Banking Crises, Early Warning Models, and Efficiency*

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Abstract

In this paper we propose a general model that combines the Mixture Hazard Model (MHM) of Farewell (1977, 1982) with the Stochastic Frontier Model (SFM) to investigate the main determinants of the probability and time to failure of a panel of U.S. commercial banks during the financial distress that began in August of 2007. Unlike the standard hazard model which would assume that all banks in the sample eventually experience the event (failure), the MHM model distinguishes between healthy (long-term survivors) and at-risk banks. On the other hand, the SFM provides a measure of the performance of banks which reflects management quality and potentially plays a key role in their failure, conditional on the usual financial ratios and other macroeconomic, structural, and geographical variables that we employ. We consider both continuous-time semi-parametric and discrete-time mixture hazard models which are separately or jointly estimated with the stochastic frontier specification. Joint estimation allows not only the performance to affect the probability and time to failure, but also the former

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to affect the latter. The estimation of these models is carried out via an expectation-maximization (EM) algorithm and the simulated maximum likelihood (SML) method due to the incomplete information regarding the identity of at-risk banks and to the fact that integration must be carried out in evaluating the likelihood function. In- and out-of-sample predictive accuracy of these models is investigated in order to assess their potential to serve as early warning tools for regulatory authorities, academic practitioners, and bank insiders. We are also able to assess the type I and type II errors implicit in bank examiners' decision process when closing banks. We find that the within sample and out-of-sample average of the two misclassification errors is less than 6% and 4% respectively for our preferred model.

JEL classification codes: C33, C41, C51, D24, G01, G21.

Key words and phrases: Financial distress, panel data, bank failures, semiparametric mixture hazard model, discrete-time mixture hazard model, bank efficiency.

1 Introduction

The financial crisis that started in summer of 2007 led the U.S. and international economies to an unprecedented economic downturn, creating political instability and uncertainty worldwide. According to most metrics it was the most severe economic crisis since the Great Depression of the 1930's. The crisis apparently began in the secondary market for residential mortgages after a dramatic increase in delinquencies and default rates on subprime residential mortgage-backed securities (RMBS) due to the collapse of housing bubble in the second half of 2006. It very quickly spread to the banking industry as many banks, in particular large banks, which were highly involved in the RMBS market, experienced widespread distress that led to closures, mergers, takeovers, or injection of heavy doses of government funds. More than 290 banks and thrifts failed, or more correctly were forced into closure by regulatory agencies from late 2007 to the middle of October of 2010. During this time the number of troubled or problem banks on the watch list of the Federal Deposit Insurance Corporation (FDIC) also dramatically increased. The sharp increase in the number of failed and troubled banks during this period is illustrated in figure 1. The states that experienced the most failures were California, Georgia, Florida, and Illinois. These four states accounted for more than half of all banking failures. Table 1 displays the number of failures per state within these three years, while figure 2 provides a map of banking failures per state for the referenced period.

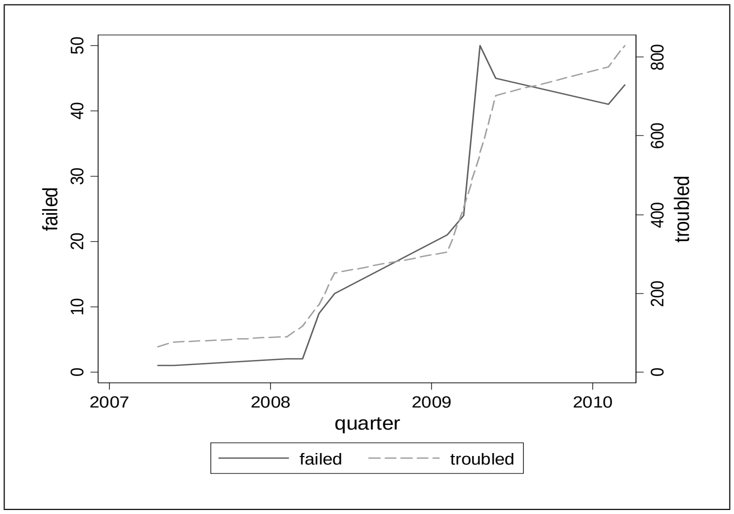
The distinguishing characteristic of the current banking failures from those of the earlier crises of the 1980's and 1990's is that the failures were not limited to the small financial institutions. Rapid credit expansion and low quality loans and investments made during a period of economic expansion mainly took their toll on large multi-billion dollar financial institutions. Approximately one out of five failed banks had asset sizes of over $1 billion. In 2008, 36% of failed banks were large banks, among them the largest bank failure in the history of U.S., that of Washington Mutual with $307 billion in assets.[1] That same year saw Lehman Brothers file for Chapter 11 bankruptcy protection and IndyMac bank, with $32 billion in assets, taken over by the FDIC.[2] These large financial institution failures created large uncertainties about the exposure of other financial institutions (healthy and troubled) to additional risks, reduced the availability of credit from investors to banks, drained the capital and money markets of confidence and liquidity, triggered the failure of smaller community banks, and raised the fears of severe instability in the financial system and the global economy.[3] Much attention has been paid to the larger financial institutions at danger, commonly described as too-big-to-fail banks, which received financial and other assistance from regulatory authorities as they thought that their failure could impose greater systemic risk that could substantially damage the economy and lead to conditions similar

[1] Continental Illinois Bank and Trust Company of Chicago that failed in 1984 had one-seventh of Washington Mutual's assets.

[2] Chapter 11 permits reorganization under the bankruptcy laws of the United States. A financial institution filling for Chapter 11 bankruptcy protection usually proposes a plan of reorganization to keep its business alive and pay its creditors over time.

[3] Community banks are banks with assets sizes of $1 billion or less. They operation is oftentimes limited to the rural communities and small cities. Community banks usually engage in traditional banking activities and provide more personal-based services.

Figure 1: Number of failed and troubled banks (2007.Q3-2010.Q4)



to, or possibly exceeding, those of the Great Depression.

As the number of failures continued to rise during the period we study (2007Q1-2010Q2) and is still rising, one may reasonably ask when failures will begin to fall. On one hand, pessimistic scenarios predicted the number of failures in 2010 to reach 200, the most since the end of the savings and loan (S&L) crisis of early 1990's. They also predicted that this rate of failure would continue at the same pace in subsequent two years.[4] On the other hand, more optimistic scenarios predicted that 2010 would be the peak year of banking distress as the financial sector gradually overcame the difficulties it faced during the recent global economic downturn and the economy was on a path to recovery, with the housing market displaying signs of stabilization. This prediction was partially born out by the fact that the number of problem institutions on the FDIC list dropped by 8% and the actual bank closures decreased by 41% in 2011.

Regulatory authorities have always considered banking failures as a major public policy concern due to the banks' special role in the economic network and in implementation of an effective monetary policy. Failures of certain banks could lead to contagion or domino effects and thus negatively affect the safety and soundness of the banking industry and of the entire economy. Confronting the crisis involved a series of extraordinary costly actions and sacrificing valuable economic resources. The two approaches typically used to calculate the costs of the banking crisis are the narrow fiscal or quasi-fiscal costs, which involve large government guarantees and central bank bailouts, and the system-wide economic costs, which include output loss, increases in unemployment rate, missed business opportunities, and etc. At the time this research was conducted it was still too early to give

[4] This prediction was from Gerard Cassidy and his colleagues at RBC Capital Markets, who were among the first analysts that predicted the rising number of banking failures very early in the financial crisis. Gerard Cassidy is the developer of the Texas ratio, a tool used to determine insolvent banks.

Table 1: Per state distribution of failed banks

State	Number of failed banks	State	Number of failed banks
Alabama	4	North Carolina	2
Arkansas	1	Nebraska	2
Arizona	7	New Jersey	3
California	32	New Mexico	2
Colorado	3	Nevada	10
Florida	41	New York	4
Georgia	44	Ohio	6
Iowa	1	Oklahoma	2
Idaho	1	Oregon	6
Illinois	37	Pennsylvania	1
Indiana	1	Puerto Rico	3
Kansas	5	South Carolina	4
Kentucky	1	South Dakota	1
Louisiana	1	Texas	8
Massachusetts	1	Utah	5
Maryland	5	Virginia	2
Michigan	9	Washington	13
Minnesota	14	Wisconsin	2
Missouri	9	West Virginia	1
Mississippi	1	Wyoming	1

figures for the fiscal or economic costs as the consequences of the banking crisis are still unfolding. Nevertheless, tentative observations can be made regarding the costs of banking failures to the FDIC's Deposit Insurance Fund (DIF) and the banking industry output and employment.[5] With regard to the first, it is estimated that the 140 failures of 2009, with combined assets of about $170 billion, cost the DIF $36.4 billion, while the cost of failures through mid-October 2010 involving banks with combined assets of more than $85 billion, is expected to exceed $20 billion. Notably, only the failures of 2008 involving 9 out of 25 large banks cost the DIF $15.8 billion. The industry's assets have shrunk by 5.3% as a result of the banking crisis, which led to fewer by 7.5% loans and declines in the economic activity. Industry employment fell by 8.5% since 2007, translating into 188,000 lost jobs. Failed banks alone left 11,210 employees without jobs.[6]

In the United States, the FDIC and state banking regulatory authorities are responsible

[5] The Deposit Insurance Fund (DIF), which is the result of the merger of the Bank Insurance Fund (BIF) and the Saving Association Insurance Fund (SAIF) in 2006, requires each FDIC insured institution to pay an insurance premium. The amount of the insurance premium to the fund is determined based on institution's balance of insured deposits and the degree of risk it poses to the fund. FDIC, as the receiver of the failed institution, liquidates its assets and compensates its depositors up to the insurance limit (currently $250,000). The amount not covered by the asset sales is provided by the DIF.

[6] Source: Wall Street Journal on-line article "Banks Keep Failing, No End in Sight" available at http://online.wsj.com.

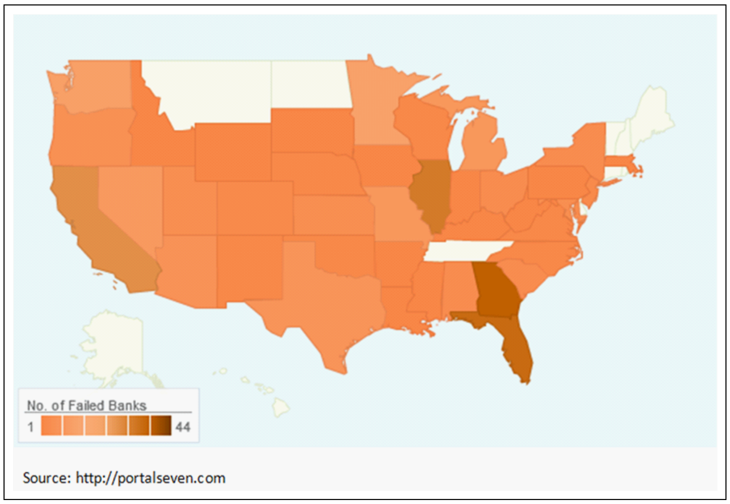


Figure 2: Map of per state banking failures

for the identification and resolution of insolvent institutions. A bank is considered at a risk of immediate closure if it is unable to fulfil its financial obligations the next day or its capital reserves fall below the required regulatory minimum.[7] In the event of a bank failure, the FDIC either liquidates the assets of a failing bank and pays insurance to the depositors up to the amount of the insurance limit or arranges the sale of some or all of the bank's assets to another institution, which also may assume the part or all of the bank's liabilities.[8] The latter is oftentimes accomplished through financial assistance provided by regulators. The FDIC is required to resolve outstanding issues with problem banks in a manner that imposes the least cost on the deposit insurance fund and ultimately on the taxpayer. Thus, early detection of insolvent institutions is of vital importance, especially if the failure of those institutions would pose a serious systemic risk on the financial system and the economy as a whole. The FDIC and state authorities utilize on-site and off-site examination methods in order to determine which institutions are insolvent and thus should be either closed or be provided financial assistance in order to rescue them. The off-site examinations are typically based on statistical and other mathematical methods and constitute complementary tools to the on-site visits made by supervisors to institutions considered at risk. There are three advantages to off-site versus on-site examinations. First, the on-site examinations are more costly as they require the FDIC to bear the cost of visits and to retain extra staff during times when economic conditions are stable. Second, the on-

[7] Under the current regulations issued by the Basel Committee on Banking Supervision (Basel II), a bank is considered as failed if its ratio of Tier 1 (core) capital to risk-weighted assets is 2% or lower. This ratio must exceed 4% to avoid supervisory intervention and prompt corrective action as underlined in Federal Deposit Insurance Corporation Improvement Act (FDICIA) of 1992. A bank with ratio of 6% or above is considered as well-capitalized.

[8] The coverage limit is temporary set at $250,000 until the end of 2013 in order to protect the funds of depositors and prevent any potential depositor runs that could harm even the healthy institutions (Emergency Economic Stabilization Act, 2008). This limit will return to the permanent limit of $100,000 in 2014.

site examinations are usually time-consuming and cannot be performed with high frequency during periods of wide-spread banking distress. Costs associated with on-site supervision typically increase with the number of troubled banks. Third, the off-site examinations can help allocate and coordinate the limited on-site examination resources in an efficient way with priority given to financial institutions facing the most severe challenges. The major drawback of the statistically based off-site tools is that they incorporate estimation errors which also affect the classification of banks as failure and nonfailures. An effective off-site examination tool must aim at identifying problem banks sufficiently prior to the time when a marked deterioration of their financial health would occur, which would force supervisors to undertake the necessary corrective actions needed to remedy the financial turmoil. Therefore, it is desirable to develop a model which would identify future failures with a high degree of accuracy in a timely manner and would rarely flag healthy banks as being at risk of closure.

Accurate statistical models that serve as early warning tools and can be alternatives or complementary to the costly on-site visits made by supervisors to institutions considered at risk have been well documented in the banking literature. Early warning models mostly refer to models that can identify and predict the realization of some event with high probability well in advance. These models have been successfully applied to study banking and other financial institutions' failures in the U.S. and in other countries. As the literature that deals with bankruptcy prediction of financial and non-financial institutions is vast and there are a myriad of papers that specifically refer to the banking industry failures, we will discuss only few papers that are closely related to our work and are viewed as early warning models.

The more widely-used statistical models for bankruptcy prediction are single-period static probit/logit models and methods of discriminant analysis.[9] These models usually estimate the probability that a firm with specific characteristics will fail or survive within a certain time interval. The timing of the failure is not provided by such models. Shumway (2001), in his bankruptcy prediction application, demonstrates with a simple example the inconsistency and the inefficiency (in a statistical sense) of these static models, as well as the superiority of a model such as his dynamic hazard model that utilizes multi-period observations. Others in this literature have employed the Cox proportional hazard models (PHM) to explain banking failures and develop early warning models.[10] Typically, in this model the dependent variable is time to occurrence of some specific event (failure in case of banks) which can be equivalently expressed either through the probability distribution function or the hazard function, the latter of which provides the instantaneous risk of failure at some specific time conditional on the survival up to this time. The Cox PHM has three advantages over the static probit/logit models: (i) it provides not only the measure of probability of failure (survival) but also the probable timing of failure; (ii) it accommodates

[9] For applications of probit/logit models and discriminant analysis see Altman (1968), Meyer and Pifer (1970), Deakin (1972), Martin (1977), Lane et al. (1986), Cole and Gunther (1995, 1998), Cole and Wu (2011), among others.

[10] The thorough discussion of the Cox proportional hazard model can be found in Cox (1972), Lancaster (1990), Kalbfleisch and Prentice (2002), and Klein and Moeschberger (2003). The application of this model to study U.S. commercial banking failures is found in Lane et al. (1986), Whalen (1991), and Wheelock and Wilson (1995, 2000).

censored observations, those observations that survive through the end of the sample period; and (iii) it does not make strong assumptions about the distribution of time to failure. The disadvantage of this model is that it requires the hazard rate to be proportional between any two cross-sectional observations and the inclusion of time-varying covariates is not as straightforward as with other models. To remedy these two shortcomings researchers recently turned their attention to the discrete time hazard model (DTHM).[11] The DTHM assumes that the failure occurs at discrete times and requires the covariates to be unchanged within a given time (month, quarter, or year). Inclusion of time-varying regressors that change over different periods allows for more efficient estimation and improved predictions as more recent prospective information is added to the retrospective information often used in less dynamic approaches.

This paper develops an early warning model based on the Mixture Hazard Model (MHM) of Farewell (1977, 1982) with continuous and discrete time specifications.[12] MHM effectively combines the static model, which is used to identify insolvent banks, and the duration model, which provides estimates of the probability of failure along with the timing of closure of the troubled banks. In our paper we view the financial crisis as a negative shock that affects banks in an unequal way. Well capitalized, well prepared, and prudently managed institutions may feel little relative distress during the financial turmoil. On the other hand, poorly managed banks that previously engaged in risky business practices will increase their probability of being on the FDIC watch list and subsequently be forced into closure or merger with a surviving bank by regulatory authorities. Unlike the standard duration model, which assumes that all banks are at the risk of failure, we will implicitly assume that there is a proportion of banks that will survive for a sufficiently long time after the end of crisis and thus are not in this absorption state. In other words, we assume that the probability of failure for a bank that has never been on the watch list is arbitrarily close to zero. The MHM is appropriate in dealing with this issue as it is able to distinguish between healthy and at-risk of failure banks. Our model also recognizes the fact that insolvency and failure are two different events. The realization of the first event is largely attributed to the actions undertaken by the bank itself, while the second usually occurs as a result of regulators' intervention following their insolvency. Supervisors tend not to seize an insolvent bank unless it has no realistic probability of survival and its closure does not threaten the soundness and the stability of the financial system through its contribution to systemic risk. We are able to assess the type I and type II errors implicit in bank examiners' decision process when closing banks.[13] We find that the within sample and out-of-sample average of the two misclassification errors is less than 6% and 4%, respectively, for our preferred model.

One of our (testable) assumptions concerns the fact that banks with low performance, as calculated by the radial measure of realized outcome to the maximum potential outcome,

[11] See Shumway (2001), Halling and Hayden (2006), Cole and Wu (2009), and Torna (2010) for applications of discrete-time hazard models.

[12] Application of the discrete-time verison of the MHM are found in Gonzalez-Hermosillo et al.(1997), Yildirim (2008) and Topaloglu and Yildirim (2009).

[13] Typically, a type I error is defined as the error due to classifying a failed bank as a nonfailed bank, while a type II error arises from classifying a non-failed bank as a failed bank.

will increase their probability of failure. Inefficiently managed banks could cumulatively save valuable funds by employing the best-practice technologies, which have shown to be important, especially during periods of banking crisis when money markets suffer from poor liquidity. Barr and Siems (1994) and Wheelock and Wilson (1995, 2000) were the first to consider the inefficiency as a potential influential factor explaining U.S. commercial banking failures during the earlier crisis. Barr and Siems (1994) estimate the efficiency scores with Data Envelopment Analysis (DEA) techniques, which are used in a static model to predict banking failures.[14] Wheelock and Wilson (1995, 2000) estimate the Cox proportional hazard model with inefficiency scores included among other regressors, allowing inefficiency to affect the probability of failure as well as the probability being acquired by other bank. They employ three measures of radial technical inefficiency, namely the parametric cost inefficiency measure, the nonparametric input distance function measure, and the inverse of the nonparametric output distance function measure. The first two appear to have statistically significant positive effects on the probability of failure, while only the first measure significantly decreases the acquisition probability. The estimation of these models is conducted in two stages. The first stage involves the parametric or nonparametric estimation of inefficiency scores. In the second stage these scores are used as explanatory variables in addition to other variables to investigate their effect on failure probability. Tsionas and Papadogonas (2006) criticize the two-step approach as it may entail an error-in-variables bias as well as introduce an endogenous auxiliary regressor. They propose a single step joint estimation procedure to overcome these problems. We follow a similar approach.

Another challenge that we face in this paper is the incomplete information associated with the troubled banks in the watch list of the FDIC. Each quarter the FDIC releases the number of problem banks but their names and identities are not disclosed. Based on our earlier assumption we can deduce that a bank that failed was on this list. Based on available information we make a prediction of which banks are on this list through an expectation-maximization (EM) algorithm which is designed to address this problem of missing information. Torna (2010), who also studies the recent U.S. commercial banking failures, identifies the number of troubled banks on the watch list through their tier 1 capital ranking. Banks are ranked according to their tier 1 capital ratio and the number of banks with the lowest value are selected to match the number provided by FDIC in each quarter. Other ratios, such as Texas ratio, also can be utilized to deduce the problem banks.[15] There are at least two limitations to this approach besides its crude approximation. First, it ignores other variables that play a pivotal role in leading banks to a distressed state. For example, the ratio of nonperforming loans is one of the major indicators of difficulties that bank will face in near future even if their capital ratios are at normal levels. Second, financial ratios that are used to classify banks as healthy or troubled cannot be subsequently employed as determinants due to possible endogeneity problem.

Another contribution of this paper is that we follow a forward step-wise procedure in

[14] Data envelopment analysis, proposed by Charnes et al. (1978), is a nonparametric approach of estimating efficiency scores based on mathematical optimization techniques.

[15] The Texas ratio was developed by Gerard Cassidy to predict banking failures in Texas and New England during recessionary periods of the 1980's and 1990's. It is defined as the ratio of nonperforming assets to total equity and loan-loss reserves. Banks with ratios close to one are identified as high risk.

model building and selecting the relevant covariates that is not only based on the conventional measures of the goodness-of-fit and statistical tests, but also on the contribution of these covariates to the predictive accuracy. As in Gonzalez-Hermosillo et al. (1997), we also include state-specific macroeconomic variables to control for factors that differentially impact particular states. The unequal distribution of banking failures among the states is revealed in Table 1. Industry-specific variables that could potentially capture the sector's condition as well as contagion effects cannot be identified in the Cox proportional hazard model and univariate probit/logit models. In the first case the constant in general is not identified, while in the second case these variables will be mixed with the constant term and thus will not be identified as well.

The remainder of the paper is organized as follows. Section 2 describes the potential decision rule adopted by the regulatory authorities in determining and closing insolvent banks, which naturally will lead to the mixture hazard model (MHM). Two variants of the MHM are discussed, the continuous-time semiparametric proportional MHM and discrete-time MHM. In section 3 we discuss the joint MHM-SFM. Section 4 deals with empirical specification issues and the data description. Estimation results for the model parameters and predictive accuracy are provided in section 5 along with a comparison of various models and specifications. Section 6 contains our main conclusions.

2 The Mixture Hazard Model

Before describing the mixture hazard model formulation in detail we establish a few definitions and describe the potential rules adopted by regulatory authorities to determine unsound banks that subsequently fail or survive. Other regulatory closure rules can be found in Kasa and Spiegel (2008). Let H_{it} define the financial health stock of bank i at time t and assume that there is a threshold level of it, H_{it}^* , such that if financial health falls bellow this level then the bank is considered at risk of closure by regulatory authorities. Formally, the difference between H_{it}^* and H_{it} can be represented as a function of bank-specific financial ratios, and structural and geographical macroeconomic variables

$$h_{it}^* = H_{it}^* - H_{it} = x_{it}'\beta + e_{it} \tag{1}$$

where e_{it} represents the error term, which is assumed to be identically and independently distributed across observations and over time.[16]

We consider three simplified scenarios that can describe the path of financial health of a bank during periods of financial turmoil, which are represented in figure 3. Case I describes a situation in which bank financial health sharply declines and falls far below its threshold level. Banks in Case I are considered as high priorities for closure by the FDIC and are placed at the top of the list of at-risk of failure banks. Case II is the scenario under which the bank experiences some difficulties and is considered as "troubled" by regulatory authorities. However, this bank recovers either by its own means or by receiving some

[16] The *iid* assumption of the error term can be relaxed in the panel data context by assuming $e_{it} = \mu_i + \xi_{it}$ with $\mu_i \sim N(0, \sigma_\mu^2)$ and $\xi_{it} \sim N(0, \sigma_\xi^2)$ independent of each other. This adds an additional complication to the model and it is not pursued in this paper.

financial assistance from regulators. Finally, Case III refers to a bank that is financially sound before and during the crisis. With some very exceptional cases, such a bank will not be considered at risk of closure during the current crisis. Note that these scenarios are very simplified ones. In practice, banks can enter and exit the watch list multiple times or remain on the watch list for multiple quarters. In addition, the current health stock may depend on the history of its past realizations, which also affect the bank's survival. We assume that the probability that a healthy bank fails is close to zero or equivalently, a bank will not be seized by the FDIC unless it is considered as problem bank. This is the usual practice adopted by the FDIC.

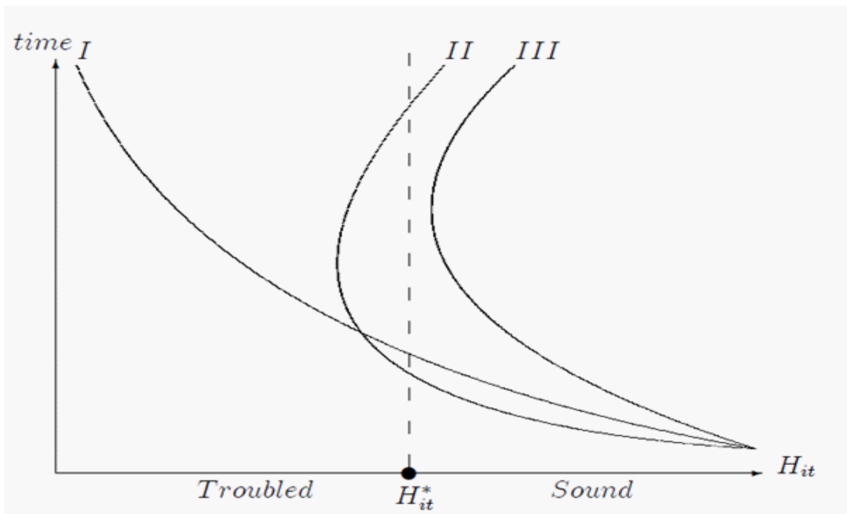


Figure 3: Illustration of the bank financial health condition during the period of financial turmoil

The financial health of a particular bank is a composite and oftentimes a subjective index and its lower bound is not observable. Therefore, h^*_{it} is also not observable even to regulatory agencies that have only partial information about an individual banks' financial health. Instead we can define a binary variable h_{it} such that

$$h_{it} = \begin{cases} 1 & \text{if } h^*_{it} > 0 \\ 0 & \text{if } h^*_{it} \leq 0 \end{cases}$$

The probability that a bank will become financially unhealthy is thus given by

$$\begin{aligned} P(h_{it} &= 1) = P(h^*_{it} > 0) \\ &= P(e_{it} > -x'_{it}\beta) = F_e(x'_{it}\beta) \end{aligned}$$

where F_e is the cumulative distribution function (cdf) of the random error e. If e is assumed to be normally distributed (the probit model) then

$$F_e(x_{it}'\beta) = \int_{-\infty}^{x_{it}'\beta} (2\pi)^{-1/2} \exp(-t^2/2) dt.$$

If e is logistically distributed (logit model) (McFadden 1974, 1981; Train, 2003) then

$$F_e(x_{it}'\beta) = \frac{\exp(x_{it}'\beta)}{1 + \exp(x_{it}'\beta)}.$$

However, as we discussed in the introductory section, information about a particular bank being at risk is not disclosed by regulatory authorities. Therefore, h_{it} is only observed by the econometrician for banks that actually failed and is not observed for those that did not. Hence, we are faced with a type of incomplete information problem. The only information available to the econometrician that relates to such information is the total number of unnamed problem institutions. In the next section we show how to deal with this type of missing information problem. In order to frame the general estimation problem we begin by treating the data as complete. Specification of the likelihood function then follows that of the standard hazard model, wherein a nonnegative random variable T represents the duration of a bank in a state of operation or the time until the occurrence of some specific event, such as failure in our case.[17] This is characterized by the conditional probability density function (pdf), f_T and the cumulative distribution function (cdf), F_T. The survivor function of a particular bank given that it is characterized as a problem bank is then given by

$$S^p(t; w_i) = \Pr(T > t | h_i = 1; w_i). \tag{2}$$

S^p represents the probability that problem bank will survive for a period longer than t and w_i is the set of individual-specific, macroeconomic, structural, and geographical variables that are related to a bank's survival. The probability that a problem bank will fail by time t is thus given by

$$F^p(t; w_i) = \Pr(T \leq t | h_i = 1; w_i) \tag{3}$$

while the similar probabilities for sound banks are

$$S^s(t; w_i) = \Pr(T > t | h_i = 0; w_i) \tag{4}$$

and

$$F^s(t; w_i) = \Pr(T \leq t | h_i = 0; w_i). \tag{5}$$

The survivor and failure probabilities of bank i are then expressed as

[17]Banks that ceased their operation due to reasons other than failure, such as merger or voluntary liquidation, or remained inactive or are no longer regulated by the Federal Reserve, have censored duration times.

$$
\begin{aligned}
S(t;x_i,w_i) &= \Pr(T>t;x_i,w_i) \qquad (6)\\
&= \Pr(T>t|h_i=1;w_i)\Pr(h_i=1;x_i)+\Pr(T>t|h_i=0;w_i)\Pr(h_i=0;x_i)
\end{aligned}
$$

and

$$
\begin{aligned}
F(t;x_i,w_i) &= \Pr(T\le t;x_i,w_i) \qquad (7)\\
&= \Pr(T\le t|h_i=1;w_i)\Pr(h_i=1;x_i)+\Pr(T\le t|h_i=0;w_i)\Pr(h_i=0;x_i).
\end{aligned}
$$

Let the binary variable d_i take on a value of 1 for observations that fail at time t and 0 for observations that are right censored when the bank does not fail by the end of the sample period or disappears during the period for reasons other than failure (mergers, acquisitions, incomplete data, etc.). Then the likelihood function for bank i is given by

$$
\begin{aligned}
L(\theta;x,w) &= f(t;x_i,w_i)^{d_i}S(t;x_i,w_i)^{1-d_i}\\
&= [F_e(x_i'\beta)f^p(t;w_i)+(1-F_e(x_i'\beta))f^s(t;w_i)]^{d_i}[F_e(x_i'\beta)S^p(t;w_i)\\
&\quad +(1-F_e(x_i'\beta))S^s(t;w_i)]^{1-d_i}
\end{aligned}
$$

where θ is the parameter vector, and x and w are covariates associated with the probability of being troubled and of having failed, respectively.

What is generally observed for the failed U.S. commercial banks is that prior to their failure they experience an extensive period of financial distress. Regulatory authorities tend to close banks that have been characterized as troubled either by means of off-site or on-site examinations. Therefore, we assume that the probability that a healthy bank fails instantaneously is arbitrarily close to zero and thus the hazard rate for such banks is also arbitrarily close to zero. Hence, the above likelihood function reduces to

$$
L_i(\theta;x,w)=[F_e(x_i'\beta)\lambda_i^p(t;w_i)S^p(t;w_i)]^{d_i}[F_e(x_i'\beta)S^p(t;w_i)+(1-F_e(x_i'\beta))]^{1-d_i} \qquad (8)
$$

where

$$
\lambda^p(t;w_i)=\lim_{\Delta t\to 0}\frac{P(t\le T<t+\Delta t|T>t,h_i=1;w_i)}{\Delta t}=\frac{f^p(t;w_i)}{S^p(t;w_i)}
$$

represents the hazard rate or probability that a troubled bank will fail during the period $(t,t+\Delta t)$, given that it was in operation for t periods earlier.

After some rearranging of the expression in (8) and dropping the superscript from measures pertaining to problem banks to reduce notational clutter, the sample likelihood for all banks can be written as[18]

[18] See the Appendix A for alternative derivation of the likelihood function.

$$
\begin{aligned}
L(\theta; x, w, d) &= \prod_{i=1}^{n} L_i(\theta; x, w, d) \qquad (9)\\
&= \prod_{i=1}^{n} F_e(x_i\beta)^{h_i}(1-F_e(x_i\beta))^{1-h_i}\{\lambda_i(t; w_i)\}^{d_i h_i}\{S_i(t; w_i)\}^{h_i}.
\end{aligned}
$$

If h_i is completely observed for each individual bank, as it is to regulators, then the estimation problem is relatively straightforward. However, given that h_i is partially observed to the econometrician, we need to address the problem of incomplete information utilizing other methods and thus turn to the expectation-maximization (EM) algorithm. In the next section we discuss the continuous-time semiparametric mixture hazard model under the assumptions of proportional hazard (Cox, 1972) and in the absence of any managerial inefficiency. The latter may affect the probability and the timing of bank survival. We also detail an algorithm for implementing the EM algorithm. We modify the proportional hazard specification and alter the potential role of managerial inefficiency by considering a discrete-time mixture hazard model with time-varying covariates, as well as integrating into the survival model an explicit performance (efficiency) measure for each bank based on constructs from the stochastic frontier production literature. We refer to the continuous-time mixture hazard model as Model I and the discrete-time mixture hazard model as Model II. Following the standard nomenclature in the medical and biological sciences, where the MHM was initially applied, we refer to the portion of the model that assesses the financial health of the bank as the incidence part and to portion of the model that assess the survival times as the latency part.

2.1 Semiparametric Continuous-Time Proportional Mixture Hazard Model

Following Kuk and Chen (1992) and Sy and Taylor (2000) the semi-parametric proportional mixture hazard model with the full log-likelihood function for i^{th} individual bank based on observed data (t_i, d_i, x_i, w_i) can be expressed as

$$
\begin{aligned}
L_i(\theta; x, w, d) &= \log L_i(\theta, \lambda_0; x, w, d) = h_i \log(F_e(x_i\beta))\\
&\quad +(1-h_i)\log(1-F_e(x_i\beta)) + d_i h_i \log(\lambda_i(t; w_i)) + h_i \log(S_i(t; w_i))\\
&= L_{1i}(\beta; x_i, h_i) + L_{2i}(\alpha, \lambda_0; w_i, h_i)
\end{aligned}
$$

where

$$\lambda_i(t; w_i) = \lambda_0(t)\exp(w_i'\alpha) \qquad (10)$$

and

$$S_i(t; w_i) = S_0(t)^{\exp(w_i'\alpha)}. \qquad (11)$$

Here $\lambda_0(t)$ and $S_0(t)$ are the conditional baseline hazard and baseline survivor functions. They are nonnegative functions of time only and are assumed to be common to all individuals at risk. Censoring is assumed to be noninformative and statistically independent of the events of distress and failure.

Given that h_i is only partially observed, the SPMHM can be estimated by the Expectation-

Maximization (EM) algorithm. The EM algorithm is an efficient iterative procedure for maximizing complex likelihood functions and handling incomplete or missing data. Each iteration of the algorithm consists of two steps: expectation (E) and maximization (M) step. The expectation step involves the projection of an appropriate functional (likelihood or log-likelihood function) containing the augmented data on the space of the original, incomplete data. Thus the missing data are first estimated given the observed data and a current estimate of the model parameters in the expectation step. In the maximization step the function is maximized while treating the incomplete data as known. Iterating between these two steps yields estimates that under suitable regulatory conditions converge to the maximum likelihood estimates (MLE). For more discussion on the EM algorithm and its convergence properties see Dempster et al. (1977) and McLachlan and Krishnan (1996).

To implement the EM algorithm we first need to take the expectation of the full log-likelihood function with the respect to h_i and the data, which completes the E-step of the algorithm. Linearity of $L(\cdot)$ with respect to h_i in this case facilitates the calculations and analysis considerably.

The log-likelihood for the i^{th} observation in the M-step is given by

$$\begin{aligned} E^{(M)}_{h|X,W,\theta,\lambda_0}\left[L_i(\theta;x,w,d)\right] &= \tilde{h}_i^{(M)}\log(F_e(x_i\beta)) + (1-\tilde{h}^{(M)})\log(1-F_e(x_i\beta)) \\ &\quad + \tilde{h}_i^{(M)} d_i \log(\lambda_i(t;w_i)) + \tilde{h}_i^{(M)}\log(S_i(t;w_i)) \end{aligned}$$

where $\tilde{h}_i$ is the probability that the i^{th} bank will eventually belong to the group of problem banks conditioned on observed data and the model parameters. It represents the fractional allocation to the problem banks and is given by

$$\begin{aligned} \tilde{h}_i^{(M)} &= E\left[h_i|\theta^{(M)}, Data\right] = \Pr(h_i^{(M)}=1|t_i>T_i) \qquad (12) \\ &= \begin{cases} \frac{F_e(x_i'\beta^{(M)})S_i(t;w_i)}{F_e(x_i'\beta^{(M)})S_i(t;w_i)+(1-F_e(x_i'\beta^{(M)}))} & \text{if } d_i=0 \\ 1 & \text{otherwise} \end{cases} \end{aligned}$$

The observed full likelihood function (9) is then expressed by

$$\begin{aligned} L(\theta;x,w,\tilde{h}^{(M)}) &= \prod_{i=1}^{n} F_e(x_i'\beta)^{\tilde{h}_i^{(M)}}(1-F_e(x_i'\beta))^{1-\tilde{h}_i^{(M)}} \qquad (13) \\ &\quad \{\lambda_0(t)\exp(w_i'\alpha)\}^{d_i\tilde{h}_i^{(M)}}\{\exp(-\tilde{h}_i^{(M)}\Lambda_0\exp(w_i'\alpha))\} \end{aligned}$$

where $\Lambda_0 = \int_0^t \lambda_0(v)dv$ is the baseline cumulative hazard function. The nuisance baseline hazard function λ_0 is not specified parametrically. It is estimated nonparametrically from the profile likelihood function as

$$\hat{\lambda}_0(t) = \frac{N(t_i)}{\sum_{j\in R(t_i)} \tilde{h}_j \exp(w_j'\alpha)} \tag{14}$$

and the baseline cumulative hazard function is then calculated as

$$\hat{\Lambda}_0(t) = \sum_{t_i \le t} \frac{N(t_i)}{\sum_{j\in R(t_i)} \tilde{h}_j \exp(w_j'\alpha)} \tag{15}$$

where $N(t_i)$ is the number of failures and $R(t_i)$ is the set of all individuals at risk at time t_i, respectively. Notice that the standard model (15) ($h = 1$ with probability one) reduces to Breslow's (1972) estimator in the case when ties are present at time t_i.[19] Substituting (14) and (15) into (13) leads to the M-step log-likelihood

$$\begin{aligned} \tilde{L}(\theta; x, w, \tilde{h}) &= \sum_{i=1}^{n} \{\tilde{h}_i \log F_e(x_i'\beta) + (1-\tilde{h}_i)\log(1-F_e(x_i'\beta))\} \\ &\quad + \sum_{i=1}^{N} \{w_i'\alpha - N(t_i)\log\left(\sum_{j\in R(t_i)} \tilde{h}_j \exp(w_j'\alpha)\right)\} \\ &= L_1(\beta; x, \tilde{h}) + \tilde{L}_2(\alpha; w, \tilde{h}) \end{aligned} \tag{16}$$

The second term in this expression is the Cox-type partial log-likelihood function for parameter α that handles the ties using the Peto (1972) and Breslow (1974) approximation method.

The full implementation of the EM algorithm involves the following four steps:

- Step 1: Provide an initial estimate for the parameter β and estimate the ordinary Cox partial likelihood model to obtain the starting values for α and $\hat{\lambda}_0$.
- Step 2 (E-step): Compute $\tilde{h}_i$ from (12) based on the current estimates and the observed data.
- Step 3 (M-step): Update the estimate of parameter β using L_1 and update the estimate of parameter α and hence $\hat{\lambda}_0$ using the partial log-likelihood $\tilde{L}_2$ and equation (14), respectively.
- Step 4: Iterate between steps 2 and 3 until convergence is reached.

After estimates of model parameters are obtained variances are calculated from the inverse of the information matrix based on the complete data log-likelihood whose elements are provided in the appendix of Sy and Taylor (2000).

[19] See Johansen (1983), Sy and Taylor (2000), and Klein and Moeschberger (2003) on this argument. Sy and Taylor (200) propose an alternative to the product-limit estimator to estimate the nuisance baseline hazard function which also can handle the zero-tail constraint in the survivor function for the last event time. It is an empirical issue whether or not this constraint holds for the Breslow type estimate of the survivor function.

2.2 Discrete-Time Mixture Hazard Model with time-varying covariates

In order to incorporate time-varying regressors in the model we consider the discrete-time mixture hazard model.[20] However, this requires that these regressors remain unchanged in the time window $[t, t+1]$, an assumption which is tenable when we consider that banks report their data on a quarterly basis. The hazard rate in the discrete-time hazard model is given by

$$\begin{aligned} P(t &\leq T < t+1 | T > t, h_{it} = 1) = 1 - \exp\left[-\exp(w_{it}'\alpha) \int_t^{t+1} \lambda(v) dv \right] \\ &= 1 - \exp\left(-\exp(\omega_t + w_{it}'\alpha) \right) = F^* \left(\omega_t + w_{it}'\alpha \right) \end{aligned} \tag{17}$$

where $\omega_t = \ln \int_t^{t+1} \lambda(v) dv$ and $F^*(\cdot)$ is the extreme value cumulative distribution function. If we assume a parametric function for the baseline hazard, then ω_t will also be a parametric function of time. Meyer (1990) proposes methods of estimating such models, both parametrically and nonparametrically.

The hazard rate in (17) can also be expressed in terms of the logistic distribution if we note that

$$\ln \int_t^{t+1} \lambda(v; w) dv = \ln \left[1 + \exp q(t; w) \right] \tag{18}$$

where

$$q(t; w) = \ln \left(\frac{1 - \exp(-\exp(\Lambda(t; w))}{\exp(-\exp(\Lambda(t; w)} \right) \tag{19}$$

which implies that $q(\cdot)$ is logistically distributed and can be linearly approximated by $w_{it}'\alpha$. Hence,

$$P(t \leq T < t+1 | T > t, h_{it} = 1; w_{it}) = \frac{\exp(w_{it}'\alpha)}{1 + \exp(w_{it}'\alpha)} \tag{20}$$

By noting that $\lambda_{ij}(t; w) = 1 - \frac{S(t_{ij})}{S(t_{i,j-1})}$ for $j = 1, 2, ..., t_i$, and writing the survivor function as the product of conditional survival probabilities $S_{ij}(t; w) = \prod_{j=1}^{t_i} \frac{S(t_{ij})}{S(t_{i,j-1})}$ with $S(t_{i0}) = 1$, we have

$$S_{ij}(t; w, u) = \prod\nolimits_{j=1}^{t_i} \left(\frac{1}{1 + \exp(w_{ij}'\alpha)} \right), \tag{21}$$

which relates the survivor function to the hazard function and is a nonincreasing step function of time. By substituting (20) and (21) into (9) we obtain the likelihood function

[20] See Cox and Oaks (1984), Kalbfleisch and Prentice (2002), and Bover et al. (2002) for discussion on discrete-time proportional hazard models.

for the Discrete-Time Mixture Hazard Model (DTMHM).

3 Stochastic Frontier Model combined with Mixture Hazard Model

In this section we consider the efficiency performance of an individual bank as a determinant of both the probability of being troubled and the timing of the event of failure. The efficiency performance of a firm relative to the best practice (frontier) technology was formally considered by Debreu (1951) and Farrell (1957). Aigner et al. (1977), Meeusen and van den Broeck (1977), and Battese and Cora (1977) introduced the parametric stochastic frontier model (SFM). In the SFM given in level form the error term is assumed to be multiplicative and composed of two parts, a one-sided term that captures the effects of inefficiencies relative to the stochastic frontier and a two-sided term that captures random shocks, measurement errors and other statistical noise, and allows random variation of frontiers across firms. The initial SFM was formulated in a cross-sectional context and was later extended to panel data models, which allowed researcher to consistently estimate unconditional efficiency scores. Excellent surveys of frontier models and their applications are found in Kumbhakar and Lovell (2000) and Greene (2008).

The general stochastic frontier panel model for the i^{th} firm is given by

$$y_{it} = g(z_{it}; \gamma) \exp(\varepsilon_{it}) \tag{22}$$

where the dependent variable y_{it} could represent cost, output, profit, revenue etc., z_{it} is a vector of independent regressors, and $g(\cdot)$ is the frontier function, which can be either linear or non-linear in coefficients and covariates. Depending on the particular dual representation of technology specified, $\varepsilon = v \pm u (= \log y_{it} - \log g(z_{it}; \gamma))$ represents the composed error term, with v_{it} representing the noise and u_i the inefficiency process. The noise term is assumed to be *iid* normally distributed with zero mean and constant variance. Inefficiencies are also assumed to be *iid* random variables with distribution function defined on the domain of positive numbers ($u \in R_+$). Both v and u are assumed to be independent of each other and independent of the regressors.[21] We follow Pitt and Lee (1981) and assume that the inefficiency process is a time-invariant random effect which follows the half-normal distribution ($u_i \sim N^+(0, \sigma_u^2)$).

Under the above assumptions the joint distribution of the noise and the inefficiency term is given by

[21] The assumption of independence of the inefficiency term and the regressors is restrictive but is necessary for our current analysis. Its validity can be tested with Hausman-Wu test. In the panel data context this assumption can be relaxed by assuming that inefficiencies are fixed effects or random effects correlated with all or some of the regressors (Hausman and Taylor, 1981; Cornwell, Schmidt, and Sickles, 1990).

$$
\begin{aligned}
f_{v,u}(v_{it}, u_i) &= f_v(v_{it})f_u(u_i) = f_v(\varepsilon_{it} \pm u_i)f_u(u_i) \\
&= \frac{2}{(2\pi)^{(T_i+1)/2}\sigma_v^{T_i}\sigma_u} \exp\left[-\frac{(\varepsilon_{it} \pm u_i)'(\varepsilon_{it} \pm u_i)}{2\sigma_v^2} - \frac{u_i^2}{2\sigma_u^2}\right]
\end{aligned}
$$

After integrating u_i from this expression we obtain the marginal density of the composed error term, which for the production or profit frontier model is derived as

$$
f_\varepsilon(\varepsilon_{it}) = \frac{2}{(2\pi)^{T_i/2}\sigma_v^{T_i-1}\sigma} \exp\left[-\frac{\varepsilon_{it}'\varepsilon_{it}}{2\sigma_v^2} + \frac{\bar{\varepsilon}_i^2\lambda^2}{2\sigma^2}\right]\left[1 - \Phi\left(\frac{T_i\bar{\varepsilon}_i\lambda}{\sigma}\right)\right] \tag{23}
$$

where $\sigma = \sqrt{\sigma_v^2 + T_i\sigma_u^2}$, $\lambda = \sigma_u/\sigma_v$, and $\bar{\varepsilon}_i = (1/T_i)\sum_{t=1}^{T_i} \varepsilon_{it}$.[22] The parameter λ is the signal-to-noise ratio and measures the relative allocation of total variation to the inefficiency term. In practice we can use an alternative parametrization called the $\gamma-$parameterization which specifies

$$
\gamma = \frac{\sigma_u^2}{\sigma^2}
$$

This reparametrization is more desirable as γ has compact support which facilitates the numerical procedure of maximum likelihood estimation, hypothesis testing, and establishing the asymptotic normality of this parameter.

It can be also shown (see Jondrow et al., 1982) that the conditional distribution of the inefficiency term is given by

$$
f_{u|\varepsilon}(u_i|\varepsilon_{it}) = \frac{f_{\varepsilon,u}(\varepsilon_i, u_i)}{f_\varepsilon(\varepsilon_i)} = \frac{\frac{1}{\sigma}\phi(\frac{u_i-\mu_i^*}{\sigma_*})}{\left[1 - \Phi\left(-\frac{\mu_i^*}{\sigma_*}\right)\right]} \tag{24}
$$

where $f_{u|\varepsilon}(\cdot)$ represents the normal distribution truncated at 0 with mean $\mu_i^* = -T_i\bar{\varepsilon}_i\sigma_u^2/\sigma^2$ $= -T_i\bar{\varepsilon}_i\gamma$ and variance $\sigma_*^2 = \sigma_u^2\sigma_v^2/\sigma^2 = \gamma\sigma^2(1-\gamma T_i)$, and $\phi(\cdot)$ and $\Phi(\cdot)$ are the pdf and cdf of the standard normal distribution. The mean or the mode of this conditional distribution provides an estimate of the technical inefficiency of each firm in the sample.

In the absence of any effect of the inefficiencies on the probability and timing of failure, (23) and (24) can be employed to obtain the maximum likelihood estimates of model parameters and efficiency scores. However, consistent and efficient parameter estimates cannot be based solely on the frontier model when there is feedback between this measure of economic frailty and the likelihood of failure and the ensuing tightening of regulatory supervision. There is a clear need for joint estimation of the system when the decision of a firm is affected by these factors.

In deriving the likelihood function for this model we maintain the assumption that censoring is noniformative and statistically independent of h_i. Following Tsionas and Papadogonas (2006) we also assume that the censoring mechanism and h_i are independent of

[22] The cost frontier is obtained by reversing the sign of the composed error.

the composed error term, conditional on inefficiency and the data. Let $\Omega_i = \{x_i, w_i, z_i\}$ denote the set of covariates and $\theta' = \{\beta, \alpha, \delta_1, \delta_2, \sigma_v^2, \sigma_u^2\}$ be the vector of structural and distributional parameters. Then the observed joint density of the structural model for bank i, given h_i and after integrating out latent unobserved inefficiency, can be written as

$$\begin{aligned} L_i(y_i, h_i, d_i|\Omega_i, \theta') &= \int_0^\infty F_e(x_i'\beta + \delta_1 u_i)^{h_i}(1 - F_e(x_i'\beta + \delta_1 u_i))^{1-h_i} \\ &\quad \times \{\lambda_i(t; w_i, u_i)\}^{d_i h_i}\{S_i(t; w_i, u_i)\}^{h_i} \underbrace{f_v(\varepsilon_{it} \pm u_i) f(u_i)}_{f_\varepsilon(\varepsilon) f_{u|\varepsilon}(u|\varepsilon)} du_i \\ &= f_\varepsilon(\varepsilon_{it}) \int_0^\infty F_e(x_i'\beta + \delta_1 u_i)^{h_i}(1 - F_e(x_i'\beta + \delta_1 u_i))^{1-h_i} \\ &\quad \times \{\lambda_i(t; w_i, u_i)\}^{d_i h_i}\{S_i(t; w_i, u_i)\}^{h_i} f_{u|\varepsilon}(u|\varepsilon) du_i. \end{aligned} \tag{25}$$

The hazard rate and survival function for the SPMHM are now given by

$$\lambda_i(t; w_i, u_i) = \lambda_0(t) \exp(w_i'\alpha + \delta_2 u_i)$$

and

$$S(t; w_i) = S_0(t)^{\exp(w_i'\alpha + \delta_2 u_i)}.$$

This is a general model which combines the stochastic frontier model with logistic regression and the proportional hazard model. Either of these three models are special cases. If, for example, there is no association between inefficiency and probability of being troubled or failed ($\delta = (\delta_1, \delta_2) = (0, 0)$), then (25) consists of two distinct parts, the stochastic frontier and the mixture hazard. Both can be estimated separately using the previously outlined methods.

The integral in the joint likelihood (25) has no closed form solution and thus the maximization of this function requires numerical techniques, such as simulated maximum likelihood (SML) or Gaussian quadrature.[23] In SML the sample of draws from $f_{u|\varepsilon}(\cdot)$ are required to approximate the integral by its numerical average (expectation). As such, the simulated log-likelihood function for the i^{th} observation becomes

$$\begin{aligned} L_i &= \log L_i(y_i, h_i, d_i|\Omega_i, \Theta') = Constant - \frac{(T_i - 1)}{2} \log \sigma^2(1 - \gamma T_i) \\ &\quad -\frac{1}{2}\log \sigma^2 + \log\left(1 - \Phi\left(\frac{T_i \bar{\varepsilon}_i \lambda}{\sigma}\right)\right) - \frac{\varepsilon_{it}' \varepsilon_{it}}{2\sigma^2(1 - \gamma T_i)} + \frac{\bar{\varepsilon}_i^2 \gamma}{2\sigma^2(1 - \gamma)} \\ &\quad + \log \frac{1}{S} \sum_{s=1}^S \left[F_e(x_i\beta + \delta_1 u_{is})^{h_i}(1 - F_e(x_i\beta + \delta_1 u_{is}))^{1-h_i}\{\lambda_i(t; w_i, u_{is})\}^{d_i h_i}\{S_i(t; w_i, u_{is})\}^{h_i}\right] \end{aligned} \tag{26}$$

[23] Tsionas and Papadogonas (2006) employ the gaussian quadrature in estimation of the model wherein the technical inefficiency has potential effect on firm exit. Sickles and Taubman (1986) used similar methods in specifying structural models of latent health and retirement status while controlling for multivariate unobserved individual heterogeneity in the retirement decision and in morbidity.

where u_{is} is a random draw from the truncated normal distribution $f_{u|\varepsilon}(\cdot)$ and S is the number of draws. We utilize the inverse cdf method to efficiently obtain draws from this distribution as

$$u_{is} = \mu_i^* + \sigma_* \Phi^{-1}\left[U_{is} + (1 - U_{is})\Phi(-\frac{\mu_i^*}{\sigma_*})\right] \tag{27}$$

where U is a random draw from uniform $U[0,1]$ distribution or a Halton draw.

By substituting (27) into (26) and treating the $h_i's$ as known we can maximize the log-likelihood function $L = \sum_i L_i$ by employing standard optimization techniques and obtain the model parameters.

Finally, after estimating the model parameters, the efficiency scores are obtained as the expected values of the conditional distribution in the spirit of Jondrow et al. (1982)

$$\begin{aligned} \hat{u}_i &= E\left[u_i|\hat{\varepsilon}_i, \tilde{h}_i, d_i\right] = \frac{\int_0^\infty u_i G(u_i;\Theta) f_{u|\varepsilon}(u|\varepsilon) du_i}{\int_0^\infty G(u_i;\Theta) f_{u|\varepsilon}(u|\varepsilon) du_i} \qquad (28) \\ \text{with } G(u_i;\Theta) &= \tilde{F}(x_i'\beta + \delta_1 u_i)^{\tilde{h}_i}(1 - \tilde{F}(x_i'\beta + \delta_1 u_i))^{1-\tilde{h}_i}\{\lambda_i(t; w_i, u_i)\}^{d_i \tilde{h}_i}\{S(t; w_i, u_i)\}^{\tilde{h}_i} \end{aligned}$$

The integrals in the numerator and denominator are calculated numerically by the SML method. It is straightforward to check that if δ is zero then (28) collapses to the Jondrow et al. formula for production frontiers

$$\hat{u}_i = E\left[u_i|\hat{\varepsilon}_i\right] = \mu_* + \sigma_* \frac{\phi(\frac{\mu_*}{\sigma_*})}{\Phi(\frac{\mu_*}{\sigma_*})} \tag{29}$$

The predicted efficiency of i^{th} firm is given by $TE_i = \exp(-\hat{u}_i)$ or it can be calculated as $TE_i^* = E\left[\exp(-u_i)|\hat{\varepsilon}_i, \tilde{h}_i, d_i\right]$ as suggested by Battese and Coelli (1988). The latter measure is optimal in the sense that it gives a lower mean squared error of prediction than the former one.

The EM algorithm for the stochastic frontier mixture model involves the following steps:

- Step 1: Provide initial estimates of the parameter vector $\theta = (\alpha, \beta, \gamma, \delta_1, \delta_2, \sigma, \gamma)$. Set the initial value of parameters δ_1 and δ_2 equal to zero and obtain the initial value of the baseline hazard function from (14). Consistent starting values of the variances of the noise and inefficiency terms are based on method of moments estimates

$$\begin{aligned} \hat{\sigma}_u^2 &= [\sqrt{2/\pi}(\frac{\pi}{\pi-4})\hat{m}_3]^{2/3} \\ \hat{\sigma}_v^2 &= \hat{m}_2 - (\frac{\pi-2}{\pi})\hat{\sigma}_u^2 \end{aligned}$$

where $\hat{m}_2$ and $\hat{m}_3$ are the estimated second and third sample moments of the OLS residuals, respectively. Estimates of σ and γ parameters are obtained through the relevant expressions provided above.

- Step 2 (E-step): Compute $\tilde{h}_i$ based on the current estimates and the observed data from

$$\begin{aligned} \tilde{h}_i^{(M)} &= E\left[h_i|\theta^{(M)}, Data\right] = \Pr(h_i^{(M)} = 1|t_i > T_i) \\ & \begin{cases} \frac{F_e(x_i'\beta^{(M)}+\delta_1^{(M)}u_i)S_i(t;w_i,u_i)}{F_e(x_i'\beta^{(M)}+\delta_1^{(M)}u_i)S_i(t;w_i,u_i)+(1-F_e(x_i'\beta^{(M)}+\delta_1^{(M)}u_i))} & \text{if } d_i = 0 \\ 1 & \text{otherwise} \end{cases} \end{aligned} \tag{30}$$

- Step 3 (M-step): Update the estimate of parameters by maximizing L via simulated maximum likelihood technique.

- Step 4: Iterate between steps 2 and 3 until convergence.

4 Empirical Model and Data

In this section we outline the empirical specification we used in estimating the four models. We also describe the data on which our estimates are based and the stepwise forward selection procedure we employ in model building and variable selection.

4.1 Empirical Specification

Following Whalen (1991) we employ a model with a two-year timeline to estimate the probability of distress and failure and the timing of bank failure. In the SPMHM the time to failure is measured in months (1-24) starting from December 31, 2007. The sample consists of 125 banks that failed during 2008 and 2009 and 5843 nonfailed banks. The covariates used in estimation are derived from the 2007.Q4 Consolidated Reports of Condition and Income (Call Reports). Banks that disappear from the sample for reasons other than failure or did not experience the event through the end of the sample period have censored duration times. Thus for these banks what we observe is the maximum duration in the sample. We have no further information on their status. Nine banks voluntarily liquidated and are excluded from the sample as we are modeling the regulatory decision. In addition, we exclude banks that were chartered and started to report their data after the first quarter of 2007. These are typically referred as "De Novo" banks and require a special treatment (DeYoung, 1999, 2003). The holdout sample consists of 92 banks that failed during 2010 including the third quarter as well as 5674 surviving banks. This sample will be used to assess the model's out-of-sample predictive accuracy.

For the DTMHM time to failure is measured in quarters as banks report their data on a quarterly basis. The sample consists of eight quarters of observations on banks that either failed or survived during the 2008-2009 period. The number of failed banks is the same as in the SPMHM. The holdout sample consists of two quarters of bank observations in 2010. Rather than calculating the probable time of failure, in this case we estimate the probability that a certain bank will fail during 2010. This excludes the fourth quarter of 2010 due to lack of data.

We employ the cost frontier in the stochastic frontier model specification. The cost frontier describes the minimum level of cost given output and input prices. The gap between the actual and minimum cost is the radial measure of total (cost) inefficiency and is composed of two parts: technical inefficiency arising from excess usage of inputs, and allocative inefficiency that results from a non-optimal mix of inputs. We do not make this decomposition but rather estimate overall cost inefficiency. We adopt the intermediation approach of Sealey and Lindley (1977) according to which banks are viewed as financial intermediaries that collect deposits and other funds and transform them into loanable funds by using capital and labor. Deposits are viewed as inputs as opposed to outputs, which is assumed in the production approach (see Baltensperger, 1980).

As in Kaparakis et al., (1994) and Wheelock and Wilson (1995) we specify a multiple output-input short-run stochastic cost frontier with a quasi-fixed input. Following the standard banking literature we specify a translog functional form to describe the cost function[24]

$$\begin{aligned}
\ln C_{it} &= \alpha_{0+} \sum_{m=1}^{5} \alpha_m \ln y_{mit} + \sum_{k=1}^{4} \beta_k \ln w_{kit} \\
&+ \frac{1}{2} \sum_{m=1}^{5} \sum_{j=1}^{5} \alpha_{mj} \ln y_{mit} \ln y_{jit} + \theta_1 t + \frac{1}{2} \theta_2 t^2 \\
&+ \frac{1}{2} \sum_{k=1}^{4} \sum_{n=1}^{4} \beta_{kn} \ln w_{kit} \ln w_{nit} + \eta_1 \ln X_{it} + \frac{1}{2} \eta_2 (\ln X_{it})^2 \\
&+ \sum_{m=1}^{5} \sum_{k=1}^{4} \delta_{mk} \ln y_{mit} \ln w_{kit} + \sum_{m=1}^{5} \lambda_{1x} \ln y_{mit} \ln X_{it} \\
& \sum_{k=1}^{4} \lambda_{2x} \ln w_{kit} \ln X_{it} + \sum_{m=1}^{5} \lambda_{mt} \ln y_{mit} t + \sum_{k=1}^{4} \phi_{kt} \ln w_{kit} t + \upsilon_{it} + u_i
\end{aligned}$$

with symmetry and linear homogeneity in input price restrictions imposed by considering capital as the numeraire and dividing the total cost and other input prices by its price. Thus

[24] The translog function provides a second-order differential approximation to an arbitrary function at a single point. It does not restrict the share of a particular input to be constant over time and across individual firms. Additional flexibility can be attained by considering the Fourier-flexible functional form, which includes Fourier trigonometric terms in addition to standard translog terms. Berger and Mester (1997) point out that there is no essential difference in average efficiencies and ranking of firms between these two truncated asymptotic approximations. Since the translog is easier to implement we utilize it here.

$$\alpha_{mj} = \alpha_{jm} \text{ and } \beta_{kn} = \beta_{nk}$$

$$\sum_{k=1}^{4} \beta_k = 1 \ , \ \sum_{k=1}^{4} \beta_{kn} = \sum_{k=1}^{4} \delta_{mk} = \sum_{k=1}^{4} \lambda_{2x} = \sum_{k=1}^{4} \phi_{kt} = 0$$

where C is the observed short-run variable cost of an individual bank at each time period, y_m is the value of m^{th} output, $m = 1, .., 5$. Outputs are real estate loans ($yreln$), commercial and industrial loans ($yciln$), installment loans ($yinln$), securities ($ysec$), and off-balance sheet items ($yobs$). The $w's$ represent input prices for total interest-bearing deposits (dep), labor (lab), purchased funds ($purf$), and capital (cap). The quasi-fixed input (X) consists of noninterest-bearing deposits. Kaparakis et al. (1994) assume that the bank takes the level of noninterest-bearing deposits as exogenously given and since there is no market price associated with this input, the quantity of it should be included in the cost function instead of its price. We also include the time and its interaction with outputs and input prices to account for non-neutral technological change.

After the technology parameters are estimated we can estimate the scale economies and technological change measures along a particular output/price ray. The scale economies are defined as the degree to which a firm's total cost of producing financial services decreases as its output of services increase proportionally and they are derived as the sum of partial derivatives of the cost with respect the outputs. That is,

$$\begin{aligned} Scale_{it} &= \sum_{m=1}^{5} \frac{\partial \ln C_{it}}{\partial \ln y_{mit}} \qquad (31) \\ &= \sum_{m=1}^{5} \left[\alpha_m + \sum_{j=1}^{5} \alpha_{mj} \ln y_{jit} + \sum_{j=1}^{4} \delta_{mk} \ln w_{kit} + \lambda_{1x} \ln X_{it} + \lambda_{mt} t \right] \end{aligned}$$

A value of this measure less than one indicates the presence of (short-run) economies of scale and would indicate that the bank is operating below its optimal scale level. Such a firm could reduce its cost by expanding output. If the measure is greater than one then the bank experiences (short-run) diseconomies of scale and should reduce its output level to achieve optimal input usage. The reciprocal of scale economies provides the measure of returns to scale (RTS). Technological change is derived as the time change in costs at constant input price and quasi-fixed factor levels.

4.2 Data

The data used in this study come from three main sources. The first is the public-use quarterly Call Reports for all U.S. commercial banks that are collected and administrated by the Federal Reserve Bank of Chicago and the FDIC. The majority of the data are from this source, which mainly consists of bank-specific variables. The second source is the FDIC website which provides information regarding failed banks and industry-level indicators.

The third source is the website of the Federal Reserve Bank of St. Louis, which provides information on regional-specific macroeconomic variables.[25]

More than forty bank-specific financial ratios, state-specific macroeconomic, geographical, and structural variables are constructed from variables obtained form these sources as potential determinants of banking distress and failure. We apply the stepwise forward selection procedure (Klein and Moeschberger, 2003) to chose the most relevant explanatory variables based on global and local tests, as well as the Akaike Information Criterion (AIC). Although these procedures are very useful for deciding how many and which variables to include in the model, we also select variables based on their contribution to the prediction accuracy of the model and exclude other due to high degrees of multicollinearity and attendant complications in obtaining the numerical solutions of our multivariate models.

The final set of variables entering both the incidence and the latency part includes capital adequacy, asset quality, management, earnings, liquidity, and sensitivity (the so-called "CAMELS"), six structural and geographical variables, and four state-specific variables. We use the same set of explanatory variables in both the incidence and latency part of our model in order to capture the different effects that these have on the probability that a particular bank is troubled, as well as the probability and timing of the resolution of the bank's troubles by the FDIC. Tables 2 and 3 provide our mnemonics for the variable names as well as their formal definitions.

The first variable in table 2 is the tier 1 risk-based capital ratio. Banks with a high level of this ratio are thought to have sufficient capital to absorb any losses occurring during the crisis and hence, have a higher chance of survival. We expect a negative sign for this variable in both incidence and latency. Banks with a ratio above, say 10%, are less likely to cause regulatory intervention. The next variable is the ratio of nonperforming loans to total loans, which consists of total loans and lease financing receivables that are nonacrual, past due 30-89 days and still accruing, and past due 90 days or more and still accruing. This variable is a primary indicator of the quality of loans made by banks and it is one of the influential factors explaining their distress and failure. The higher this ratio, the higher the probability that the bank will enter the watch list and subsequently fail. The next five ratios also reflect the asset quality of banks. We expect the ratio of allowance for loan and lease loss to average total loans to have a positive effect on a bank's survival. Higher ratios may signal banks to anticipate difficulties in recovering losses and thus this variable may positively impact incidence. Similarly, charge-offs on loan and lease loss recoveries provide a signal of problematic assets that increase the probability of insolvency and failure. Provision for loan and lease losses are based upon management's evaluation of loans and leases that the reporting bank intends to hold. Such a variable can expect to decrease the probability of distress and increase the probability of survival. We can also view this as a proxy to control for one of the several ways in which different banks pursue different risk strategies (Inanoglu, et al., 2012). An often-used measure of credit risk is gross charge-off rates (dollar gross charge-offs normalized by lending book assets), both of which are controlled for in our analysis. Proxies for market risk and liquidity risk are bundled in our other controls for the

[25] Websites for the data sources are: (i) Federal Reserve Bank of Chicago (http://www.chicagofed.org/webpages/banking), (ii) FDIC (http://www2.fdic.gov/hsob/)(iii) FDICFederal Reserve Bank of St. Louis (http://research.stlouisfed.org/fred2/).

various CAMEL measures of Capital Adequacy (C), Asset Quality (A), Managerial Quality (M), Earnings (E), and Liquidity (L) detailed in table 2.

Two of the three management quality proxies that we include are constructed from the balance sheet items of the reporting banks. The ratio of the full-time employees to average assets has an ambiguous sign in both the incidence and latency parts of our model. However, we conjecture a negative sign on this variable as the FDIC may face constraints in seizing large banks with a large number of employees. The intermediation ratio shows the ability of a bank to successfully transform deposits into loans and thus we expect its impact to be negative. Earnings are also expected to have a negative effect on both the incidence and latency parts of our model. From the liquid assets we expect cash and core deposits to have negative signs, while the direction of the effect of Jumbo CD's is uncertain. Banks with more rate sensitive liabilities and illiquid assets should be considered at higher risk of failure ex ante The state-specific variables that we include in the model are expected to have a positive impact on survival with the exception of the unemployment rate, which is expected to have a negative effect on their viability. The structural and geographical variables have ambiguous signs.

Means and standard deviations of financial ratios for the fourth quarter of 2007 and 2009 are reported in Table 4. The last column of the table reports the p-values of the hypothesis of no difference between the means of variables of failed and nonfailed banks based on the two-group mean comparison test for the two periods. This shows the difference in the financial health of nonfailed and failed banks.[26] Table 5 reports the descriptive statistics of variables that enter the cost function for the sample of failed and nonfailed banks for the same selected periods. It is worth noting that on average banks that failed had issued more real estate loans than their nonfailed peers prior to the crisis. This is consistent with the prevailing view that failed banks were highly engaged in residential mortgage loans, which resulted in unusually high default rates after the collapse of the housing bubble. Failed banks also paid higher salaries than did the nonfailed banks. For the DTMHM it is informative to look at the evolution of these variables over time. These are given in Figure 4 where the large discrepancy between the financial health of failed and non-failed banks is evident for most of the financial ratios. For example, the key financial variables, such as capital adequacy and nonperforming loans, display significant mean differences which amplify as we move in time.[27]

5 Results and Predictive Accuracy

Table 6 reports the results for the continuous-time semiparametric and discrete-time MHM under the assumption that inefficiencies have no effect on the probability of incidence and latency. Both models produce qualitatively similar results. The influential factors that were believed to have a strong effect on both probabilities a priori turn out to have the

[26] Notice that there are troubled banks among the nonfailed banks that fail in subsequent periods. Hence, the difference must be larger than that reportered in the table.

[27] We reject the null hypothesis of no mean difference for these two variables between failed and nonfailed banks at any conventional significance level based on the two-group mean comparison test with Satterthwaite's degrees of freedom for all periods.

correct sign and are statistically significant at any conventional significance level in both models. Results indicate that there is a large marginal effect of the tier 1 capital ratio on the incidence probability. Other measures of earnings proxies and asset quality also have a large and significant effect on this probability. In other words, well capitalized banks with positive earnings and quality loans are less likely to appear on the FDIC watch list. In contrast, banks that are already on this list will increase their probability of failure in the industry if their capital ratio is insufficient, their ratio of nonperforming loans is high, and their earnings are negative and have a decreasing trend. Certificates of deposits and core deposits have the expected effect though not a statistically significant one. On the other hand, cash has a positive and significant effect. One explanation of this could be, after controlling for profitability, that banks that remain cash idle have a higher opportunity cost. It would only stand to reason for these banks to be costly and inefficient. Banks with a large number of full-time employees have less chances to fail. Banks that successfully transform deposits into vehicles of investment are considered potentially stronger, while others with more rate sensitive liabilities appear to be less promising. The state-specific variables have the expected economic congruences which appear to be nonsignificant in the incidence part of the model. We would expect these variables to significantly affect the probability of incidence of banks in states with higher unemployment rates, lower growth in personal income, limited construction permits, and falling housing prices, all of which would give cause for an on-site inspection. Only two of the four geographical variables have a significant effect. Banks that are FR members have a higher probability of failure than those that are not. This is associated with behavior consistent with moral hazard. Such banks have felt secure as members of FR and hence may have assumed higher risks than they would have had they not had FR banking. The positive result of the FR district code indicates that the probability of insolvency and failure is higher for banks in the Atlanta (6) district than for banks in the Boston (1) district and it is lower than for banks in the San Francisco (12) district. Recall that Washington, D.C. is the reference district. The size of the bank, as it is measured by the natural logarithm of its gross total assets, has a negative and significant sign only in the incidence part of model II, which implies that larger banks are less likely to find themselves on the watch list and then subsequently fail. Older and well-established banks have lower failure probabilities than their younger counterparts.

Table 7 contains the results for the continuous-time semiparametric and discrete-time MHM with the stochastic frontier specification. With few exemptions, the results are qualitatively similar to those reported in Table 6. Inefficiency has a positive effect on the incidence and failure probabilities. The effect is only significant on the latter probability and this is consistent with the view that bank performance is not the criterion for on-site examination but rather a factor affecting a bank's longer term viability. The distributional parameters are significant at the 1% significant level. The descriptive statistics for the efficiency score obtained from the models III and IV, as well as from the standard time-invariant random effects (RE) model for the sample of nonfailed and failed banks are summarized in Tables 8 and 9, respectively. There is a small but statistically significant difference between average efficiencies obtained form models III and IV. This difference is not statistically significant for efficiencies derived from the random effects model. Figure 6 plots the distribution of inefficiencies (non-truncated) obtained from these three models.

It is interesting to note that the RE model reports some surviving banks as extremely inefficient while the most efficient banks are banks that failed. Hence, we suspect that the two-step approach would yield the opposite sign on inefficiency component from what we would expect. The difference in average efficiencies from the single step estimation can be mainly attributed to the fact that distressed banks that subsequently fail typically devote their efforts to overcome the difficulties and clean up their balance sheets. These impose additional costs on banks and worsen an already bad situation.

In Figure 5 we plot the average returns to scale for failed and nonfailed banks estimated from model III and model IV, our preferred model. We also provide 95% confidence intervals. Results for model I-II are comparable. Both types of banks display slight scale economies although they are only marginally significant at the 95% confidence level.

In Figures 7 and 8 we plot the survival profile of the average bank that failed during the $2008-2009$ period for all four models. The average survival profile based on results of the SPMHM is constructed from (11) and are based on the average characteristics of failed banks. Similarly, the average profile based on the DTMHM results is calculated from (21), which is a step function with steps occurring at discrete failure times. From figure 7 it can be seen that average failed banks in SPMHM are predicted to have a duration time of 22 months. After controlling for inefficiencies the time to failure drops to 21 months. Based on the DTMHM results, Figure 8 demonstrates that a bank with the same characteristics as the representative failed bank will survive up to 7 quarters after accounting for inefficiency.

It is also interesting to look at the survival profile of the most and the least efficient banks derived from models III and IV. Figure 9 displays the survival profiles obtained from SPMHM. The least efficient bank with an efficiency score of 0.149 is predicted to fail in 8 months. This bank was closed by FDIC in the end of August of 2008. On the other hand, the most efficient bank with efficiency score of 0.971 has a survival probability of one throughout the sample period. This is also illustrated in Figure 10, where the least efficient bank with an efficiency score of 0.154 is predicted to fail by fifth quarter, using the DTMHM results. This bank failed in the third week of April of 2009.[28] The most efficient bank with an efficiency score of 0.969 has an estimated survival probability that exceeds 0.95.

We next examine our results by recasting our model estimates as early warning tools that can correctly classify failed and nonfailed banks within our sample used for estimation as well as in our hold-out sample. The tests are based on two types of errors, similar to those that arise in any statistical hypothesis testing. These are type I and type II errors (see Lane et al. 1986; Whalen, 1991; and Thompson, 1992 among others). A type I error is defined as the error due to classifying a failed bank as a nonfailed bank, while a type II error arises from classifying a non-failed bank as a failed bank. There is a trade-off between these two type of errors and both are important from a public policy standpoint. Models with low type I error are more desirable since timely identification of failed banks allows the regulator to undertake any prompt corrective action to ensure the stability and the soundness of the financial system. On the other hand, models with high type II error will be unnecessary flagging some banks as failures while they are not, and hence could waste

[28] The identity of the least efficient bank is not the same in these two models. However, the identity of the most efficient bank is the same.

regulators' time and resources. However, it is oftentimes hard to interpret the costs of a type II error since various constraints faced by FDIC could delay the resolution of an insolvent bank. Thompson (1992) attributes this to information, administrative, legal and political constraints, among others. Whalen (1991) notes that some type II error predictions actually represent failures that occur in the near future and so should be considered as a success of the model rather than its failure.

Table 10 reports the in-sample predictive accuracy for the four models based on type I, type II, and overall classification error. Overall classification error is a weighted sum of type I and type II errors. In what follows we set the weights at 0.5 for both errors. Clearly this weighting scheme is arbitrary and alternative weighting schemes could be based on different risk preference assumptions, implicit and explicit costs of regulation, etc. In our predictive accuracy analysis each bank is characterized as a failure if its survival probability falls bellow a probability cutoff point, which we base on the sample average ratio of failed to nonfailed banks (0.021). The DTMHM specification yields a lower type I error than does the SPMHM. This is to be expected since the DTMHM incorporates multiperiod observations for each bank and thus is more informative on bank financial health than the single-period cross-sectional observations. There is a significant drop in type I error in both specifications when the performance of a bank is added to the model as an additional factor. On the other hand, type II error is increased in the DTMHM and it is doubled when inefficiency is included. Based on the overall classification error, Model IV seems to perform slightly better than Model III, but it largely outperforms the Models I and II.

Table 11 presents the errors that judge the out-of sample classification accuracy of the models. The SPMHM errors are based on the survival profile of banks using the 2009 end-year data and can predict failures that may occur through the end of 2010. We consider banks that have failure times of up to nine months in order to compare the errors from this model with those based on the discrete-time alternative. The survival probabilities in the DTMHM are calculated from (21). In order to account for the third quarter failures we keep the financial ratios the same from the second quarter to the third quarter since the Call Reports of 2010 have not yet been released as of the date of this analysis. We first compare these results with the in-sample classifications. There is a significant drop in type I error for all four models. This is mainly due to the fact that the data used to calculate the survival profiles of each banks are more informative than what was used to estimate the model parameters and is reasonable since the end of 2009 is considered the peek year of the banking crisis during which the financial health of some banks deteriorated significantly (see Table 4). The inter-model comparison is the same as above with Model IV favored over the other models based on predictive accuracy.

6 Concluding Remarks

Massive banking failures during the financial turmoil of the Great Recession has resulted in enormous financial losses and costs to the U.S. economy, not only in terms of the bailouts by regulatory authorities in their attempt to restore liquidity and stabilize the financial sector, but also in terms of the lost jobs in banking and other sectors of economy, failed businesses, and ultimately slow growth of the economy as a whole. The design of early warning models that accurately predict the failures and their timing is of crucial importance in order to ensure the safety and the soundness of the financial system. Early warning models that can be used as off-site examination tools are useful for at least three reasons. They can help direct and efficiently allocate the limited resources and time of on-site examination so that banks in immediate help are examined first. They are less costly than on-site visits made by supervisors to institutions considered at risk and can be performed with high frequency to examine the financial condition of the same bank. Finally, they can predict failures at a reasonable length of time prior to the marked deterioration of bank's condition and allow supervisors to undertake any prompt corrective action that will have the minimal cost to a taxpayer.

In this paper we have considered early warning models that attempt to explain the recent failures in the U.S. commercial banking sector. We employ a duration analysis model combined with a static logit model to determine troubled banks which subsequently fail or survive. Both continuous and discrete time versions of the mixed model are specified and estimated. These effectively translate the bank-specific characteristics, state-related macroeconomic variables, and geographical and structural variables into measures of risk. Capital adequacy and nonperforming loans were found to play a pivotal role in determining and closing insolvent institutions. State-specific variables appeared to significantly affect the probability of failure but not insolvency. The discrete-time model outperformed the continuous-time model as it is able to incorporate time-varying covariates, which contain more and reacher information. We also found that managerial efficiency does not significantly affect the probability of a bank being troubled but plays an important role in their longer term survival. Inclusion of the efficiency measure led to improved prediction in both models.

7 Appendix A: Derivation of the likelihood function

In this appendix we show the derivation of the sample likelihood function given in expression (9). For this purpose we first note that at time t, each bank can fall into four mutually exclusive states of nature:

$$States = \begin{cases} h_i = 1, d_i = 1 \text{ (Troubled\&Failed)} & \text{with prob. } F_e(x_i'\beta)\lambda_i^p(t; w_i)S_i^p(t; w_i) \\ h_i = 0, d_i = 1 \text{ (Healthy\&Failed)} & \text{with prob. } (1 - F_e(x_i'\beta))\, \lambda_i^s(t; w_i)S_i^s(t; w_i) \\ h_i = 1, d_i = 0 \text{ (Troubled\&Censored)} & \text{with prob. } F_e(x_i'\beta)S_i^p(t; w_i) \\ h_i = 0, d_i = 0 \text{ (Healthy\&Censored)} & \text{with prob. } (1 - F_e(x_i'\beta))\, S_i^s(t; w_i) \end{cases}$$

Then

$$\begin{aligned} L(\theta; x, w, d) &= \prod\nolimits_{i=1}^{n} L_i(\theta; x, w, d) \\ &= \prod\nolimits_{i=1}^{n} \left\{ \left(F_e(x_i'\beta)\lambda_i^p(t; w_i)S_i^p(t; w_i)\right)^{h_i} \left(\left(1 - F_e(x_i'\beta)\right) \lambda_i^s(t; w_i)S_i^s(t; w_i)\right)^{1-h_i} \right\}^{d_i} \\ &\qquad \times \left\{ \left(F_e(x_i'\beta)S_i^p(t; w_i)\right)^{h_i} \left(\left(1 - F_e(x_i'\beta)\right) S_i^s(t; w_i)\right)^{1-h_i} \right\}^{1-d_i} \\ &= \prod\nolimits_{i=1}^{n} F_e(x_i'\beta)^{h_i} \left(1 - F_e(x_i'\beta)\right)^{(1-h_i)} [\lambda_i^p(t; w_i)]^{d_i h} \\ &\qquad \times [\lambda_i^s(t; w_i)]^{d_i(1-h_i)} [S_i^p(t; w_i)]^{h_i} [S_i^s(t; w_i)]^{1-h_i} \end{aligned}$$

By assumption, $\lambda_i^s(t; w_i) = 0$ if and only if $h_i = 0$ and $d_i = 0$ i.e., a bank is healthy and is not observed failing. Similarly $S_i^s(t; w_i) = 1$ if and only if $h_i = 0$ i.e., a bank is healthy. The final sample likelihood function is then given by

$$L(\theta; x, w, d) = \prod\nolimits_{i=1}^{n} F_e(x_i'\beta)^{h_i} \left(1 - F_e(x_i'\beta)\right)^{(1-h_i)} [\lambda_i^p(t; w_i)]^{d_i h_i} [S_i^p(t; w_i)]^{h_i}$$

which implies that the completely healthy banks contribute to the likelihood function only through their probability being troubled.

8 Appendix B: Tables and Figures

Table 2: CAMELS proxy Financial Ratios

	Capital Adequacy (C)
tier1	Tier 1 (core) capital/riskweighted assets
	Assset Quality (A)
rnpl	Nonperforming loans/total loans
alll	Allowance for loan and lease loss/average loans and leases
reln	Commercial real estate loans/total loans
coffs	Charge-off on loans and leases/average loans and leases
lrec	Recoveries on allowance for loan and lease losses/average loans and leases
llp	Provision for loan and lease losses /average loans and leases
	Managerial Quality (M)
fte	(Number of fulltime equivalent employees/average assets)*1000
imr	Total loans/total deposits
u	Random Effects inefficiency score
	Earnings (E)
oi	Total operating income/average assets
roa	Net income (loss)/average assets
roe	Net income (loss)/total equity
	Liquidity (L)
	Noninterest-bearing balances, currency, and coin/average assets
cd	Total time deposits of USD 100,000 or more/total assets
coredep	Core deposits/total assets
	Sensitivity (S)
sens	Difference in rate sensitive assets and liabilities repricing within one year/total assets

Table 3: Structural, geographical, and State-Specific Macroeconomic variables

Structural and geographical variables	
chtype	Charter type (1if state chartered, 0 otherwise)
frsmb	FRS membership indicator (1 if Federal Reserve member, 0 otherwise)
ibf	International banking facility (1 if bank operates an international based facility, 0 otherwise)
frsdistrcode	FRS district code (Boston(1), New York (2), Philadelphia (3), Cleveland (4), Richmond (5), Atlanta (6), Chicago (7), St. Louis (8), Minneapolis (9), Kansas City (10), Dallas (11), San Francisco (12), Washington, D.C. (0-referense district))
lgta	log of total assets
age	Age (measured in quarters)
State-Specific Macroeconomic variables	
ur	Unemployment rate
chpi	% Change in personal income
chphi	% Change in house price index
chnphu	Change in new private housing units authorized by building permits

Table 4: Descriptive Statistics for CAMELS proxy financial ratios for the fourth quarter of 2007 and 2009

	Non-Failed Banks				Failed Banks				p-value
Variable	2007.Q4		2009.Q4		2007.Q4		2009.Q4		2007.Q4/2009.Q4
	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D	
tier1	0.1072	0.0333	0.1025	0.0301	0.1011	0.0384	0.0253	0.0219	0.049/0.000
alll	0.0129	0.0065	0.0169	0.0094	0.0161	0.0100	0.0450	0.0221	0.000/0.000
reln	0.4583	0.1703	0.4590	0.1652	0.6254	0.1440	0.6070	0.1372	0.000/0.000
rnpl	0.0260	0.0231	0.0435	0.0395	0.0539	0.0528	0.2114	0.1043	0.000/0.000
roa	0.0097	0.0076	0.0023	0.0158	0.0030	0.0137	-0.0636	0.0296	0.000/0.000
roe	0.0957	0.0771	0.0064	0.3224	0.0178	0.1980	-1.5493	55.774	0.000/0.801
cd	0.1563	00749	0.1644	0.0757	0.2082	0.1010	0.2302	0.1092	0.000/0.000
coredep	0.8228	0.0741	0.8334	0.0659	0.8068	0.0798	0.9054	0.0665	0.013/0.000
coffs	0.2493	0.3995	0.5687	0.6542	0.2902	0.3376	1.5778	1.1923	0.135/0.000
lrec	0.0008	0.0033	0.0008	0.0021	0.0004	0.0012	0.0014	0.0017	0.001/0.011
llp	0.0027	0.0067	0.0120	0.0169	0.0092	0.0119	0.0724	0.0370	0.000/0.000
fte	0.3169	0.1290	0.2838	0.1174	0.2737	0.1999	0.2134	0.0796	0.007/0.000
imr	0.8126	0.2053	0.7792	0.1873	0.9647	0.1526	0.8149	0.1271	0.000/0.014
sens	-0.1433	0.1490	-0.1348	0.1270	-0.0505	0.1748	-0.2095	0.1440	0.000/0.022
cash	0.0323	0.0182	0.0310	0.0269	0.0209	0.0135	0.0230	0.0307	0.000/0.000
oi	0.0718	0.0121	0.0581	0.0115	0.0786	0.0178	0.0511	0.0111	0.000/0.000
N	5843		5674		125		92		

The calculation of the mean and standard deviation for 2007.Q4 sample of failed banks is based on banks that failed between 2007.Q42009. Q4. Figures for 2009.Q4 are based on failures of 2010.Q12010.Q3 Pvalues under the null hypothesis of no difference between the means of variables of failed and nonfailed banks based on the twogroup mean comparison test with Satterthwaite's degrees of freedom.

Table 5: Descriptive Statistics for variables that enter the cost function for the fourth quarter of 2007 and 2009

	Non-Failed Banks				Failed Banks				p-value
Variable	2007.Q4		2009.Q4		2007.Q4		2009.Q4		2007.Q4/2009.Q4
	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D	
Cost	53395	955229	46259	780129	42967	105935	24717	31302	0.488/0.049
yreln	485820	7426706	625015	9671132	532470	1432030	329015	436220	0.745/0.003
yciln	165465	3061182	179833	3128254	67053	181888	44812	65765	0.021/0.001
yinln	78985	1587319	110304	2343919	15900	68652	6952	17501	0.003/0.001
ysec	195045	3420833	335307	6913427	118358	379112	56332	108157	0.155/0.003
yobs	136245	2736033	212630	3947440	74323	290364	104491	215157	0.146/0.060
X	163124	3369938	250018	5307998	58179	124646	58179	65623	0.694/0.718
wdep	0.0297	0.0066	0.0165	0.0052	0.0367	0.0065	0.0248	0.0054	0.001/0.000
wlab	55.078	14.016	58.598	14.645	66.127	16.279	69.801	17.747	0.000/0.000
wcap	0.2875	0.2119	0.2900	0.2131	03041	0.2507	0.3551	0.2949	0.409/0.050
wpurf	0.0447	0.0083	0.0267	0.0076	0.0458	0.0091	0.0311	0.0096	0.132/0.000
N	5843		5674		125		92		

The calculation of the mean and standard deviation for 2007.Q4 sample of failed banks is based on banks that failed between 2007.Q42009.Q4.

Figures for 2009.Q4 are based on failures of 2010.Q12010.Q3. The price of labor is measured in thousands of US dollars.

Pvalues under the null hypothesis of no difference between the means of variables of failed and nonfailed banks based on the twogroup mean comparison test with Satterthwaite's degrees of freedom.

Table 6: Estimates from the ContinuousTime Semiparametric Proportional Mixture Hazard Model (Model I) and DiscreteTime Mixture Hazard Model (Model II)

	Model I				Model II			
Variable	Latency		Incidence		Latency		Incidence	
Intercept			-2.5989	(2.8512)			4.9130	(2.9266)
lgta	0.0797	(0.0885)	0.0607	(0.1103)	0.0531	(0.0875)	-0.3320***	(0.1056)
age	-0.0004*	(0.0002)	0.0004	(0.0003)	-0.0003	(0.0002)	0.0001	(0.0003)
tier 1	-48.417***	(3.0567)	-86.791***	(5.3156)	-47.060***	(3.0856)	-88.728***	(5.3516)
alll	-9.5829**	(4.7047)	16.473**	(7.9759)	-8.8615*	(4.6962)	8.8671	(7.7594)
reln	4.4321***	(1.1801)	2.0116	(1.2748)	3.7811***	(1.1731)	3.9762***	(1.2796)
rnpl	7.2555***	(1.3348)	6.3838***	(2.1574)	6.1802***	(1.3433)	9.6447***	(2.1510)
roa	-6.1672	(5.1795)	-11.248**	(5.5416)	-7.2727	(5.0983)	-8.8145	(6.1201)
roe	0.0003	(0.0003)	0.0002	(0.0013)	0.0003	(0.0004)	0.0003	(0.0017)
cd	1.0098	(0.8644)	1.6651	(1.0274)	1.2499	(0.8425)	0.8245	(1.0003)
coredep	-2.7654	(1.7546)	-1.2140	(2.0839)	-2.5466	(1.7496)	-3.1272	(2.0927)
coffs	0.2351***	(0.0804)	0.3168***	(0.1183)	0.2319***	(0.0848)	0.2703**	(0.1243)
lrec	38.162**	(18.672)	14.463	(56.448)	35.681*	(21.726)	37.945	(42.003)
llp	-10.427**	(4.9577)	-15.501**	(6.5158)	-11.688**	(4.8628)	-13.155**	(6.6190)
fte	-0.8228	(1.0468)	-3.0004**	(1.4396)	-0.8329	(1.0512)	-3.1287**	(1.4021)
imr	-4.2141***	(1.0634)	-1.7238	(1.2254)	-3.7792***	(1.0603)	-4.4020***	(1.2016)
sens	2.3255***	(0.8386)	2.5869**	(1.0320)	2.0025**	(0.8403)	5.6444***	(1.0042)
cash	6.7983***	(2.0542)	6.7497**	(3.2628)	6.9211***	(2.0472)	4.5465	(3.6333)
oi	-3.9670	(4.4353)	-6.1756	(6.6955)	-3.1670	(4.3948)	-4.9651	(6.6585)
ur	0.1198***	(0.0379)	0.0196	(0.0490)	0.0655*	(0.0390)	0.0548	(0.0482)
chpi	-15.091*	(8.1323)	-10.555	(9.7490)	-20.313**	(8.0823)	-10.645	(10.017)
chhpi	-8.1375*	(4.9453)	-3.1678	(5.8411)	-9.8817**	(4.8428)	-5.4824	(5.8215)
chnphu	-0.6570***	(0.2490)	0.0006	(0.0523)	-0.5246**	(0.2417)	0.0047	(0.0581)
chtype	-0.2151	(0.5058)	0.4441	(0.6871)	0.0223	(0.5051)	-0.7143	(0.5943)
frsmb	0.4707***	(0.1797)	0.4018*	(0.2352)	0.4617***	(0.1808)	0.3466	(0.2363)
ibf	1.1171	(0.7589)	1.4405	(0.8883)	1.2816*	(0.7592)	-2.5959***	(0.7825)
frsdistrcode	0.2465***	(0.0329)	0.2615***	(0.0430)	0.2295***	(0.0325)	0.2457***	(0.0427)
LogL	–1763.87				-1714.92			
N	5968				38571			

p*<0.1, p**<0.05, p***<0.01 (Robust standard errors in parentheses)

Table 7: Estimates from the Stochastic Frontier ContinuousTime Semiparametric Proportional Mixture Hazard Model (Model III) and Stochastic Frontier DiscreteTime Mixture Hazard Model (Model IV)

	Model III				Model IV			
Variable	Latency		Incidence		Latency		Incidence	
Intercept			-2.6934	(2.8039)			4.7694*	(2.9201)
lgta	-0.0408	(0.0935)	-0.0087	(0.1243)	-0.0742	(0.0958)	-0.3466***	(0.1117)
age	-0.0004*	(0.0002)	0.0004	(0.0003)	-0.0004*	(0.0002)	0.0001	(0.0003)
tier 1	-48.647***	(3.0631)	-86.280***	(5.3068)	-48.452***	(3.0678)	-88.684***	(5.3396)
alll	-8.5073*	(4.6488)	17.003**	(7.9738)	-8.8587*	(4.6066)	8.8881	(7.7741)
reln	4.6588***	(1.1259)	2.1044*	(1.2631)	4.4871***	(1.0878)	3.9288***	(1.2805)
rnpl	6.9014***	(1.3206)	6.0653***	(2.1661)	6.7347***	(1.3210)	9.5835***	(2.1554)
roa	-6.1672	(5.1423)	-11.451***	(5.5328)	-6.4175	(5.0868)	-8.8129	(6.1180)
roe	0.0002	(0.0004)	0.0001	(0.0013)	0.0002	(0.0003)	0.0002	(0.0017)
cd	0.8641	(0.8608)	1.5840	(1.0277)	0.7565	(0.8579)	0.7329	(1.0244)
coredep	-2.3913	(1.6224)	-1.0244	(2.0568)	-1.5432	(1.6367)	-2.9196	(2.1285)
coffs	0.2447***	(0.0801)	0.3232***	(0.1172)	0.2516***	(0.0798)	0.2720**	(0.1243)
lrec	37.309**	(19.148)	14.661	(56.167)	37.219**	(19.011)	38.569	(41.568)
llp	-11.175**	(4.9577)	-15.784**	(6.5199)	-11.654**	(4.7671)	-13.211**	(6.6345)
fte	-2.1781**	(1.0195)	-3.8780**	(1.5932)	-2.8670***	(1.0298)	-3.3559**	(1.5165)
imr	-3.7660***	(0.9728)	-1.4553	(1.2128)	-3.2640***	(0.9832)	-4.2466***	(1.2601)
sens	2.2143***	(0.8294)	2.5264**	(1.0309)	2.0894**	(0.8282)	5.6036***	(1.0068)
cash	7.4166***	(2.0368)	7.1461**	(3.2558)	7.6605***	(2.0375)	4.6012	(3.6396)
oi	-3.9483	(4.3968)	-6.4722	(6.6946)	-4.1980	(4.3825)	-5.0126	(6.6601)
ur	0.1210***	(0.0377)	0.0234	(0.0491)	0.1208***	(0.0378)	0.0555	(0.0487)
chpi	-15.567**	(8.1081)	-9.7061	(9.7811)	-15.551*	(8.0642)	-10.639	(10.021)
chhpi	-8.1886*	(4.9593)	-3.2387	(5.8526)	-8.1802**	(4.9731)	-5.4864	(5.8139)
chnphu	-0.6300***	(0.2471)	-0.0001	(0.0531)	-0.6171***	(0.2456)	0.0046	(0.0578)
chtype	-0.1496	(0.5045)	0.4875	(0.6876)	-0.1293	(0.5028)	-0.7224	(0.5953)
frsmb	0.4960**	(0.1801)	0.3994*	(0.2349)	0.4977***	(0.1801)	0.3487	(0.2512)
ibf	1.1325	(0.7574)	1.4718*	(0.8945)	1.1295*	(0.7571)	-2.5923***	(0.7815)
frsdistrcode	0.2612***	(0.0332)	0.2725***	(0.0445)	0.2663***	(0.0334)	0.2469***	(0.0429)

Table Cont'd

p*<0.1, p**<0.05, p***<0.01 (Robust standard errors in parentheses)

Table 7: Cont'd

Variable	Model III				Model IV			
	Latency		Incidence		Latency		Incidence	
SFM								
δ_1			0.2062	(0.1577)			0.0343	(0.0828)
δ_2	0.3058***	(0.0468)			0.4137***	(0.0750)		
σ	0.0552*** (0.0011)				0.0548*** (0.0011)			
γ	0.5173*** (0.0017)				0.5278*** (0.0015)			
LogL	-67701				-66360			
N	5968				38571			

p*<0.1, p**<0.05, p***<0.01 (Robust standard errors in parentheses)

Table 8: Cost efficiencies results for the sample of NonFailed Banks

	Mean	Standard Deviation	Minimum	Maximum
Model III	0.6817	0.0691	0.3167	0.9705
Model IV	0.7295	0.1630	0.1992	0.9688
Random Effects	0.6466	0.0662	0.4636	0.9650

The top and bottom 5% of inefficiencies scores are trimmed to remove the effects of outliers

Table 9: Cost efficiencies results for the sample of Failed Banks

	Mean	Standard Deviation	Minimum	Maximum
Model III	0.6721	0.1022	0.1499	0.8722
Model IV	0.6804	0.0824	0.1539	0.8488
Random Effects	0.6408	0.0798	0.3845	0.8626

The top and bottom 5% of inefficiencies scores are trimmed to remove the effects of outliers

Table 10: In-sample classification error decomposition

	I	II	III	IV
Type I error	0.3840	0.2882	0.1123	0.0644
Type II error	0.0047	0.0051	0.0231	0.0476
Overall classification error	0.1937	0.1465	0.0581	0.0573

Overall classification error is a simple average of type I and type II errors

Table 11: Out-of-sample classification error decomposition

	I	II	III	IV
Type I error	0.2283	0.1630	0.0543	0.0217
Type II error	0.0049	0.0062	0.0244	0.0503
Overall classification error	0.1157	0.0840	0.0394	0.0360

Overall classification error is a simple average of type I and type II errors

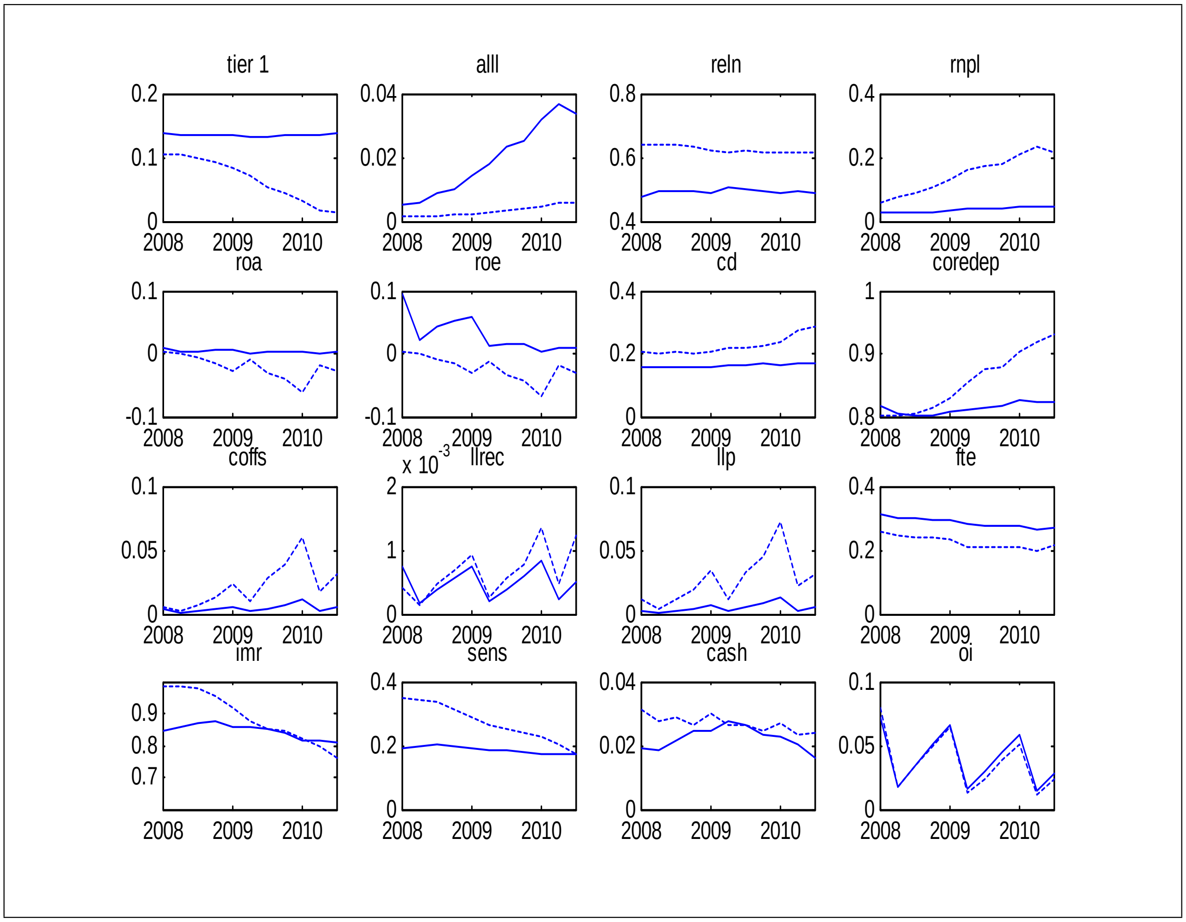


Figure 4: Financial ratios over the 2007.Q4-2010.Q2 period. Solid line is for non-failed banks and dashed line is for failed banks.

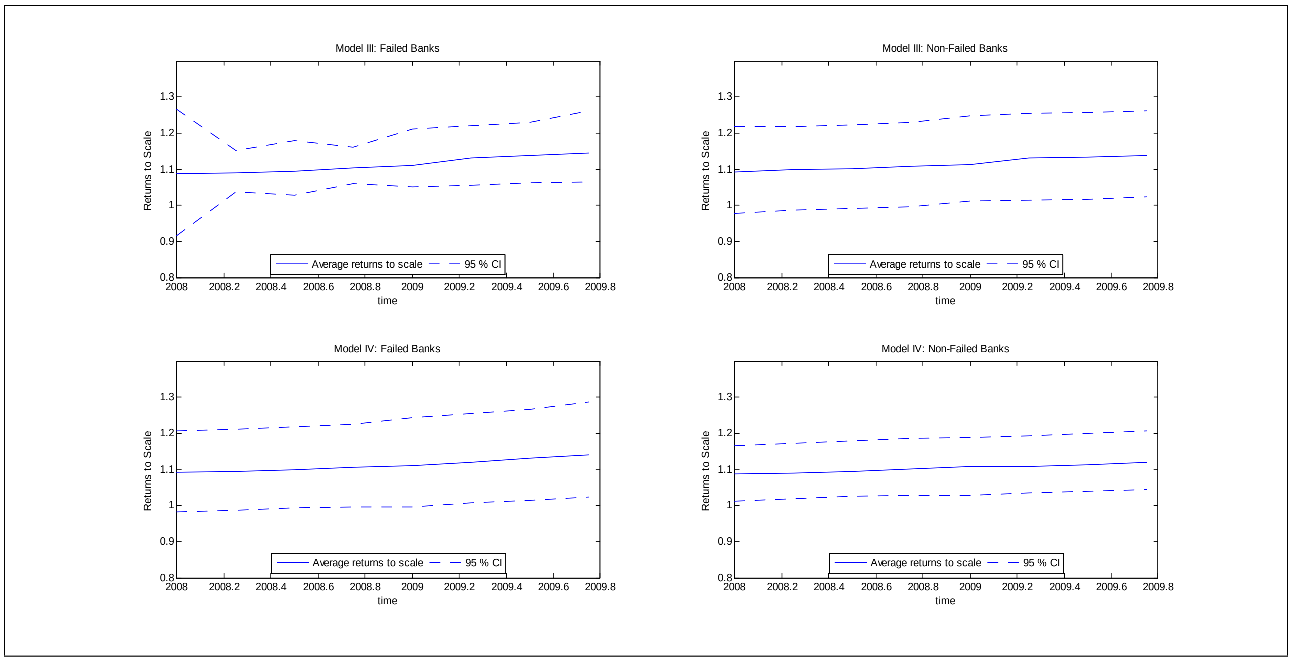


Figure 5: Returns to Scale for Failed and Non-Failed Banks (Model III and IV)

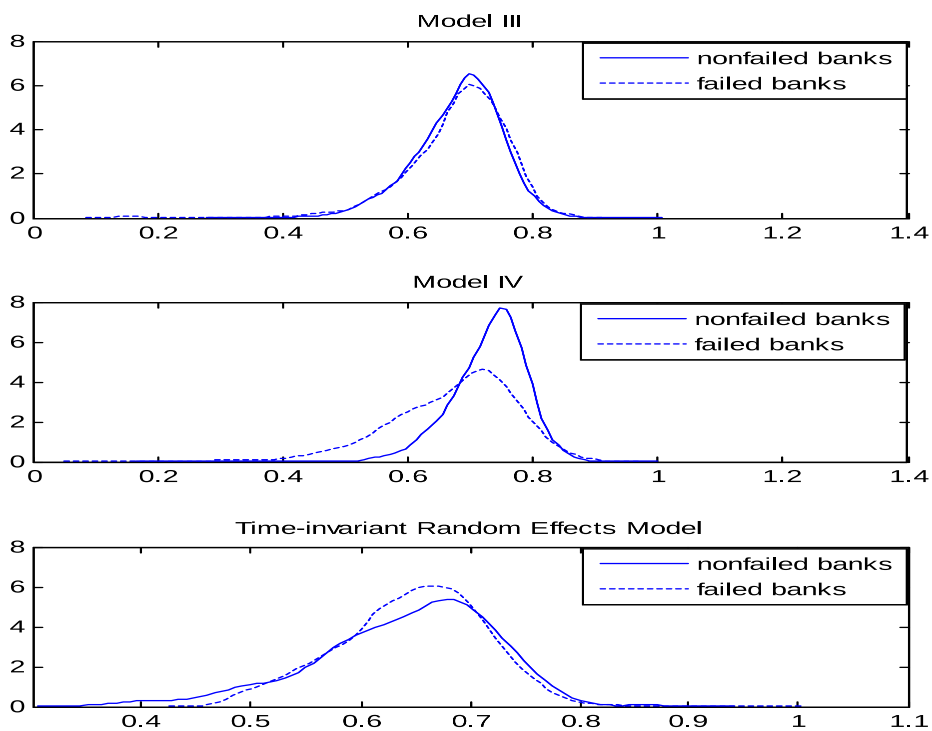


Figure 6: Distribution of estimated cost efficiencies obtained from Models III, IV and the Random Effects Model.

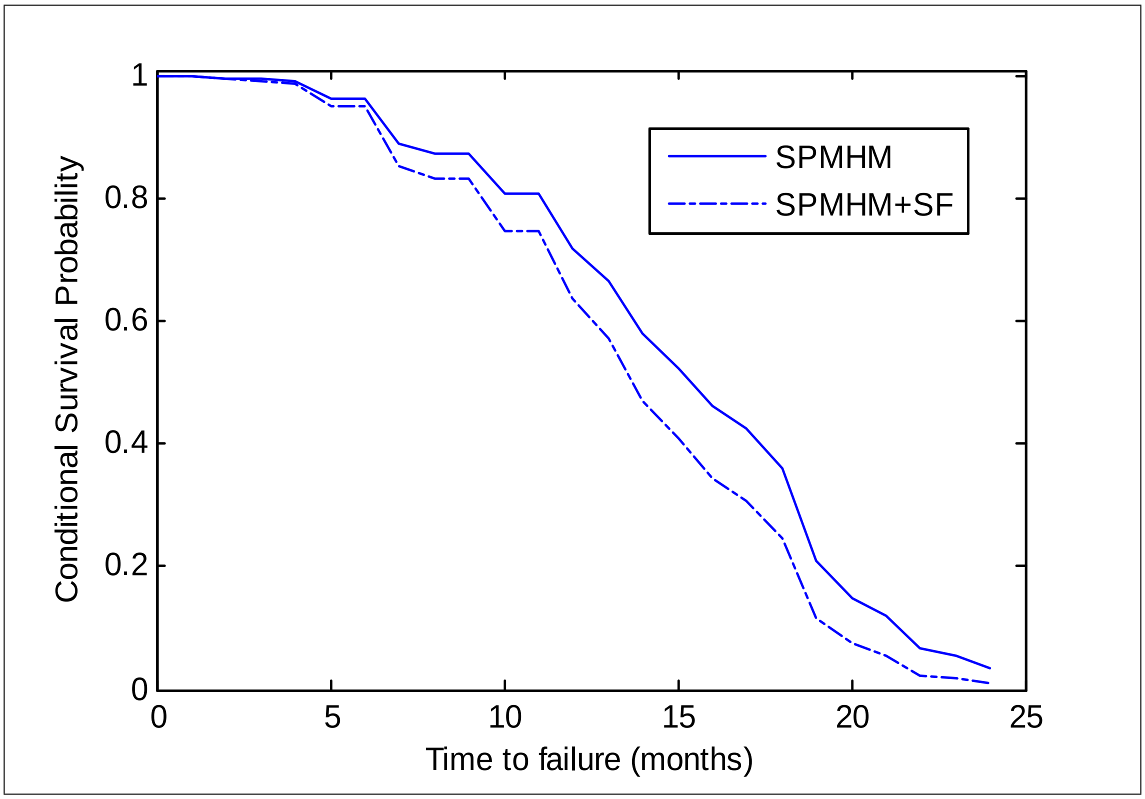


Figure 7: SPMHM - Survival profile of the average failed bank (2008-2009)

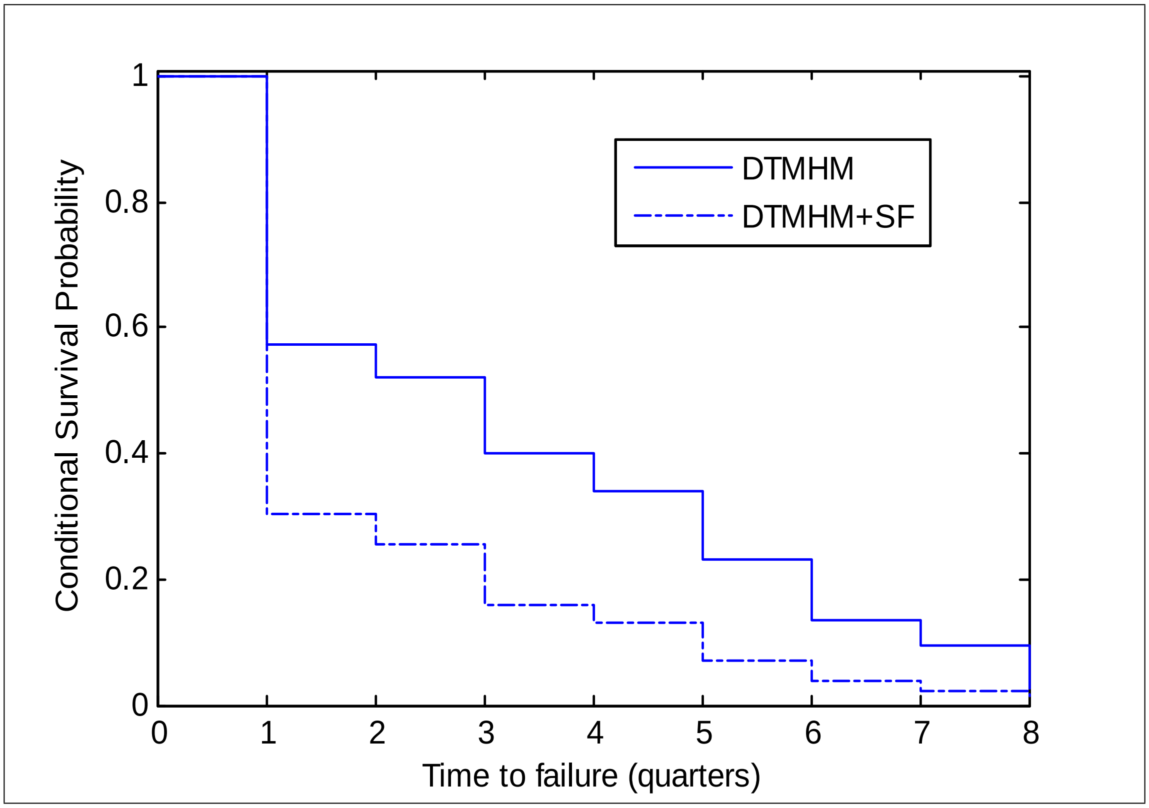


Figure 8: DTMHM - Survival pofile of the average failed bank (2008-2009)

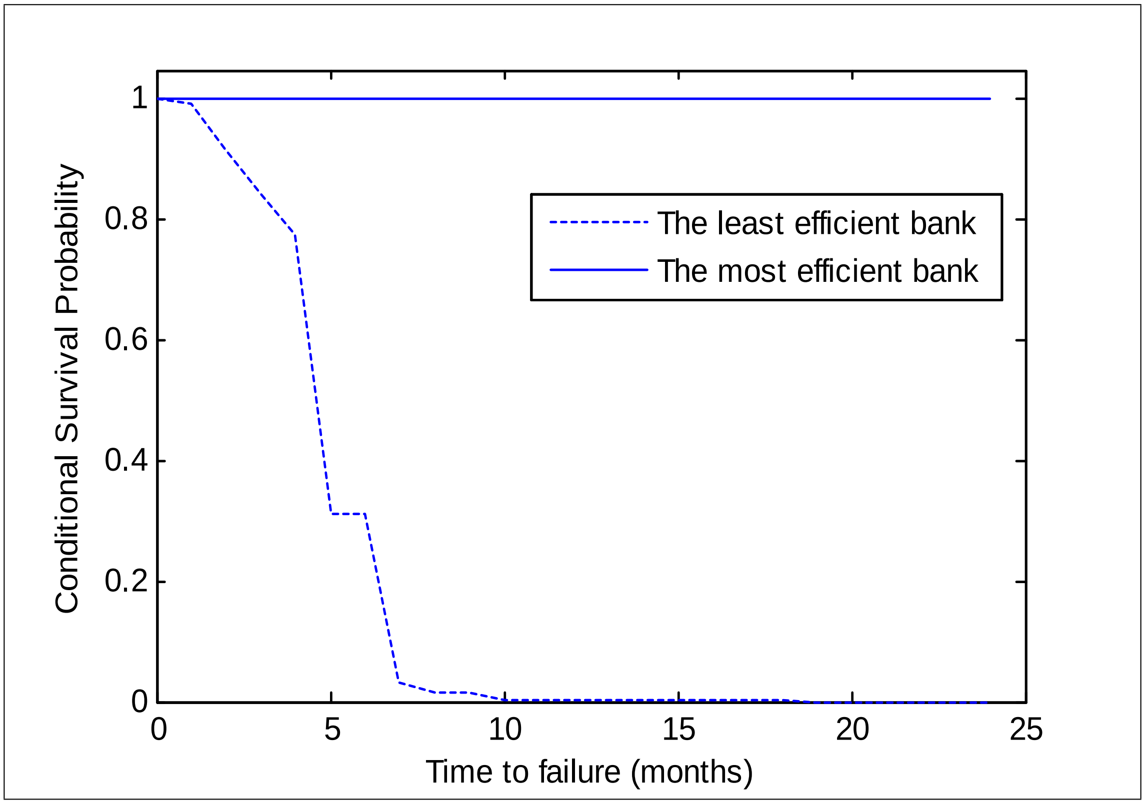


Figure 9: Model III - Survival profile of the most and the least efficient bank

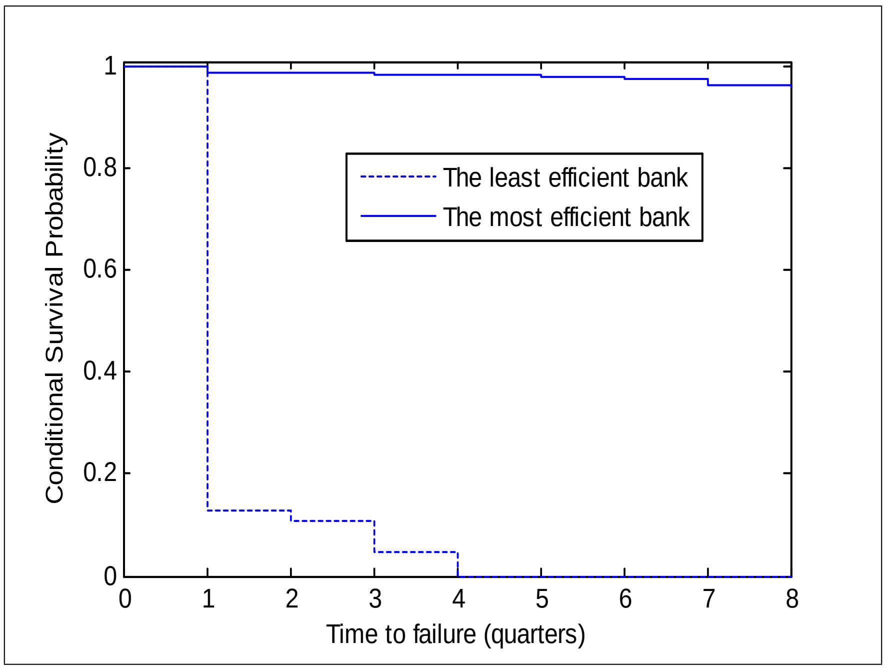


Figure 10: Model IV - Survival profile of the most and the least efficient bank

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