Predicting bank failures using a simple dynamic hazard model

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Abstract:
We use a simple dynamic hazard model with time-varying covariates to develop a bank-failure early warning model, and then test the out-of-sample forecasting accuracy of this model relative to a simple one-period probit model, such as is used by U.S. banking regulators. By incorporating time-varying covariates, our model enables us to utilize macro-economic variables, which cannot be incorporated into in a one-period model. We find that our model significantly outperforms the simple probit model with and without the macro-economic variables. The improvement in accuracy comes both from the time-series bank-specific variables and from the time-series macro-economic variables.

Keywords: bank, bank failure, early warning system, failure prediction, forecasting, hazard model, time-varying covariates

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1. Introduction

Recent empirical research strongly supports the theoretical view that a well-functioning banking system is 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 can cause serious disruptions of a country's economic activities (Hoggarth *et al*. 2002).

During the past decade, a housing boom-and-bust in the U.S. led to massive losses on securitized mortgage-related securities, which were magnified by massive amounts of leverage in derivatives tied to those securities. These losses have forced regulators to seize a growing number of banks and other financial institutions in the U.S. and other countries around the world, leading to a freeze-up in credit markets and a global recession..

How to differentiate sound banks from troubled banks in order to ensure that banks continue to private credit to the private sector is a primary concern of both policy makers and bank regulators, and has risen to the top of the agenda at the recent world government summits.[1] Consequently, development of more effective early warning models of bank failures would prove of great value in dealing with the current crisis as well as in preventing future crises.

[1]For example, a two-day G20 summit in Washington DC beginning November 14, 2008 and followed by a four-day U.N. conference on Financing for Development (FfD) in Qatar, beginning November 29, 2008, both focused on the ongoing financial crisis. Financial crisis also dominated the agenda of the G20 London Summit 2009 held on April 2, 2009, where the world leaders gathered in London to address the global financial crisis; and financial crisis was the central agenda of the 14th ASEAN Summit scheduled for April 10, 2009 (but cancelled because violence in Thailand). The United Nations plans to convene a global summit on financial crisis in June 2009.

In this study, we use a simple dynamic hazard model to develop an early warning model for predicting future bank failures, and compare the out-of-sample forecasting accuracy of this model to that of a simple static model similar to those used by U.S. banking regulators.[2] We also compare the early warning indicators of bank failure in the U.S. based upon the two alternative methodologies, i.e., what variables are statistically significant in a model based upon each methodology. Our findings have important policy implications for banking regulators facing the current and future global financial crises. A more accurate early warning model provides regulators with additional lead time during which they can take supervisory action to avert a bank's failure, or, in the event of a bank failure, mitigate the impact of that failure on the functioning of the banking system.

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)). 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 is CAMELS, which stands for *C*apital Adequacy, *A*sset Quality, *M*anagement, *E*arnings, *L*iquidity, and *S*ystemic Risk.[3] However, Cole and Gunther (1998) find 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

[2] King, Nuxoll and Yeager (2005) 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").

3 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.

publicly available bank-level accounting data almost always provides a more accurate prediction of bank failure than does a bank's CAMEL rating.

In this study, we demonstrate that a simple dynamic hazard model can significantly improve the out-of-sample forecasting accuracy of bank failure relative to a static probit model such as the one used by Cole and Gunther (1998). A static probit model uses only one set of explanatory variables for each bank taken from one point in time. Hence, the estimation results, to a large extent, depend on the decision regarding what time period from which to select each bank's characteristics, and does not take into account the fact that the financial data of a healthy bank can deteriorate over time.

On the contrary, a dynamic hazard model considers the health of a bank as a function of its latest financial conditions and incorporates the time-varying explanatory variables into the estimation; therefore, it corrects for the selection bias inherent in the static probit model.

Shumway (2001) cites three reasons why hazard models are preferable to static models in predicting the bankruptcy or failure of a firm. First, static models do not, whereas hazard models do, control for how long a firm is at risk of failure. Some firms fail quickly while others fail after a much longer period at risk. Failure to correct for period at risk introduces a selection bias to static models, such that parameter estimates are biased and inconsistent.

Second, dynamic hazard models incorporate information from panel data whereas static models rely upon cross-sectional data exclusively. Consequently, dynamic hazard models can impound information from incorporate macro-economic variable and firm age whereas static models cannot.

Third, dynamic hazard models produce more accurate out-of-sample forecasts because they incorporate information from many more observations. For example, we analyze ten years of data, so that our hazard model can utilize ten times as many observations as a static model that uses cross-sectional data from a single year. Were we to use quarterly data, this advantage would rise from a factor of 10 to a factor of 40. More observations result in more precise parameter estimates and more accurate forecasts.

Shumway (2001) goes on to demonstrate that a simple dynamic hazard model provides more consistent in-sample estimations and more accurate out-of-sample predictions for U.S. corporate bankruptcies occurring during the 1962-92 period than do the traditional static bankruptcy prediction models.

In this study, we apply the Shumway methodology to the task of predicting U.S. bank failures. Using more than 120,000 bank-year observations from 1985-93, we confirm that a dynamic hazard model significantly improves the forecast accuracy of bank failure relative to a static probit model. In the out-of-sample prediction over the period of 1990 to 1993, our dynamic hazard model identifies 91.7% of failed banks among banks within the highest 5% of predicted failure probabilities, and 93.1% of failed banks among banks within the highest 10% of predicted failure probabilities; by comparison, our static probit model identifies only 58.4% and 72.3% of failed banks within the highest 5% and 10% of predicted failure probabilities, respectively. The results for different out-of-sample prediction periods are generally similar.

The remainder of our manuscript is organized as follows. Section 2 provides a review of the literature on failure prediction, while Section 3 describes our data and methodology. Section 5 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.

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, McNichols and Rhie (2005) extends Shumway (2001) 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.

Although the hazard model has been widely applied to the prediction of corporate bankruptcy (Chava and Jarrow (2004), Bharath and Shumway (2008), Campbell, Hilscher, and Szilagyi (2008), Nam, Kim, Park and Lee (2008), Bonfim 2009), surprising little

attention has been paid to applying hazard model to bank failure prediction.[4] 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 bank.

One notable exception is Wheelock and Wilson (2000), which uses the Cox proportional hazard model with time-varying covariates, estimated by partial likelihood, to analyze bank failures during 1984-93. They analyze traditional CAMEL variables and find that poorly capitalized banks, less profitable banks, less liquid banks and less managerial efficient banks are more likely to fail, as are banks holding more risky asset portfolios. Hence, they provide strong evidence confirming the CAMEL paradigm.

Our study differs from Wheelock and Wilson (2000) in a number of important ways. First, our primary focus is on out-of-sample forecasting accuracy rather than on identifying specific factors that explain the time to failure. Wheelock and Wilson do not examine out-of-sample forecasting accuracy. We augment the specification of Cole and Gunther (1998) for bank failure prediction, and find that the dynamic hazard model significantly improves both in-sample and out-of-sample failure forecasting accuracy relative to a static Probit model.

[4] Notable exceptions are Lane, Looney and Wansley (1986), Whalen (1991) and Brown and Dinc (2005), each of which uses a static hazard model.

Second, we analyze virtually the entire population of U.S. banks, using data on more than 12,000 banks, of which 1,277 failed. Wheelock and Wilson analyze a non-random selected sample of only 4,022 banks, of which only 231 failed.

Third, we utilize the full-information likelihood hazard model proposed by Shumway (2001), which is much more tractable and more efficient than the partial-likelihood Cox model estimated by Wheelock and Wilson (see Effron, 1977). As demonstrated in a proof by Shumway (2001), the discrete-time hazard model can be estimated using a Logit program with appropriate adjustment of the test statistics, and can produce more consistent and efficient estimators than alternative estimators.

Fourth, 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. We demonstrate that a dynamic hazard model using publicly available accounting ratios is superior to a static probit model in out-of-sample forecasting of bank failures.

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 high 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 about one third, from more than 12,000 in 1990 to only 8,000 in 2008. 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. Thus, the specifications we document for the 1985-93 period may not be appropriate for predicting bank failures in the 2009 environment. As a sufficient number of bank failures become available to researchers, this becomes a critically important direction for future research.

3. Data and methodology

3.1 Data

Our data are taken from the quarterly 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").[5] Our data are taken from the year-end Call Reports for 1980 – 1992, and include basic balance-sheet and income-statement information. We obtain information on the identity and closure dates of individual banks from the FDIC's website.

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.

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 on 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 loan: measured by loans 90 days or more past due divided by total assets.

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

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

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

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

Variable on bank profitability is measured by *earning ratio* which is the 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 have two sets of variables measuring bank liquidity:

Investment securities: 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): 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 set of bank liquidity variables 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 defined as the natural logarithm of total assets. We expect that small banks are more vulnerable to failure, 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. The figures reported in each table are for this restricted sample. Estimation results with the full untruncated dataset and with the full dataset with outliers winsorized at the 99th percentiles are not reported here, but generally are similar to 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 cumulated percentage of 9.42 over the sample period.[6]

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 summary statistics for the financial ratios over the whole sample period, the in-sample period, and the out-of-sample period. The *t*-tests show that the mean difference of each variable for the in-sample and out-of-sample period is not statistically different from

[6] 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.

zero. 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.

3.2 Methodology

We utilize a simple dynamic hazard model as proposed by Shumway (2001) in our estimation. Shumway (2001) suggests that a dynamic hazard model is superior to a 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, this paper is the first empirical research of applying Shumway's dynamic hazard model to the prediction of U.S. bank failures. Our results demonstrate that a dynamic hazard model significantly improves the forecasting accuracy in predicting bank failures relative to a static probit model.

We assume that banks can only fail at a discrete points of time, $T_i = 1, 2, 3, \ldots$, and define a dummy variable Y_i that equals to one if a bank failed at time T_i, and otherwise zero. Let $F(t_i, X; \gamma)$ be the probability mass function of failure, where γ 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 program with appropriate adjustment on the test statistics producing from the Logit program. The test statistics estimated from a Logit model assume that the bank-years are independent observations. However, for a time-discrete 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 per bank.

4. Empirical results

In this section, we first perform the in-sample estimations for both the traditional static probit model and the simple dynamic hazard model; we 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 our ability to accurately forecast bank failures.

4.1 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 sets of bank financial variables: one substitutes *non-performing loans* for *Past due loan*, *Nonaccrual loans* and *Other real estate owned;* and the other one substitutes *Investment securities* and *Large CDs* for *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.

Both models produce the same expected sign 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, on the contrary, larger banks with higher capital adequacy and profitability, and maintaining a higher liquidity level are relatively safe. As indicated in panel B of Table 3, the coefficients for all bank financial variables under the Probit model are all statistically significant at 1% level, with the P-values close to zero.

However, the coefficient of the *Earnings ratio* loses its significance for the hazard model, which indicates that, the marginal impact of a temporal 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 the in-sample bank failures.

4.2 Out-of-sample prediction

Table 4 presents the out-of-sample prediction accuracy for the static Probit model and the dynamic hazard model. 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 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 98% for probit model. However, the hazard model performs much better in predicting bank failures and classifies 400 out of 436 failures, namely 91.7% of all bank failures, from the top 5% worst predicted failure probability, while the Probit model only classifies 52.4% of them. Our 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.

4.3. 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 private banks whose market data are not available, 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: it's measured 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: it's measured by the 91-day T-bill rates, which 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 5 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 5 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 the market variable of individual firm while we use a macro market variable of bank portfolio. Our finding is 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). Although incorporating market and macroeconomic variables does not improve the predictive accuracy of bank failure, our model identifies the channel through which macroeconomic shocks affect banks and contribute to bank failure. Therefore, our finding has important implication for policy maker and risk management of individual bank.

5. Conclusion

In this study, we use a simple hazard model with time-varying covariates to develop a bank-failure early warning model and then test the out-of-sample forecasting accuracy versus a simple one-period probit model, such as is used by U.S. banking regulators. By incorporating time-varying covariates, our model enables us to utilize macro-economic

variables, which cannot be used in a one-period model. We find that our model significantly outperforms the simple static Probit model and substantially improve the out-of-sample prediction of bank failures. The improvement in accuracy comes from dynamic nature of the hazard model, which incorporates information on time at risk, as well as information on a much larger number of observations available from panel data and information on macro-economic variables.

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 bank failure is more bank-specific, including macroeconomic variables into the model does not increase the prediction adequacy. However, our model identifies the channel through which the macroeconomic shocks contribute to bank failures. Therefore, this research has very important implication for policy marker and risk management of individual banks.

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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

Variables	Obs.	Mean	Median	Std Dev	Minimum	Maximum
Full sample period (1985-1993)						
Capital Adequacy	120,728	0.086	0.081	0.033	-0.479	0.293
Earnings Ratio	120,728	0.006	0.009	0.015	-0.497	0.237
Past Loan Due	120,100	0.005	0.002	0.008	0.000	0.269
Nonaccrual Loan	120,100	0.009	0.004	0.014	0.000	0.318
Other Real Estate	120,728	0.006	0.002	0.013	0.000	0.422
Non-Performing Loan	120,728	0.019	0.011	0.026	0.000	0.502
Investment Securities	120,728	0.312	0.294	0.176	0.000	1.194
Large CDs	120,728	0.110	0.084	0.095	0.000	1.000
Securities to Assets	120,728	0.284	0.269	0.156	0.000	0.983
Large CDs to Assets	120,728	0.100	0.077	0.086	0.000	0.948
Size	120,728	10.832	10.678	1.266	6.641	18.914
In-sample period (1985-1989)						
Capital Adequacy	71,077	0.085	0.080	0.033	-0.479	0.293
Earnings Ratio	71,077	0.005	0.009	0.016	-0.497	0.194
Past Loan Due	70,449	0.006	0.003	0.009	0.000	0.269
Nonaccrual Loan	70,449	0.009	0.004	0.015	0.000	0.318
Other Real Estate	71,077	0.006	0.002	0.012	0.000	0.422
Non-Performing Loan	71,077	0.020	0.012	0.027	0.000	0.502
Investment Securities	71,077	0.302	0.284	0.174	0.000	1.146
Large CDs	71,077	0.116	0.086	0.105	0.000	1.000
Securities to Assets	71,077	0.275	0.261	0.155	0.000	0.967
Large CDs to Assets	71,077	0.106	0.079	0.096	0.000	0.948
Size	71,077	10.723	10.577	1.246	6.641	18.853
Out-of-sample period (1990-1993)						
Capital Adequacy	49,651	0.088	0.082	0.032	-0.455	0.293
Earnings Ratio	49,651	0.007	0.009	0.013	-0.364	0.237
Past Loan Due	49,651	0.003	0.001	0.006	0.000	0.157
Nonaccrual Loan	49,651	0.008	0.004	0.013	0.000	0.251
Other Real Estate	49,651	0.007	0.002	0.014	0.000	0.220
Non-Performing Loan	49,651	0.018	0.010	0.024	0.000	0.431
Investment Securities	49,651	0.327	0.307	0.178	0.000	1.194
Large CDs	49,651	0.101	0.083	0.077	0.000	0.973
Securities to Assets	49,651	0.296	0.281	0.158	0.000	0.983
Large CDs to Assets	49,651	0.092	0.076	0.070	0.000	0.884
Size	49,651	10.987	10.821	1.278	6.655	18.914

Note: Obs. is the number of observations. The construction of variables is explained in section 3.1.

Table 3. In-Sample Prediction of Bank Failures

A. Hazard Model

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

B. Probit Model

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

Note: The results for the hazard model in Panel A are estimated by using lagged bank financial variables to predict bank failures over the period of 1985 to 1989, while the results of the 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 Prediction Accuracy

Decile	Probit	Accumulated	Hazard	Accumulated
1	72.34	72.34	93.12	93.12
2	13.15	85.49	1.61	94.72
3	7.71	93.20	2.52	97.25
4	2.95	96.15	1.15	98.39
5	1.81	97.96	1.15	99.54
6 to 10	2.04	100	0.46	100

Note: Table 4 presents the out-of-sample prediction accuracy for a static Probit model and a dynamic hazard model. Both models use the same explanatory variables identified in Table 3 with the financial data available from 1984 to 1992 combined with the bank failure data from 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 the Hazard model, coefficients estimated from bank failures from 1985 to 1989 using bank financial data from 1984 to 1988 are combined with bank financial data from 1989 to 1992 to forecast bank failures from 1990 to 1993.
The first column presents the rankings of worst predicted probability. The second and fourth 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 third and last columns are the accumulated percentage of accuracy for Probit and Hazard model respectively.

Table 5. 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 portoflio 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.