effective

¹ For example, a two-day G20 summit in Washington DC beginning November 14 2008 followed by a four-day U.N. conference on Financing for Development in Qatar, beginning November 29, 2008 all focused on current financial crisis; financial crisis dominated the agenda of the G20 London Summit 2009 held on 2 April 2009, where the world leaders

statistical models for predicting future bank failures, i.e., early warning models, would prove of great value in dealing with the current crisis,² as well as in preventing future crises. In this study, we develop two bank early warning models based upon two alternative and widely used methodologies—the **time-varying hazard model** developed by Shumway (2001) and a **simple static Probit model**³ similar to the one used by Cole and Gunther (1998). We then compare the out-of-sample forecasting accuracy of these two alternatives in order to identify the best tool for this task. We also compare the early warning indicators of U.S. bank failures based upon the two alternative methodologies, i.e., what variables are statistically significant in a model based upon each methodology. The years 1985 – 1992, during which more than a thousand U.S. banks failed, with more than 100 failing in each year, provides a rich sample period for conducting our comparison of forecasting accuracy.⁴ We then combine the coefficients estimated from this period with bank financial information at the end of 2008 to

gathered in London to address the global financial crisis; financial crisis was the central agenda of the 14th ASEAN Summit held on 10 April 2009 (cancelled due to violence in Thailand); The United Nations has convened a global summit on financial crisis in June 2009.

² As of September 30, 2010, there were 860 banks on the “problem bank list” of the Federal Deposit Insurance Corporation (FDIC). These are banks that the FDIC deems at serious risk of failure, based upon information gathered during onsite examinations. Elizabeth Warren, chairwoman of the Congressional Oversight Panel for the Troubled Asset Relief Program (TARP), has publicly stated that as many as 3,000 U.S. banks “face serious problems” as a result of bad real-estate loans made during the financial bubble.

³ **King, Nuxoll and Yeager (2006)** provide a survey of research on bank-failure early warning models and also provide a summary of early warning models used by the three major bank regulators in the U.S.: the Office of the Comptroller of the Currency (“OCC”), the Federal Deposit Insurance Corporation (“FDIC”), and the Federal Reserve System (“FRS”).

⁴ Fewer than 40 banks failed in each year from 1993 – 2008, and more than 15 failed only during 1993 and 2008.

test how accurately these models perform in predicting bank failures over the period 2009 – 2010.

Most previous studies of bank failures rely upon bank-level accounting data, occasionally augmented with market-price data (e.g., Meyer and Pifer 1970; Martin 1977; Pettaway and Sinkey 1980; Cole and Gunther 1995; Cole and White 2010). These studies aim to develop models of an early warning system for individual bank failure. The indicators of these early warning models are closely related to supervisory rating system of banks. The most widely known rating system for banks is the CAMELS system, which stands for Capital Adequacy, Asset Quality, *Management*, *Earnings*, *Liquidity*, and *Systemic Risk*.⁵ However, Cole and Gunther (1998) provide evidence that the information content of the CAMEL rating decays as the financial conditions of banks change over time, becoming obsolete in as little as six months; they also report that a static Probit model using only publicly available bank-level accounting data almost always provides a more accurate prediction of bank failure than do bank CAMEL ratings.

In this study, we apply both a static probit model similar to that use by Cole and Gunther (1998) and a time-varying hazard model as developed by Shumway (2000) to the task of predicting U.S. bank failures. This variant of the hazard methodology models the health of a bank as a function of its financial condition over a number of different time periods, whereas the static Probit methodology models the health of a bank as a function of

⁵ The Uniform Financial Rating System, informally known as the CAMEL ratings system, was introduced by U.S. regulators in the November 1979 to assess the health of individual banks. Following an onsite bank examination, bank examiners assign a score on a scale of one (best) to five (worst) for each of the five CAMEL components; they also assign a single summary measure, known as the “composite” rating. In 1996, CAMEL evolved into CAMELS, with the addition of sixth component (“S”) to summarize Sensitivity to market risk.

its financial condition taken from a single point in time. Shumway (2001) cites three econometric reasons why a time-varying hazard model should out-perform a static probit or logit model in predicting the bankruptcy or failure of a firm: (1) static models fail to control for the period that a firm is “at risk,” whereas the time-varying hazard model does; (2) static models measure information from only a single point in time, whereas the time-varying hazard model incorporates information that changes over time, such as macroeconomic variables; and (3) static models utilize less information, from only a single time period, whereas time-varying hazard models utilize information from multiple time periods.

Shumway (2001) goes on to demonstrate that a simple hazard model provides more consistent in-sample estimations and more accurate out-of-sample predictions for U.S. corporate bankruptcies occurring during the 1962 – ‘992 period than do several bankruptcy prediction models. However, when he runs a horse race between a simple one-period logit model and his time-varying hazard model, he finds that the hazard model does not perform the logit model, but attributes this to peculiarities of his dataset (p. 121).

Our research is distinguished from the previous studies (e.g., Shumway 2001; Mannasoo and Mayes, 2009) in that we focus on comparison of the predictive accuracy of the time-varying hazard model and the static Probit model from both an econometric and a regulatory perspective. Academics primarily focus on the theoretical soundness and accuracy of an early warning model, whereas regulators care more about the practical application. We find that, from an econometric perspective, the hazard model significantly outperforms the Probit model, but this improvement in accuracy comes from incorporating more recent information in the hazard model, but not the Probit model.

However, bank regulators are most concerned about identifying potential bank failures with sufficient lead time to take supervisory action that might forestall a bank's failure, or, in the event of failure, mitigate the impact of that failure on the functioning of the banking system. When our predictions of future bank failures can only rely only upon the most recently currently available bank financial data, we find that the static Probit model slightly outperforms the hazard model. This finding is most surprising, given the three econometric advantages of the hazard over the probit cited by Shumway.

Even more surprising is our finding that our simple and parsimonious Probit model fit using data from the 1980s is highly accurate in predicting bank failures occurring almost two decades later—during 2009 – 2010. This result provides strong support for use of the simple static Probit model as the model of choice for regulatory early warning systems, even though the hazard model dominates static Probit model from an econometric perspective.

The remainder of our manuscript is organized as follows. Section 2 provides a review of the literature on failure prediction and identifies our contribution to the current literature. Section 3 describes our data and methodology. Section 4 presents our empirical results, while Section 5 provides a summary and conclusion.

2. Literature review

The literature on forecasting bankruptcy and firm failure dates back to the 1960s. Altman (1993) provides a summary of this research through the early 1990s. The vast majority of these studies rely upon static methodologies, primarily discriminant analysis during the early years and probit/logit models during the later years.

Time-varying hazard analysis (or its variants), combined with the traditional default risk prediction models, have been employed to predict corporate bankruptcy in recent empirical studies. Using the corporate bankruptcy data over the period 1962 – 1992 in the U.S., Shumway (2001) demonstrates that the hazard model outperforms the traditional bankruptcy models (Altman 1968, Zmijewski 1984), and that a new hazard model combining both accounting and market variables can substantially improve the accuracy in predicting corporate bankruptcy.

Beaver *et al.* (2005) extend Shumway's (2001) research by analyzing the corporate bankruptcy data over the period from 1962 – 2002, and find that the traditional accounting ratios remain robust in predicting corporate bankruptcy, but that a slight decline in the predictive ability of financial ratios can be compensated for by adding market-driven variables into the hazard model estimation. In contrast, Agarwal and Taffler (2008) compare the performance of market-based and accounting-based bankruptcy prediction models, and find little difference between the market-based and accounting-based models in terms of predictive accuracy.

Shumway's hazard model has been widely applied to the prediction of corporate bankruptcy in recent empirical studies (Chava and Jarrow 2004; Bharath and Shumway 2008; Campbell *et al.* 2008; Nam *et al.* 2008; Bonfim 2009). Campbell *et al.* (2008) finds that the

Shumway (2001) and Chava and Jarrow (2004) specifications appear to behave differently in financial-services industry. The financial-services industry, and especially commercial banking, plays a crucial role in a country's economic development, and is subject to heavy regulations relative to other industries. Moreover, standard financial ratios for commercial banks differ from those for other corporate sectors, so that traditional specifications of corporate bankruptcy prediction models cannot be applied to commercial banks.

Empirical studies applying hazard models to bank-failure prediction are relatively sparse. Lane *et al.* (1986) first apply the static Cox (1972) proportional hazard model to the analyses of bank failures in the U.S. They develop an early warning model for a selected sample of failed and peer comparison non-failed banks over 1979 to 1983 and compare the Cox model with multiple discriminant analysis (MDA), they find that the classification accuracy of the Cox model is similar to that of MDA. Since then, the Cox model has been only occasionally used to predict bank failures (e.g., Whalen 1991; Wheelock and Wilson 2000; Molina 2002; Brown and Dinc 2005; Mannasoo and Mayes 2009; Brown and Dinc 2010).

Our research differs from these previous studies on a number of dimensions. First, ours is the first study to apply the simple discrete-time hazard model proposed by Shumway (2001) to bank failure analyses; previous empirical studies have used variants of the Cox proportional hazard model⁶. The Cox hazard model is estimated from a sample of failed banks and non-failed banks, either a peer comparison group (Lane *et al* 1986) or a selected

⁶ Early empirical research relies on a static Cox model by using one set of explanatory variables at a point of time (Lane et al 1986; Whalen 1991). A time-varying Cox model is utilized in the later empirical research by using one-year lagged explanatory variables (Wheelock and Wilson 2000; Molina 2002; Brown and Dinc 2005; Mannasoo and Mayes 2009; Brown and Dinc 2010).

group of non-failed banks (e.g, Whalen 1991; Wheelock and Wilson 2000; Molina 2002; Brown and Dinc 2005; Mannasoo and Mayes 2009; Brown and Dinc 2010), by utilizing partial-likelihood estimation. In contrast, we analyze the entire population of U.S. banks overall the sample period ⁷ utilizing the full-information maximum likelihood hazard model proposed by Shumway (2001), which is much more tractable and more efficient than partial-likelihood Cox models (see Effron, 1977). As demonstrated in a proof by Shumway (2001), the discrete-time hazard model can be estimated using a the logistic (or probit) methodology, and can produce more consistent and efficient estimators than alternative estimators. It does require adjustments to test statistics to account for the fact that the appropriate number of degrees of freedom is based upon the number of banks rather than the number of bank-year observations.

Secondly, our primary focus is on the out-of-sample forecasting accuracy, whereas previous empirical research has focused on the *posterior* probability of bank failure for the in-sample estimations. For example, Wheelock and Wilson (2000) use the Cox proportional hazard model with time-varying covariates, estimated by partial likelihood, to identify specific factors that explain time to bank failures during 1984-93. Utilizing the proportional hazard model to study the large private banks in 21 major emerging markets in the 1990s, Brown and Dinc (2005) find that political concerns play a significant role in delaying government interventions to failing banks; they also find that the government is less likely to take over or close a failing bank if the country's banking system is weak (Brown and Dinc 2010). Our primary concern is on the *anterior* probability of banking failure by comparing

⁷ Wheelock and Wilson (2000) use the data over the same sample period by analyzing a non-random selected sample of only 4,022 banks, of which only 231 failed, while we analyze the entire population of U.S. banks, using data on more than 12,000 banks of which 1,277 failed.

the out-of-sample accuracy of the time-varying hazard model and the static Probit model in predicting bank failures, although we also conduct the in-sample prediction for both models.

Thirdly and most importantly, our research is distinguished from previous research by comparing the predictive accuracy of hazard model and static model from the academic and regulator's perspective respectively. Previous research using hazard model primarily examines this issue from the academic perspective. For example, Shumway (2001) combines the coefficients estimated from the in-sample period over 1962-1983 with the subsequent annual data to predict the out-of-sample corporate bankruptcy in the U.S. over the period of 1984-1992, Mannasoo and Mayes (2009) employ the discrete time hazard model estimated over the years 1997-2001 to predict bank distress over 2002-2004 for 19 Eastern European transition economies. Both papers use one-year lagged variables for the hazard model and actually can only predict failure/bankruptcy one year ahead. In practice, bank regulators are more concerned about bank failures at least two or three years ahead in order to take supervisory action to avert the failure of bank. However, future bank financial data are not available at a point of time, e.g., in 2009, bank financial data exist for the prediction of failure in 2010, while 2010's bank financial data are not available for the prediction of failure in 2011 yet. We find that econometrically the hazard model substantially outperforms the static Probit model in bank failure prediction, and this improvement of prediction accuracy comes from the latest time-varying covariates. Nevertheless, when only currently available bank financial data are used to predict bank failures two or three years ahead, the static Probit model slightly outperforms the hazard model. Therefore, how to bridge the econometrically superior model with practical application opens a new direction for future research. We also find that the simple Probit model performs well in predicting recent banks failures in the U.S.

Fourthly, we incorporate market and macroeconomic variables into the model, and identify the channels through which macroeconomic shocks contribute to bank failures. Numerous previous studies have documented that accounting variables measuring bank capital adequacy, asset quality, and liquidity are significant in predicting bank failure in accounting-based model (Gajewski 1989; Whalen 1991; Demirguc-Kunt 1991; Thomson 1992; Cole and Gunther 1995, 1998). The market-based models use past bank stock returns (Pettaway and Sinkey 1980; Curry *et al.* 2007), volatility of stock returns (Bharath and Shumway 2008, Campbell et al. 2008), and bond spread (Jagtiani and Lemieux 2001). However, the market-based models are only applicable to publicly listed banks, while, in U.S. and many other countries, privately held banks are a major component of a country's banking sector. For example, in the U.S. as of year-end 2008, there were about 400 publicly traded banks but almost 8,000 privately held banks. Therefore, we use exclusively bank accounting data in this study.

We extend our analysis by incorporating market and macroeconomic variables into the model. We find that including bank portfolio excess return, the GDP growth rate and a short-term interest rate does not improve the predictive accuracy, which suggests that bank-specific characteristics are more essential in predicting bank failures. However, our model identifies the channel through which macroeconomic conditions affect bank failure. Declining economic growth contributes to the failure of banks with higher ratio of non-performing loans, while a shock of interest rates makes those banks heavily relying on long-term borrowing more susceptible to failure. Therefore, this research has very important implication for policy maker as well as the risk management of individual banks.

We must acknowledge that bank failure prediction is a dynamic process and that the generality of our results is limited by our data set, which only covers the period from mid 1980s to early 1990s. Since that period, the U.S. banking industry has experienced substantial consolidation, with the number of banks falling by more than one third, from more than 12,000 in 1990 to fewer than 8,000 in 2010. The industry also has seen a shift from holding mortgage assets to securitizing mortgages and holding mortgage-related securities, largely in response to the implementation of risk-based capital requirements. At larger institutions, there has been increasing engagement in off-balance-sheet activities, as evidenced by problems at large banks using structured investment vehicles to hold mortgage-related securities. Surprisingly, the parsimonious specifications we document for the 1985-93 period still perform well in predicting bank failures in the 2009 environment when a sufficient number of bank failures become available. When we combine the coefficients estimated from the 1985-1993 period with bank financial data up to the end of 2008 to predict bank failures during 2009 and the first half of 2010, we find that the Probit model works well in identifying an average of 63% and 76% failed banks among the top 5% and 10% worst predicted failure probabilities, respectively.

3. Data and methodology

3.1 Data

Bank financial data are taken from the year-end Call Reports filed by all FDIC-insured commercial banks with the Federal Financial Institutions Examination Council (“FFIEC”), which collects this information on behalf of the three primary U.S. banking regulators—the Federal Deposit Insurance Corporation (“FDIC”), the Federal Reserve System (“FRS”) and the Office of the Comptroller of the Currency (“OCC”).⁸ The data include basic balance-sheet and income-statement information of individual banks over the period of 1984-1992, and the information on the identity and closure dates of individual banks over the period of 1985-1993 obtained from the FDIC website. This sample period, during which many banks failed, provides us the best data to compare these two econometric approaches to modeling bank failures. We also obtain the financial information of individual banks over 2007 to 2008 bank failure information over 2008 to 2010, and use estimated the coefficients over the period of 1985-1993 to predict bank failures over the latest years⁹.

We construct financial variables that measure the capital adequacy, asset quality, profitability, and liquidity of banks. Numerous previous studies (e.g., Martin 1977; Gajewski 1989; Demirguc-Kunt 1989; Whalen 1991; Thomson 1992; Cole and Gunther 1995, 1998) have found these variables to be statistically significant in predicting bank failures.

⁸ These datasets, along with supporting documentation for their use, are publicly available for download from the website of the Federal Reserve Bank of Chicago.

⁹ There were only 15 failures in 1994 and few than 12 failures over 1995-2007, too few for estimating both models.

Capital adequacy: measured by the ratio of the total equity capital against the total assets. Bank capital can absorb unexpected losses and preserve confidence of banks. Thus capital adequacy is expected to be negatively associated with the probability of bank failure.

We have four variables that measure bank asset quality. These variables reflect bank asset quality difficulties and are expected to contribute to the likelihood of bank failures. The variables on bank asset quality include:

Past due loans: is measured by loans 90 days or more past due divided by total assets.

Nonaccrual loans: is measured by nonaccrual loans divided by total assets.

Other real estate owned: is measured by other real estate owned divided by total assets.

Nonperforming loans: is measured by the sum of past due loans, nonaccrual loans and other real estate owned divided by total assets.

We measure bank profitability using the *earnings ratio*, which we define as net income divided by total assets. The more profitable a bank is, the less likely the bank will fail. *Earning ratio* is expected to have a negative sign of coefficient.

We measure bank liquidity using two different variables—one on the asset side and one on the liability side of the balance sheet.

Investment securities: is measured by investment securities divided by total liabilities. Banks mostly hold government bonds as investment securities. Investment securities tend to be more liquid than loans and enable banks to minimize fire-sale losses in response to unexpected demands of cash. Therefore, the sign of the coefficient of *investment securities* is expected to be negative.

Large CDs (certificates of deposit): is measured by large certificates of deposit (\$100,000 or more) divided by total liabilities. Banks heavily relying on purchased funds, such as large

certificates of deposit, rather than core deposits, often have a more aggressive liquidity management strategy and face higher funding cost. Hence, we expect that the sign of the coefficient will be positive.

We also construct an alternative pair of bank liquidity variables that were used by Cole and Gunther (1995).

Securities to assets measured by investment securities divided by total assets, and

Large CDs to assets measured by large CDs divided by assets.

Besides the above variables, we construct a proxy variable for *Bank Size*, which we define as the natural logarithm of total assets. We expect that small banks are more vulnerable to failure because, in general, their asset portfolios are less diversified; thus the probability of failure will be negatively associated with bank size.

There are a number of extreme values among the variables constructed from the raw financial data. For example, the maximum earnings ratio ranges from -200% to +495%. In order to reduce the impact of outliers on the statistical results, we sort all observations based on these variables and drop the observations with extreme values.

This restriction reduces the number of bank-year observations from 121,950 to 120,728 for the period of 1984 – 1992, and 15,472 to 15,462 for the period of 2007 – 2008.. The figures reported in each table are for this restricted sample. Estimation results with the full dataset where these variables are winsorized at the 1st and 99th percentile values are not reported here, but qualitatively unchanged from the results we report here.

Table 1 reports summary statistics for the data set. The second column is the number of banks at the beginning of each year; the third column reports the number of failed banks during each year, while the last column is the percentage of failed banks for each year. As

shown in Table 1, more than one percent of banks failed each year during the period of 1987 to 1990. Total number of bank-year observation is 120,728 with 1,277 banks failed, which constitutes a cumulative failure rate of 9.42% over the sample period.¹⁰

We use lagged independent variables in the hazard-model estimation so that the financial ratios are observable in the beginning of the year in which bank failure occurs. Table 2 reports the mean values and standard deviations of the bank financial ratios for each year and over the whole sample period respectively. The mean values of the bank financial ratios vary slightly each year, the years with relatively low capital adequacy ratio and investment securities, and relatively high non-performing loans and large CDs (e.g. 1986-1988) are followed by years with relatively higher percentage of bank failure (e.g., 1987-1989, as shown in Table 1). In year 1992 when there was the least number of bank failures in the subsequent year, the mean values of capital adequacy, earnings ratio, and investment securities are much higher while the mean values of the non-performing loans and large CDs are much lower compared the corresponding mean values over the sample period presented in the last column of Table 2. We use three different sets of financial data in our estimation, besides the set of financial ratios reported in section 3, we also substitute *non-performing loans* with *Past due loan*, *Nonaccrual loans* and *Other real estate owned*; and substitute *Investment securities* and *Large CDs* with *Securities to assets* and *Large CDs to assets* respectively. The results for another two sets of financial ratios are not reported but are generally similar to the results we report.

¹⁰ In a study of large international banks in emerging-market countries over 1993-2000 period, Brown and Dinc (2005) report that about 25 percent of their sample banks failed.

3.2 Methodology

We utilize a simple discrete-time hazard model as proposed by Shumway (2001) in our estimation. Shumway (2001) suggests that the time-varying hazard model is superior to the traditional static forecast model in that it incorporates the time-varying explanatory variables and treats a firm's health as a function of its latest financial condition and, therefore, produces more efficient out-of-sample forecasts. To our knowledge, ours is the first study to apply Shumway's hazard model to the prediction of U.S. bank failures. More importantly, we evaluate both models from the perspective of both academics and regulators.

We assume that banks can only fail at a discrete points of time, $T_i = 1, 2, 3, \dots$. We define a dummy variable Y_i that is equal to one if a bank failed at time T_i , and otherwise is equal to zero. Let $F(t_i, X; \square)$ be the probability mass function of failure, where \square represents a vector of parameters and X represents a vector of explanatory variables. Following the hazard model conventions, the survivor function that gives the probability of surviving up to time T can be defined as:

$$S(T, X; \gamma) = 1 - \sum_{J < T} F(J, X; \gamma)$$

And the hazard function that gives the probability of failure at T conditional on surviving to T can be expressed as:

$$H(T, X; \gamma) = \frac{F(T, X; \gamma)}{S(T, X; \gamma)}$$

The likelihood function of the discrete-time hazard model is given by:

$$L = \prod_{i=1}^n H(T_i, X_i; \gamma)^{Y_i} S(T_i, X_i; \gamma)$$

The discrete-time hazard model is equivalent to a multiple-period Logit model with the following likelihood function (Cox and Oakes 1984; Shumway 2001):

$$L = \prod_{i=1}^n \left\{ F(T_i, X_i; \gamma)^{Y_i} \prod_{J < T_i} [1 - F(J, X_i; \gamma)] \right\}$$

Where F is the cumulative density function (CDF) of failure that depends on T , which can be interpreted as a hazard function.

Therefore, a discrete-time hazard model can be easily estimated using a logit model with appropriate adjustment to the test statistics. The test statistics estimated from a logit model assume that the bank-years are independent observations. However, for a discrete-time hazard model, the bank-year observations of a particular bank cannot be independent because a bank cannot fail in period T if it failed in period $T-1$; similarly, a bank surviving to period T cannot have failed in period $T-1$. Thus each bank's life span only makes one observation for the hazard model; the correct number of independent observations is the number of banks in the data instead of the number of bank years. As a result the correct test statistics of the hazard model can be derived by dividing the tests statistics of a Logit model by the average number of bank-years observations.

4. Empirical results

4.1 Econometric performance of hazard and Probit models

In this section, we assess the traditional Probit model and the hazard model from the academic perspective assuming the latest bank financial data are available for estimating the hazard model, e.g., similar as previous empirical research (e.g., Shumway 2001; Mannasoo and Mayes 2009), we use one-year lagged explanatory variables for the hazard model estimations. We first perform the in-sample estimations for both models; and then compare

the out-of-sample forecast accuracy of the two alternative models. Finally, we incorporate market and macroeconomic variables into the hazard model in order to assess their impact on the predictive accuracy of the hazard model.

4.1.1 In-sample estimation

Table 3 presents the in-sample estimation results for both models. Panel A is the estimation results of the hazard model for the bank failure data over 1985 to 1989 by employing the lagged bank financial variables, while panel B reports the results of a Probit model for the same period by using the bank financial variables at the end of 1984. The Chi-squares for the hazard model have been adjusted for the average number of firm years per bank. We also estimate another two specifications: one substitutes *Non-performing loans* for *Past due loans*, *Nonaccrual loans* and *Other real estate owned*; the other substitutes *Investment securities* and *Large CDs* for *Securities to assets* and *Large CDs to assets*, respectively. The results for these additional specifications are not reported here, but are qualitatively unchanged from the results we report here.

Both models produce the expected signs of the coefficients for the financial variables: smaller banks with higher level of non-performing loans and relying more on large CDs for finance are more likely to fail, while larger banks with higher capital adequacy, profitability, and liquidity level are less likely to fail. As indicated in panel B of Table 3, the coefficient of each bank financial variable from the Probit model is statistically significant at 1% level, with the *p*-values close to zero. However, the coefficient of the *Earnings ratio* loses its statistical significance in the hazard model; this indicates that the marginal impact of a temporary higher ratio of earnings to assets is negligible when the failure probability of a bank is higher, and a temporary loss will not lead to bank failure when the failure probability

of a bank is relatively low. This result is consistent with Wheelock and Wilson (2000), who find that the earning ratio is not significant in predicting in-sample bank failures.

4.1.2 Out-of-sample prediction

Table 4 presents the out-of-sample prediction accuracy for the static Probit model and the time-varying hazard model. The first panel “1990-1993” of Table 4 shows the overall predictive accuracy for the full out-of-sample period. The second to fifth panels decompose the overall out-of-sample accuracy result presented in the first panel into each out-of-sample year. Both models use the same explanatory variables identified in Table 3 with the bank financial data available from 1984 to 1992 combined with the bank failure data over 1985 to 1993. For the Probit model, coefficients estimated from bank failures from 1985 to 1989 using 1984 bank financial data are combined with 1989 bank financial data to forecast bank failures between 1990 to 1993. For hazard model, coefficients estimated from bank failures from 1985 to 1989 using bank financial data from 1984 to 1988 are combined with the bank financial data from 1989 to 1992 to forecast bank failures over the period of 1990 to 1993. We also estimate different combinations of in-sample and out-of-sample periods (e.g., the bank failure in-sample period over 1985 to 1988 with out-of-sample period of 1989 to 1993; the in-sample period of 1985 to 1990 with the out-of-sample period of 1991 to 1993), the results are not reported but are generally similar as what we report.

We sort all banks each year from the out-of-sample period based on their predicted failure probability values estimated using the fitted coefficients from the in-sample estimation. The predicted failure probability values are ranked from worst to best and are classified into each of the five highest probability deciles in the failed years and the least likely 50% of banks to fail. The first column of Table 4 shows the out-of-sample years. The

second column presents the rankings of worst predicted probability. The third and fifth columns are the percentage of accuracy ratios, measured as the number of predicted bank failure of the probability rankings against the actual number of bank failure, for Probit and Hazard model respectively. The fourth and last columns are the accumulated percentage of accuracy for Probit and Hazard model respectively. As shown in the first panel, the Hazard model substantially outperforms the Probit model. Among the worst 5% predicted probabilities, the Probit model identifies 52.90% of failed banks over the out-of-sample period, compared with 91.74% for the Hazard model. The hazard model classifies 406 out of 436 bank failures during 1990 to 1993, or 93% of all bank failures in the highest failure probability decile, while the probit model only classifies 72% of all bank failures. Both models do well in identifying failed banks from above the median predicted failure probability, with 99.5% for hazard model and 97.9% for probit model. These results are consistent with Shumway (2001) who finds that a static model can not match a hazard model in terms of accuracy in predicting corporate bankruptcy.

Using the same approach, we also estimate different combinations of in-sample and out-of-sample periods. The results are not reported but are similar as Tables 3 and 4. The hazard models classifies 89% of all bank failures during the 1991 to 1993 in the top five percent predicted failure probability, and 90% of all bank failures in top ten percent worst predicted failure probability, compared with the Probit model of 66% and 80% respectively. For the out-of-sample period of 1989 to 1993, the hazard model prediction accuracy ratio is 92% from the worst five percent predicted failure probability, and 95% from the worst ten percent predicted failure probability, while the corresponding figure for the Probit model is only 53% and 69% respectively.

We decompose the overall accuracy results over the out-of-sample period in the first panel of Table 4 into the accuracy results for each out-of-sample year presented in the second to fifth panels. We find that the predictive accuracy for the Hazard model is persistent over time. Among the worst 5% predicted probabilities, the Hazard model identified more than 90% of failed banks for each out-of-sample year except for the third out-of-sample year (81.74% for 1992). The Probit model performs very well in identifying the failed banks in the first out-of-sample year, with the accuracy ratio of 88.20% among the worst 5% predicted probabilities (96.27% for Hazard model) and 95.65% among the worst 10% predicted probabilities (98.76% for Hazard model). However, the predictive accuracy of Probit model deteriorates quickly from the second out-of-sample year, with the accuracy ratio of 47.5% and 77.5% for the worst 5% and 10% predicted probabilities respectively for year 1991, 18.26% and 41.74% for year 1992, and 20% and 42.5% for year 1993. The results support the conception that the health of a bank is the function of its latest financial condition.

One concern is that the results reported in Table 4 may have a possible bias against the Probit model because the coefficients obtained from the in-sample period for the Probit model rely on less recent bank financial data (e.g., using bank financial data of 1984 to obtain the fitted coefficients) and therefore it will affect its out-of-sample prediction accuracy. We use two different ways to address this issue and test the robustness of the results reported in Table 4.

Firstly, we fit the out-of-sample data using coefficients obtained from different in-sample periods for both models, so that the fitted coefficients are estimated from the bank financial data covering the most to the least recent year for Probit model. For the Probit model, we estimate the coefficients from five different in-sample periods (1989, 1989-1989,

1987-1989, 1986-1989, 1985-1989) respectively using the bank financial data covering the most recent year (1988 for bank failures in 1989) to the least recent one (1984 for bank failures during 1985-1989). Similarly we estimate the coefficients from four different in-sample periods (1989-1989, 1987-1989, 1986-1989, 1985-1989)¹¹ respectively for the Hazard model to fit into the out-of-sample data. Tables 5A and 5B report the out-of-sample accumulated prediction accuracy using fitted coefficients from different in-sample periods for the Probit model and Hazard model respectively. The second row of the third column to seventh column (sixth column for Table 5 B) shows the years of the bank financial data using in the in-sample estimations. The first panel of each table presents the accumulated predictive accuracy for the full out-of-sample period while the second to fifth panels decompose the overall out-of-sample accuracy result presented in the first panel into each out-of-sample year. As indicated in Table 5A, using more recent bank financial data for the in-sample estimation does not significantly improve the out-of-sample prediction accuracy for Probit model. The accumulated prediction accuracy ratio only increases by about 2% among the worst 5% predicted probabilities, most of which comes from the improvement of accuracy in the first year (about 4% increase of prediction accuracy for the worst 5% prediction probabilities in 1990). The prediction accuracy of Probit model deteriorates substantially from the second out-of-sample year regardless of the use of more recent bank financial data in the in-sample estimation, with the decrease of about 40% and 20% in prediction accuracy among the worst 5% and 10% predicted probabilities respectively. On the other hand, as shown in Table 5B, the Hazard model persistently outperforms the Probit model, and the

¹¹ We should have at least two-year in-sample period to estimate the time-varying hazard model.

prediction accuracy is consistent for each out-of-sample year with different length of in-sample periods.

Secondly, we use the combinations of a moving two-year in-sample and out-of-sample period and rerun all the tests for both the Probit and Hazard model. This method enables the use of more recent bank financial data for the Probit and facilitates direct comparison with Hazard model. The combinations of a moving in-sample and out-of-sample period also smooth out the possible selection bias of different sample periods. The results are presented in Table 6. The first column of Table 6 shows the out-of-sample periods, the in-sample period for each out-of-sample period is a two-year period prior to the out-of-sample period. For example, the in-sample period for the last panel of Table 6 (1992-1993) is 1990-1991, coefficients estimated from bank failures from 1990 to 1991 using 1989 bank financial data are combined with 1991 bank financial data to forecast bank failures between 1992 to 1993 for the Probit model. For the Hazard model, coefficients estimated from bank failures from 1990 to 1991 using bank financial data from 1989 to 1990 are combined with bank financial data from 1991 to 1992 to forecast bank failures from 1992 to 1993. The Probit model performs much better compared to the results in Table 4, it identifies a minimum of 66% and 82% of failed banks among the worst 5% and 10% predicted probabilities respectively, compared with the corresponding figures of 53% and 72% respectively in Table 4. However, the Hazard model still persistently outperforms the Probit model, identifying a minimum of 80% and a maximum of 95% of failed banks among the worst 5% predicted probabilities, and a minimum of 89% and a maximum of 98% of failed banks among the worst 10% predicted probabilities. On average, the Probit model differentiates 76% and 87% of failed banks among the worst 5% and 10% predicted probabilities respectively, compared

with the average predicted accuracy of 87% and 93% respectively for the Hazard model. The results again support the perception that the health a bank is the function of its most recent financial conditions.

4.1.3. Hazard model with market and macroeconomic variables

In this section, we incorporate the market and macroeconomic variables into the hazard model, which would not be able to be done for the static Probit model. The variables we consider include:

Bank portfolio excess return: Previous research has documented that past stock returns are strongly related to bankruptcy (Pettway 1980; Pettway and Sinkey 1980; Shumway 2001; Curry *et al.* 2007; Campbell *et al.* 2008). As most of the banks we examined are privately held banks for which market data do not exist, we construct a bank portfolio that contains all listed banks in the U.S., and calculate the annual value-weighted bank portfolio return. The weight is based on each bank's market capitalization at the end of the previous year. Then we subtract the annual value-weighted bank portfolio returns with the short-term interest rates to compute the bank portfolio excess return. The stock prices and market capitalization of each bank, and the short-term interest rates (the 91-day T-bill rates) are extracted from Datastream International. Listed banks can be a broad representative of a country's banking sector, and bank portfolio excess returns are closed linked with a country's future economic growth (Cole *et al.* 2008). We use bank portfolio excess return as a proxy of the market performance of the banking sector.

Real GDP growth rate: We measure this variable as the difference between GDP growth rate and inflation rate. The GDP volume and the consumer price index are derived from International Financial Statistics (IFS).

Interest rate: We measure this variable using the 91-day T-bill rates that are derived from Datastream International.

At first, we include these variables into the hazard model in last section. The values of market and macroeconomic variables are the same for all banks in each year. However, we find that the coefficients for these variables are not significantly different from zero. Some recent empirical research suggests that taking the macroeconomic conditions into account may improve the prediction of corporate default although firm-specific characteristics are the major determinant of corporate default (Carling *et al.*, 2007; Bonfim, 2009; Pesaran *et al.* 2006) also indicate that default probabilities are driven by how firms are tied to business cycle. Arena (2008) studies the relationship of bank failures and bank fundamentals during the 1990s Latin America and East Asia banking crises, and finds that individual bank conditions explain the bank failures, while macroeconomic shocks that triggered the crises primarily destabilized the weak banks *ex ante*. Built on these recent empirical studies, we examine the impact of macroeconomic conditions from a different way, instead of including the macroeconomic variables into the model directly, we study the channel through which the macroeconomic shocks affect bank failures.

An economic slowdown will increase the likelihood of corporate default and therefore affect the performance of banks' loan portfolio. We construct the dummy variable, *Dgrowth*, that takes a value of one when the GDP growth rate is lower than the previous year, and interact *Dgrowth* with the *non-performing loan*, we expect that the coefficient of the interaction term, *Dgrowth*NPL*, will have a positive sign as an economic slowdown will worsen the quality of bank loans. We construct a dummy variable *DI* to stand for a shock of interest rates. *DI* takes a value of one when the interest rate increased compared to the

previous year. We then interact *DI* with *investment securities* and *large CDs* respectively. An increase of interest rates may increase the refinance cost of banks, we expect the coefficient of the interaction term between *DI* and *large CDs* will be positive. An increase of interest rate will have a negative impact on the market value of the investment securities as banks generally hold fixed-income securities, however, it also increases the reinvestment income of banks, therefore the expected sign of the coefficient for the interaction term between *DI* and *investment securities* is not clear.

Table 7 presents the results of hazard model incorporated with market and macroeconomic variables. Panel A reports the in-sample estimation result while Panel B presents the out-of-sample prediction accuracy for the hazard model with and without market and macroeconomic variables. As indicated in Panel A, the coefficient for *earnings ratio* remains negative but insignificant, and the magnitude of the coefficient is smaller compared to the one in Table 3. The coefficient of *bank portfolio excess return* has an expected negative sign but is not significantly different from zero, which indicates that bank failure is more bank-specific. The coefficient for the interaction term of *Dgrowth* and *non-performing loan* is positive and significant at 5% level, which shows that a macroeconomic shock will exacerbate the loan quality and marginally contribute to the failure of those banks with higher non-performing-loan ratio. The coefficient for the interaction term between *DI* and *investment securities* is negative but not statistically different from zero, therefore the marginal impact of the shock of interest rates on the banks with higher ratio of investment securities is negligible. The coefficient for the interaction term of *DI* and *large CDs* is positive and statistically significant at 5% level, while the coefficient of *large CDs* loses its significance and the magnitude is much smaller relative to the one in Table 3. Thus banks

relying more heavily on large CDs as a source of finance would be more vulnerable to the shock of interest rates.

Panel B of Table 7 presents the out-of-sample prediction accuracy of the hazard model with and without market and macroeconomic variables. Both models classify 400 out of 436 bank failures, representing 91.7% of all bank failures during 1990 to 1993, from the top 5% worst predicted failure probability. The hazard model with market and macroeconomic variables classifies 407 out of 436 bank failures, compared with 406 out of 436 bank failures for the model without market and macroeconomic variables, from the top 10% worst predicted failure probability. However, the hazard model without market and macroeconomic variables classifies 99.5% of failed banks from above the median predicted failure probability, compared with 98.9% for the model with market and macroeconomic variables. Therefore, there is no evidence that the hazard model with market and macroeconomic variables will improve the out-of-sample predictive accuracy of bank failures.

This finding does not contradict with the findings of previous research that including market variables will substantially improve the predictive accuracy of bankruptcy (Shumway 2001, Beaver *et al.*, 2005), as previous studies use market variables of individual firm whereas we use a macro market variable that is the same for all firms. Our finding is consistent with recent empirical research which suggests that firm-specific characteristics are the major determinants of bankruptcy or failure (Pesaran *et al.*, 2006; Carling *et al.*, 2007; Arena, 2008; Bonfim, 2009). Although incorporating market and macroeconomic variables does not improve the predictive accuracy of our bank failure models, we do identify a channel through which macroeconomic shocks contribute to bank failures. Therefore, our

finding has important implication for policy makers and for the risk managers of individual banks.

4.2 Practical application of Probit and hazard models

In last section, we conduct the in-sample and out-of-sample estimations for both hazard model and Probit model, and incorporate the market and macroeconomic variables into the hazard model to predict bank failure. We find that the hazard model substantially outperforms the Probit model in predicting bank failures, and the improvement of predictive accuracy primarily comes from the use of time-varying latest bank financial data. Similar as previous empirical research that applies time-varying hazard model to predicting bankruptcy/failure, either the empirical research exclusively focusing on in-sample prediction (e.g., Wheelock and Wilson 2000; Molina 2002; Brown and Dinc 2005; Brown and Dinc 2010), or the research including out-of-sample prediction (Shumway 2001; Beaver *et al.*, 2005; Mannasoo and Mayes 2009), we use one-year lagged explanatory variables for the estimation of hazard model. Therefore, technically the hazard model only predicts bank failure one-year ahead as, in practice, the bank financial data of next year are not available for the failure prediction in the year after. However, bank regulators are more concerned about bank failure in two or three years ahead so that they will have sufficient lead time to take supervisory action to avert the failure of a bank. When future bank financial data are not available and the prediction of bank failures exclusively relies on currently available data at the time of prediction, then which model will perform better?

We address this issue in two stages. In the first stage, we compare the second- and the third-year predictive accuracy of both models over the 1985-1993 periods. In the second stage, we compare the average accuracy of both models in 2009-2010 predicting bank

failures by combining the coefficients estimated over 1985-1993 with the bank financial data up to 2008.

We use bank financial variables up to two-year lags for the hazard model and construct the combinations of a moving in-sample and out-of-sample period for both models. For the Probit model, coefficients estimated from bank failures over 1985 to 1987 using 1984 bank financial data are combined with 1987 bank financial data to predict bank failures between 1988 to 1989. For the hazard model, coefficients estimated from bank failures from 1985 to 1987 using bank financial data from 1984 to 1985, up to two-year lagged variables, are combined with the bank financial data from 1986 to 1987 to predict bank failures over 1987 to 1989. Therefore, we use currently available bank financial data to predict bank failures over the two-year out-of-sample period and avoid using lead bank financial data to predict the bank failure a year later for the hazard model. Totally we have five combinations of moving in-sample and out-of-sample periods over the years from 1985 to 1993. We focus on the predictive accuracy of the second year of two-year out-of-sample period, e.g., two year ahead from the time of prediction. Panel A of Table 8 reports the predictive accuracy ratios of the second year of the two-year out-of-sample period for five combinations of in-sample and out-of-sample periods. Similarly, we use bank financial data up to three-year lags for the hazard model and construct combinations of a moving in-sample and out-of-sample period for both models, and we focus on the predictive accuracy of the third year of the three-year out-of-sample period, which leaves us a total of four different combinations of in-sample and out-of-sample periods. Panel B of Table 8 presents the predictive accuracy ratios three years ahead of the time of prediction.

Similar as what we have done in Sections 4.1.1 and 4.1.2, we sort all banks each year of the out-of-sample period based on their predicted failure probability values estimated using the fitted coefficients from the in-sample estimation. The first column of Table 8 shows the rankings of the worst predicted probabilities. The second row indicates the out-of-sample year of interest, e.g., the second year of the two-year out-of-sample period for Panel A, and the third year of the three-year out-of-sample period for Panel B. Both models perform very well in identifying failed banks two or three years ahead from above the median predicted failure probabilities. Overall, the Probit model slightly outperforms the hazard model in identifying failed banks among the worst 10% predicted probabilities. The Probit model identifies an average of 63.40% and 29.79% of banks failed in two and three years ahead respectively among the worst 5% predicted probabilities, compared with the corresponding figures of 60.87% and 27.86% for the hazard model. Both models identify an average of more than 80% and 50% of banks failed two years and three years ahead respectively among the worst 10% predicted probabilities, with the Probit model slightly outperforms the hazard model (81.34% against 80.23%, and 54.75% against 50.65%, respectively).

Compared with the results of Panel A and Panel B in Table 8, we find that the predictive accuracy drops substantially when bank failures in further years ahead are predicted using currently available bank financial data. Among the worst 5% predicted probabilities, the predictive accuracy for Probit model declines from an average of 63.40% in predicting bank failures two years ahead to 29.79% in predicting bank failures three years ahead; similarly, the predictive accuracy decreases from an average of 60.87% to 27.82% for the hazard model. Among the worst 10% predicted probabilities, the predictive accuracy for hazard model shrinks from an average of 80.23% in predicting bank failures two years ahead

to 50.65% in predictive bank failures three years ahead, compared with a reduction from an average of 81.34% to 54.75% for Probit model. The marginal reduction in predictive accuracy is smaller when we examine the ranking of worst predicted probabilities with higher percentage, and both models still correctly identify an average of about 95% of failed banks in three years ahead from above the median worst predicted failure probabilities.

Similarly, in the second stage, we combine the coefficients estimated from a moving three-year in-sample periods over 1985-1993 with bank financial data up to 2008 to predict the bank failures over 2009 to 2010, with two-year-lagged bank financial variables for the hazard model. Numerous banks failed over 2009-2010, with 119 failures in 2009 and 80 in the first half of 2010 respectively, which is comparable with the bank failures over the period of 1985-1993. Table 9 presents the predictive accuracy of bank failures using coefficients estimated from different in-sample periods. Expectedly, the predictive accuracy ratios decline substantially compared with those reported in Table 6 as the fitted coefficients are estimated from the in-sample periods far away from the prediction time¹². However, on average, the Probit model still correctly identifies 63.2% and 75.6% of failed banks among the top 5% and 10% worst predicted probabilities. This may indicate that, even banking activities have experienced substantial changes after the mid-1990s, a parsimonious model capturing key variables of the CAMELS remains effective as an early warning system of bank failures. The hazard model again underperforms the Probit more, only identifying 50.5% and 60.3% of failed banks among the top worst 5% and 10% predicted probabilities respectively.

The results again support the perception that the health of a bank is the function of its latest financial condition. The substantial improvement of predictive accuracy for the hazard

¹² Too few banks failed during 1993 – 2007 to conduct in-sample estimations for both models.

model, as documented in previous empirical research and confirmed in our results of last section, virtually comes from the use of latest bank financial data. When lead bank financial data are not available for predicting bank failures further year ahead, and the prediction of bank failures exclusively relies on currently available bank financial data at the time of prediction, as we have conducted in this section, then the hazard models lost its advantage of using time-varying covariates and slightly underperforms the static Probit model. Our findings explain why bank regulators prefer the static Probit model, although econometrically the hazard model is superior to the Probit model. This finding also points to critical future research on bridging econometrically superior model with practical application.

5. Conclusions

In this paper, we apply a simple time-varying hazard model as proposed by Shumway (2001) to develop a bank-failure early warning model. We then compare the out-of-sample predictive accuracy of the hazard model with that of a simple static probit model, such as is used by the U.S. banking regulators. Consistent with previous empirical research, we find that, from an econometric perspective, the hazard model outperforms the probit model, but that this improvement of predictive accuracy comes permitting the hazard model to use more timely information than is used by the probit model. In practice, regulators are more concerned about identifying potential bank failures with sufficient lead time to take supervisory action to avert these failures. When we limit the hazard model and the probit model to the same information set, we find that the hazard model underperforms the probit model, and that the predictive accuracy of both models declines substantial when predicting bank failures more than one year ahead. We also find that the simple parsimonious Probit model performs much better in predicting bank failures over 2009-2010. Our findings

support the perception that the health of a bank is the function of its latest financial conditions, and explain why the static Probit model is preferred by bank regulators for early warning systems, even though the hazard model appears, from an econometric perspective,, to be more accurate than the Probit model (Shumway 2001).

Consistent with recent empirical research which suggests that firm-specific characteristics are the major determinant of bankruptcy or failure (Pesaran *et al.*, 2006; Carling *et al.*, 2007; Arena, 2008; Bonfim, 2009), we find that including macroeconomic variables into the bank failure model does not increase predictive accuracy. However, our model identifies a channels through which the macroeconomic shocks contribute to bank failures. Declining economic growth contributes to the failure of banks with higher ratio of non-performing loans, while a shock of interest rates makes those banks heavily relying on long-term borrowing more susceptible to failure. Thus, this research has very important implication for policy marker and risk management of individual banks.

Inferences from our results are limited to financial institutions. We leave it to future research to determine if these results hold up for predictions about the financial distress of non-financial firms.

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Table 1. Summary of the Dataset

Year	Total No. of banks	No. of failed banks	Percentage of failed banks
1985	14,564	112	0.77
1986	14,606	135	0.92
1987	14,485	196	1.35
1988	14,002	203	1.45
1989	13,420	195	1.45
1990	13,021	161	1.24
1991	12,643	120	0.95
1992	12,219	115	0.94
1993	11,768	40	0.34
Total	120,728	1,277	9.42

Note: The second column shows the total number of banks at the beginning of the year, the third column presents the number of banks failed during the year, while the last column is the percentage of failed bank during the year.

Table 2. Summary Statistics of bank financial variables by year

Variables		1984	1985	1986	1987	1988	1989	1990	1991	1992	1984-1992
Capital Adequacy	Mean	0.087	0.086	0.084	0.085	0.085	0.087	0.087	0.088	0.091	0.086
	Std	0.031	0.031	0.033	0.034	0.035	0.034	0.033	0.031	0.029	0.033
Earnings Ratio	Mean	0.007	0.005	0.004	0.004	0.005	0.007	0.006	0.007	0.009	0.006
	Std	0.013	0.016	0.018	0.017	0.018	0.029	0.014	0.013	0.011	0.015
Past Loan Due	Mean	0.007	0.007	0.006	0.005	0.004	0.004	0.004	0.003	0.002	0.005
	Std	0.010	0.010	0.010	0.008	0.007	0.007	0.006	0.006	0.005	0.008
Nonaccrual Loan	Mean	0.007	0.010	0.010	0.009	0.008	0.008	0.008	0.008	0.007	0.009
	Std	0.013	0.015	0.017	0.015	0.015	0.013	0.014	0.013	0.011	0.014
Other Real Estate	Mean	0.004	0.005	0.006	0.007	0.007	0.007	0.007	0.007	0.006	0.006
	Std	0.008	0.010	0.012	0.015	0.015	0.014	0.014	0.014	0.013	0.013
Non-Performing Loan	Mean	0.018	0.021	0.023	0.021	0.019	0.018	0.019	0.018	0.015	0.019
	Std	0.022	0.026	0.029	0.029	0.028	0.025	0.025	0.025	0.022	0.026
Investment Securities	Mean	0.304	0.297	0.292	0.308	0.310	0.300	0.315	0.340	0.355	0.312
	Std	0.161	0.170	0.177	0.182	0.179	0.174	0.175	0.179	0.178	0.176
Large CDs	Mean	0.119	0.120	0.114	0.114	0.114	0.116	0.110	0.095	0.081	0.110
	Std	0.109	0.110	0.109	0.101	0.091	0.086	0.080	0.071	0.064	0.095
Securities to Assets	Mean	0.277	0.270	0.266	0.280	0.282	0.272	0.286	0.308	0.321	0.284
	Std	0.143	0.152	0.158	0.162	0.159	0.154	0.155	0.159	0.158	0.156
Large CDs to Assets	Mean	0.109	0.110	0.105	0.105	0.105	0.106	0.100	0.087	0.074	0.100
	Std	0.099	0.100	0.100	0.094	0.084	0.078	0.072	0.065	0.058	0.086
Size	Mean	10.604	10.668	10.739	10.778	10.839	10.901	10.963	11.016	11.078	10.832
	Std	1.218	1.231	1.241	1.255	1.273	1.287	1.279	1.273	1.265	1.266
Number of Observations		14,564	14,606	14,485	14,002	13,420	13,021	12,643	12,219	11,768	120,728

Note: The construction of variables is explained in section 3.1.

Table 3. In-Sample Prediction of Bank Failures**A. Hazard Model (1985-1989)**

Variable	Coefficient	Adjusted χ^2	P-value
Intercept	2.33	4.90	0.027
Capital adequacy	-46.17	121.63	0.000
Earnings ratio	-3.41	0.89	0.347
Non-performing loan	16.60	80.34	0.000
Investment securities	-2.97	11.92	0.001
Large CDs	2.24	9.22	0.002
Size	-0.42	20.92	0.000
No. of failed banks	841		
No. of observations	71,077		

B. Probit Model (1985-1989)

Variable	Coefficient	χ^2	P-value
Intercept	0.38	2.04	0.153
Capital adequacy	-6.34	64.59	0.000
Earnings ratio	-7.75	30.31	0.000
Non-performing loan	9.90	145.30	0.000
Investment securities	-1.93	103.89	0.000
Large CDs	2.81	264.67	0.000
Size	-0.17	60.76	0.000
No. of failed banks	841		
No. of observations	14,564		

Note: The result of hazard model in Panel A is estimated by using lagged bank financial variables to predict bank failures over the period of 1985 to 1989, while the result of Probit model in Panel B is estimated by using the year-end financial variables in 1984 to predict bank failures from 1985 to 1989. The Chi-square values for the hazard model are adjusted for the average number of firm years per firm.

Table 4. Out-of-Sample (1990-1993) Prediction Accuracy with decomposition of years.

Out-of-sample year	Worst predicted probability (%)	Probit (%)		Hazard (%)	
		Accuracy	accumulated	accuracy	accumulated
1990-1993	5	52.90	52.90	91.74	91.74
	10	19.49	72.39	1.38	93.12
	20	12.99	85.38	1.61	94.72
	30	7.89	93.27	2.52	97.25
	40	2.78	96.06	1.15	98.39
	50	1.86	97.91	1.15	99.54
	50-100	2.09	100.00	0.46	100.00
1990	5	88.20	88.20	96.27	96.27
	10	7.45	95.65	2.48	98.76
	20	2.48	98.14	0.62	99.38
	30	1.24	99.38	0.62	100.00
	40	0.00	99.38	0.00	100.00
	50	0.00	99.38	0.00	100.00
	50-100	0.62	100.00	0.00	100.00
1991	5	47.50	47.50	95.83	95.83
	10	30.00	77.50	0.00	95.83
	20	11.67	89.17	2.50	98.33
	30	4.17	93.33	0.83	99.17
	40	2.50	95.83	0.83	100.00
	50	0.83	96.67	0.00	100.00
	50-100	3.33	100.00	0.00	100.00
1992	5	18.92	18.92	81.74	81.74
	10	24.32	43.24	0.87	82.61
	20	22.52	65.77	0.87	83.48
	30	19.82	85.59	7.83	91.30
	40	5.41	82.61	3.48	94.78
	50	5.41	82.61	3.48	98.26
	50-100	3.60	100.00	1.74	100.00
1993	5	20.51	20.51	90.00	90.00
	10	23.08	43.59	2.50	92.50
	20	33.33	76.92	5.00	97.50
	30	12.82	89.74	0.00	97.50
	40	7.69	97.44	0.00	97.50
	50	2.56	100.00	2.50	100.00
	50-100	0.00	100.00	0.00	100.00

Table 5A. Prediction accuracy of Probit model with different in-sample periods

Out-of-sample years	Worst predicted probability (%)	Accumulated predictive accuracy (%)				
		1988	1987	1986	1985	1984
1990-1993	5	55.22	55.92	54.76	52.44	52.90
	10	72.85	75.41	72.85	74.25	72.39
	20	87.24	88.86	88.40	87.70	85.38
	30	91.18	93.74	94.90	94.90	93.27
	40	93.27	96.06	97.45	97.91	96.06
	50	94.90	97.68	98.84	99.30	97.91
	50-100	100.00	100.00	100.00	100.00	100.00
1990	5	92.55	92.55	89.44	86.34	88.20
	10	98.76	98.14	97.52	95.65	95.65
	20	99.38	100.00	98.76	98.76	98.14
	30	100.00	100.00	100.00	99.38	99.38
	40	100.00	100.00	100.00	99.38	99.38
	50	100.00	100.00	100.00	100.00	99.38
	50-100	100.00	100.00	100.00	100.00	100.00
1991	5	50.00	52.50	52.50	49.17	47.50
	10	76.67	80.00	76.67	80.00	77.50
	20	91.67	93.33	93.33	93.33	89.17
	30	94.17	95.00	95.83	95.00	93.33
	40	95.00	96.67	97.50	97.50	95.83
	50	95.83	97.50	98.33	99.17	96.67
	50-100	100.00	100.00	100.00	100.00	100.00
1992	5	18.92	19.82	19.82	18.92	18.92
	10	41.44	48.65	45.05	46.85	43.24
	20	71.17	74.77	74.77	72.07	65.77
	30	79.28	86.49	88.29	89.19	85.59
	40	85.59	92.79	95.50	95.50	90.99
	50	90.09	96.40	98.20	98.20	96.40
	50-100	100.00	100.00	100.00	100.00	100.00
1993	5	20.51	17.95	17.95	17.95	20.51
	10	43.59	43.59	38.46	46.15	43.59
	20	69.23	69.23	69.23	69.23	76.92
	30	79.49	84.62	89.74	92.31	89.74
	40	82.05	87.18	92.31	100.00	97.44
	50	84.62	92.31	97.44	100.00	100.00
	50-100	100.00	100.00	100.00	100.00	100.00

Table 5B. Prediction accuracy of Hazard model with different in-sample periods

Out-of-sample year	Worst predicted probability (%)	Accumulated predictive accuracy (%)			
		1987-88	1986-88	1985-88	1984-88
1990-1993	5	91.74	91.74	91.97	91.74
	10	94.04	93.35	93.35	93.12
	20	95.87	95.41	94.95	94.72
	30	97.48	97.48	97.48	97.25
	40	98.85	98.62	98.62	98.39
	50	99.31	99.77	99.77	99.54
	50-100	100.00	100.00	100.00	100.00
1990	5	97.52	97.52	97.52	96.27
	10	99.38	98.76	98.76	98.76
	20	100.00	100.00	99.38	99.38
	30	100.00	100.00	100.00	100.00
	40	100.00	100.00	100.00	100.00
	50	100.00	100.00	100.00	100.00
	50-100	100.00	100.00	100.00	100.00
1991	5	96.67	95.83	95.83	95.83
	10	98.33	96.67	96.67	95.83
	20	99.17	99.17	98.33	98.33
	30	100.00	100.00	100.00	99.17
	40	100.00	100.00	100.00	100.00
	50	100.00	100.00	100.00	100.00
	50-100	100.00	100.00	100.00	100.00
1992	5	80.00	80.87	80.87	81.74
	10	82.61	82.61	82.61	82.61
	20	86.96	84.35	84.35	83.48
	30	91.30	91.30	91.30	91.30
	40	96.52	95.65	95.65	94.78
	50	97.39	99.13	99.13	98.26
	50-100	100.00	100.00	100.00	100.00
1993	5	87.50	87.50	90.00	90.00
	10	92.50	92.50	92.50	92.50
	20	95.00	97.50	97.50	97.50
	30	97.50	97.50	97.50	97.50
	40	97.50	97.50	97.50	97.50
	50	100.00	100.00	100.00	100.00
	50-100	100.00	100.00	100.00	100.00

Table 6. Predictive accuracy with moving in-sample and out-of-sample periods.

Out-of-sample period	Worst predicted probability (%)	Probit (%)		Hazard (%)	
		accuracy	accumulated	accuracy	accumulated
1987-1988	5	66.18	66.18	79.70	79.70
	10	15.70	81.88	9.27	88.97
	20	10.87	92.75	5.51	94.49
	30	4.11	96.86	2.76	97.24
	40	1.21	98.07	1.75	99.00
	50	0.48	98.55	0.25	99.25
	50-100	1.45	100.00	0.75	100.00
1988-1989	5	69.76	69.76	82.41	82.41
	10	18.05	87.80	8.04	90.45
	20	9.27	97.07	6.03	96.48
	30	2.20	99.27	2.01	98.49
	40	0.49	99.76	1.01	99.50
	50	0.00	99.76	0.00	99.50
	50-100	0.24	100.00	0.50	100.00
1989-1990	5	82.64	82.64	94.10	94.10
	10	9.62	92.27	3.93	98.03
	20	4.14	96.41	1.12	99.16
	30	1.66	98.07	0.56	99.72
	40	0.55	98.62	0.28	100.00
	50	0.55	99.17	0.00	100.00
	50-100	0.83	100.00	0.00	100.00
1990-1991	5	78.52	78.52	95.37	95.37
	10	11.97	90.49	2.49	97.86
	20	6.69	97.18	1.42	99.29
	30	0.70	97.89	0.36	99.64
	40	0.70	98.59	0.36	100.00
	50	0.35	98.94	0.00	100.00
	50-100	1.06	100.00	0.00	100.00
1991-1992	5	80.00	80.00	88.51	88.51
	10	7.50	87.50	1.70	90.21
	20	7.50	95.00	3.40	93.62
	30	3.33	98.33	3.83	97.45
	40	0.83	99.17	0.85	98.30
	50	0.00	99.17	0.85	99.15
	50-100	0.83	100.00	0.85	100.00
1992-1993	5	77.56	77.56	83.87	83.87
	10	3.21	80.77	6.45	90.32
	20	8.97	89.74	5.81	96.13
	30	5.13	94.87	2.58	98.71
	40	1.92	96.79	0.00	98.71
	50	1.28	98.08	0.00	98.71
	50-100	1.92	100.00	1.29	100.00

Table 7. Hazard Model Estimation with Market and Macroeconomic Data**A. In-sample estimation (1985-1989)**

Variable	Coefficient	Adjusted χ^2	P-value
Intercept	2.31	4.79	0.029
Capital adequacy	-47.76	121.15	0.000
Earnings ratio	-2.76	0.57	0.452
Non-performing loan (NPL)	13.94	37.70	0.000
Investment securities	-2.84	8.74	0.003
Large CDs	1.59	3.79	0.051
Size	-0.42	20.46	0.000
Bank portfolio excess return	-1.43	0.76	0.384
Dgrowth*NPL	4.87	4.30	0.038
DI*investmet securities	-0.68	0.35	0.557
DI*large CDs	2.02	4.02	0.045

B. Out-of-sample accuracy (1990-1993)

Decile	Hazard	Accumulated	Hazard*	Accumulated
1	93.12	93.12	93.35	93.35
2	1.61	94.72	1.15	94.50
3	2.52	97.25	1.83	96.33
4	1.15	98.39	1.15	97.48
5	1.15	99.54	1.38	98.85
6 to 10	0.46	100	1.15	100

Note: Hazard* is for the hazard model accuracy with market and macroeconomic data.

Table 8. Predicting bank failures using currently available data

A. Prediction accuracy of bank failures two-year ahead

Worst predicted probability (%)	Accumulated Predictive accuracy ratios (%)										Average accuracy (%)	
	1989		1990		1991		1992		1993			
	Probit	Hazard	Probit	Hazard	Probit	Hazard	Probit	Hazard	Probit	Hazard	Probit	Hazard
5	64.25	63.77	65.87	63.47	60.98	55.28	62.50	60.83	63.41	60.98	63.40	60.87
10	88.41	87.44	83.83	85.03	77.24	78.86	79.17	76.67	78.05	73.17	81.34	80.23
20	97.10	95.65	92.22	90.42	93.50	92.68	90.00	89.17	87.80	87.80	92.12	91.15
30	99.03	98.07	97.01	94.61	95.93	95.12	95.00	95.83	92.68	92.68	95.93	95.26
40	99.03	99.52	98.20	97.01	97.56	95.93	97.50	97.50	95.12	95.12	97.48	97.02
50	99.52	99.52	98.80	97.60	98.37	96.75	99.17	98.33	95.12	95.12	98.20	97.46

B. Prediction accuracy of bank failures three-year ahead.

Worst predicted probability (%)	Accumulated Predictive accuracy ratios (%)								Average accuracy (%)	
	1990		1991		1992		1993			
	Probit	Hazard	Probit	Hazard	Probit	Hazard	Probit	Hazard	Probit	Hazard
5	34.94	33.73	24.58	22.03	23.08	21.37	36.59	34.15	29.79	27.82
10	59.64	56.63	45.76	39.83	45.30	42.74	68.29	63.41	54.75	50.65
20	87.95	86.75	66.95	67.80	76.07	75.21	87.80	87.80	79.69	79.39
30	91.57	90.96	77.12	76.27	88.89	89.74	90.24	90.24	86.95	86.81
40	95.18	93.98	82.20	85.59	95.73	96.58	95.12	95.12	92.06	92.82
50	96.39	95.18	91.53	92.37	98.29	98.29	95.12	95.12	95.33	95.24

Table 9. Predictive accuracy of bank failures in 2009-2010 with currently available data.

Worst predicted probability (%)	Accumulated predictive accuracy ratio (%)														Average accuracy (%)	
	1985-1987		1986-1988		1987-1989		1988-1990		1989-1991		1990-1992		1991-1993			
	Probit	Hazard	Probit	Hazard	Probit	Hazard	Probit	Hazard	Probit	Hazard	Probit	Hazard	Probit	Hazard	Probit	Hazard
5	59.3	46.0	58.3	46.6	61.8	49.3	62.3	50.4	66.8	52.5	67.3	54.3	66.3	54.3	63.2	50.5
10	68.3	55.2	70.9	56.0	74.9	58.7	75.4	60.2	80.4	63.1	82.4	64.3	76.9	64.3	75.6	60.3
20	79.9	68.7	81.9	69.0	83.4	74.0	84.9	74.9	88.4	75.5	88.9	75.2	88.4	74.3	85.1	73.1
30	86.9	75.8	90.5	78.5	92.5	80.8	92.0	80.5	94.5	81.4	95.0	81.1	94.0	80.5	92.2	79.8
40	93.5	81.7	94.5	82.9	97.5	85.0	96.0	85.5	97.5	86.1	97.0	86.1	96.0	84.4	96.0	84.5
50	94.0	85.3	97.5	86.1	97.5	88.5	98.0	88.5	98.0	88.8	98.0	90.3	97.0	90.3	97.1	88.2