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Abstract

We contribute to the better understanding of the key factors related to the operation of the banking system that led to the global financial crisis through the development of a dual earning warning model that explores the joint determination of the probability of a distressed bank to face a licence withdrawal or to be bailed out. The underlying patterns of distress are analysed based upon a wide spectrum of bank-specific and environmental factors. We obtain precise parameter estimates and superior in- and out-of-sample forecasts. Our results show that the determinants of failures and those of bailouts differ to a considerable extent, revealing that authorities treat a distressed bank differently in their decision to let it fail or to bail it out. Overall, we provide a reliable mechanism for preventing welfare losses due to bank distress.

JEL Classification: C24; C53, G01; G21; G28

Keywords: financial crisis; bank distress; early warning model; forecasting power

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1. Introduction

During the global financial crisis, a large number of banks worldwide either failed or were bailed out thus inflicting substantial losses on the system. From an economic viewpoint, the recapitalisation of banks doubled with the cost of failures and that of the large stimulus programmes which governments launched to revive demand led to the explosion of public debt in many advanced economies. Laeven and Valencia (2012) highlight that episodes of banking crises result in a 23% cumulative output loss as well as substantial increases in fiscal debt. Therefore, the need for the development of an early warning system capable to predict bank distress has recently come to the forefront in the relevant literature which dates back to Meyer and Pifer (1970), Sinkey (1975), Martin (1977), and Pettway and Sinkey (1980).

In this short paper, we design a system that detects the early bankruptcy signals as well as the early warnings for distressed banks, which are likely to need support in case of a financial debacle. The distress events are treated as competing hazards in our analysis. This is the first time that such a dual system of distress is developed. An additional innovative feature of our study is that the analysis is conducted within the dynamic framework proposed by Shumway (2001), which allows the distress probability assigned to each bank to vary with time. Notwithstanding its attracting features, the Shumway approach has been only marginally applied in the banking literature.

The paper is organised as follows. Section 2 describes the sample banks and the data. The model is developed in Section 3. Section 4 presents and discusses the in- and the out-of-sample estimation results, and Section 5 concludes.

2. Sample banks and data

We focus on U.S. commercial and savings banks that file a Report on Condition and Income (Call Report). Distressed banks either filed for bankruptcy or were bailed out during the crisis. Acquired banks as well as those which were merged with some other institution not at the initiative of the Federal regulatory agencies are considered to be a third group of distressed banks. As such, and in order to avoid any spurious effects on the probabilities of failure and bailout, the latter banks are excluded from our sample. Banks that do not fall in any of the aforementioned categories are labelled ‘non-distressed’.

Failed banks are the insured banks that were closed requiring disbursements by the authorities. In the event of failure, the institution's charter is terminated and assets and liabilities are transferred to a successor charter. In total, 167 bankruptcies were recorded during the examined period.

Bailed out banks are those that received capital injections under the Capital Purchase Program (CPP) of the Troubled Asset Relief Program (TARP). We obtain the complete list of TARP/CPP recipients from the U.S. Treasury and trace all banks which participated in the programme either directly, or through their parent holding companies. In total, we identify 824 assisted institutions.

Our data are of quarterly frequency and extend from the beginning of 2003 (2003q1) to the end of 2009 (2009q4), because the final TARP/CPP investment was made on December 30, 2009. We begin with 8,722 banks that filed a Call Report in 2003q1. By checking the data for reporting errors and other inconsistencies, we end up with a set of 7,602 banks of which 167 are failed, 824 are bailed out, and 6,611 are non-distressed.

3. The model

Failed and bailed out banks exit from our sample the quarter they went bankrupt or received TARP/CPP assistance, respectively. We define the event-specific hazard function of survival time *T*:

$$h_j(t;x) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t,\ J = j \,\big|\, T \geq t, x)}{\Delta t}, \qquad (1)$$

where $h_j(t;x)$is the instantaneous rate of exit due to distress event *J* at *t* given *x*; *j*=1, 2, where 1 stands for failure and 2 for bailout; *x* is the vector of covariates; and, *t* represents quarters, where *t*=1 corresponds to 2003q1, and *t*=28 reflects 2009q4.

The bailout of a bank precludes its failure and *vice versa*. Hence, the overall hazard is the sum of the two individual hazards:

$$h(t;x) = \sum_{j=1}^{2} h_j(t;x). \qquad (2)$$

A bank's probability to survive longer than *t* is:

$$S_j(t;x) = P[T > t; x] = \exp\left[-\int_0^t h_j(u;x)du\right]. \quad (3)$$

The probability density function is:

$$f_j(t;x) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t,\ J = j \,|\, T \geq t, x)}{\Delta t} = h_j(t;x) S_j(t;x). \quad (4)$$

Failures and bailouts occur at t_{ij}, where i=1, 2,…, n (n=7,602) indexes the sample banks. A censoring term d_{ij} equals to unity if bank i exits the sample at t_{ij} due to any of the distress events and zero if otherwise.

The partial likelihood function is:

$$L = \prod_{j=1}^{2} \prod_{i=1}^{n} ((h_{j_i}(t_{ij}; x_{ij}))^{d_{ij}}\ S(t_{ij}; x_{ij})), \quad (5)$$

where j_i stands for the type of distress of bank i, which does not enter into Equation (5) if d_{ij} equals to 0, implying that a censored observation is assumed for each competing distress event.

Recall that we made no functional assumptions to obtain Equation (1). Since time is continuous and both failure and bailout hazards remain constant over discrete time intervals, the piecewise exponential approach is preferable:

$$h_j(t;x) = h_{0j}(t) \exp(\beta_j' x), \quad (6)$$

where $h_{0j}(t)$ reflects the baseline hazard function, which is allowed to differ between the two types of distress; $\beta_j'$is the coefficient vector that indicates the effects of covariates for the event type j, showing that different sets of coefficients are jointly estimated for each j.

Following Shumway (2001), we generalise Equation (6) to incorporate time-varying covariates:

$$h_j(t; x(t)) = h_{0j}(t) \exp\left[\beta_j' x(t)\right]. \tag{7}$$

In Equation (7), both failure and bailout hazards are independent from each other. In reality, however, the two hazards are directly associated to the decisions of authorities and, hence, to one another: a distressed bank either receives TARP/CPP money, or it is left to go bankrupt. Not only may a bank be more likely to be bailed out if it is in distress, but regulators' decision to approve or reject a TARP/CPP application is also linked to the health of the applicant institution. We, therefore, introduce a heterogeneity term v_j:

$$h_j(t; x(t)) = h_{0j}(t) \exp[\beta_j' x(t) + v_j]. \tag{8}$$

Equation (8) allows dependence between the two distress events, as it does not require v_j and v_l to be independent for $j \neq l$, where l = 1, 2. Hence, we allow banks which are more likely to receive assistance for reasons not captured by our model specification to be more/less likely to be closed by regulators.

The patterns of distress are analysed based upon the following set of covariates x. We proxy the components of CAMELS system, which is utilised by U.S. authorities to monitor bank soundness. Equity-to-assets ratio measures capital strength (*CAP*); asset quality is reflected in the ratio of non-performing loans to total loans (*ASSETQLT*); management expertise is proxied by total operating income divided by earning assets (*MNGEXP*); returns on assets measure earnings strength (*EARN*); the ratio of cash and balances to total deposits captures liquidity (*LQDT*); and, sensitivity to market risk (*SENSRISK*) is given by the change between the 10-year and 3-month T-bill rates divided by earning assets.

We account for three indicators of systemic importance: first, bank size (*SIZE*), which is measured by the logarithm of total assets; second, organisational complexity (*ORGCOMPL*), proxied by the logarithm of the product of the number of branches of each bank and the number of U.S. States in which the bank has branches; and, third, business complexity, captured by the amount of outstanding balance of securitised assets divided by total assets (*SECASSET*), as well as the ratio of the amount of outstanding derivative contracts to equity capital (*DERIV*). [1]

We construct two dummy variables: *POLCON* that accounts for bank connections with policy-makers, and *FEDCON* that indicates if an executive at a bank has been on the board of directors of one of the 12 Federal Reserve Banks. We resort to the Center for Responsive Politics (CRP)'s Revolving Door database to construct *POLCON*. For the construction of *FEDCON*, we first obtain data on the top executives of our sample banks from BoardEx and then match them to the list of directors found in the Fed's website. In addition, we capture whether a bank is involved in a M&A transaction as acquirer (*MA*), and whether it is located in a Metropolitan Statistical Area (*MSA*). *MA* relies on data from the relevant files of the Federal Reserve Bank of Chicago. To construct *MSA*, we identify the geographical location of each sample bank through Call Reports; detailed data for Metropolitan Statistical Areas are taken from the U.S. Office of Management and Budget. We also account for banks less than five years old (*DENOVO*) and for listed banks (*PUBLIC*); the relevant data are collected from Call Reports. The quarterly change in the U.S. Consumer Price Index (*INF*), and the GDP output gap (*GDP*) are employed in our model to control for macroeconomic conditions. Data for *GDP* are obtained from the Bureau of Economic Analysis of the U.S. Department of Commerce; *INF* is taken from the Bureau of Labor Statistics of the U.S. Department of Labor.

4. Results

4.1. In-sample estimation

We estimate Equation (8) using non-distressed banks as the holdout group. The coefficients for failure and bailout hazards are jointly estimated.

As shown in Table 1, capital (*CAP*) is beneficial for banks' health, as it reduces both hazards under examination. When credit quality (*ASSETQLT*) worsens, the failure hazard becomes higher, while that of bailout is not significantly affected. Efficient management (*MNGEXP*) exerts a decreasing impact on the likelihood of failure, but has no significant effect on that of bailout. Profitability (*EARN*) and liquidity (*LQDT*) lower both failure and bailout probabilities. By contrast, market risk sensitivity (*SENSRISK*) increases both probabilities.

[1] All accounting variables are collected from Call Reports. Interest rates are obtained from the Federal Reserve Board and the U.S. Department of Treasury.

Table 1. In-sample estimation

	Failure	Bailout
CAP	-1.59*** (-3.94)	-1.42*** (-4.33)
ASSETQLT	1.32*** (3.20)	0.80 (1.48)
MNGEXP	-2.02*** (-2.69)	1.12 (1.42)
EARN	-1.19*** (-3.95)	-1.48** (-2.19)
LQDT	-1.48*** (-2.80)	-1.23** (-2.36)
SENSRISK	0.78** (2.31)	0.97** (2.44)
SIZE	-1.43*** (-5.02)	1.62*** (4.49)
ORGCOMPL	-0.58** (-1.96)	1.00** (2.28)
SECASSET	-2.03*** (-3.91)	5.95*** (3.31)
DERIV	-2.85*** (-2.68)	5.46*** (3.70)
POLCON	-1.95*** (-5.03)	2.50*** (3.21)
FEDCON	-1.04** (-2.08)	1.04** (2.10)
MA	-0.35*** (-3.40)	-0.21 (-1.38)
MSA	-0.06** (-2.32)	0.11*** (3.87)
DENOVO	0.19** (2.41)	0.40 (1.44)
PUBLIC	-0.11** (-2.57)	0.10** (2.29)
INF	0.14** (1.97)	-0.18 (-1.14)
GDP	-0.21** (-2.42)	-0.09 (-1.18)
Pseudo R^2 (%)	41.15	

Heteroskedasticity-robust Huber-White t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Further, large (*SIZE*) and complex (*ORGCOMPL*, *SECASSET*, *DERIV*) banks are less likely to face a licence withdrawal and more likely to be bailed out. These evidences provide strong support to the Too-Big-To-Fail and the Too-Complex-To-Fail phenomena in banking. Moreover, authorities are more prone to bail out a distressed bank, which is well-connected with politicians and regulators (*POLCON*, *FEDCON*) and less prone to let it fail. Crucially, the effects of the additional bank-specific variables (*MA*, *MSA*, *DENOVO*, *PUBLIC*) and the environmental variables (*INF*, *GDP*) confirm that, on the whole, the determinants of failures and those of bailouts differ from each other to a considerable degree. This implies that authorities treat a bank differently in their decision to let it fail or to bail it out.

4.2. Out-of-sample estimation

We resort to the decile forecasting accuracy test that captures the model's ability to predict an event from which actual probabilities of that event can be inferred once the coefficients of the examined model are estimated. Sample banks are sorted into deciles in each quarter from 2009q2 to 2009q4 based on the fitted probability values of the model covariates. Fitted probabilities are then created by combining the coefficients estimated using 2003q1-2009q1 data with data for each subsequent quarter, i.e., 2009q2 to 2009q4.

Table 2. Out-of-sample estimation

Decile	Prob. (%)	Cum Prob. (%)	Failures	Prob. (%)	Cum Prob. (%)	Bailouts
1	62.30	62.30	104	60.80	60.80	501
2	19.70	82.00	33	18.80	79.60	155
3	4.30	86.30	7	5.20	84.80	43
4	3.00	89.30	5	4.70	89.50	39
5	4.20	93.50	7	1.70	91.20	14
6-10	6.50	100.00	11	8.80	100.00	72
			167			824

Table 2 shows that our model classifies 62.30% of failures (104 banks) in the highest probability decile at the quarter in which they declare bankruptcy. Moreover, it predicts 19.70% of failures (33 banks) in the second top decile. Overall, it predicts 82.00% of failures (137 banks) in the top two deciles. Similarly, the model classifies 79.60% of bailouts (656 banks) in the highest two deciles. In sum, the out-of-sample ability of our model to predict distress is very strong.

The dynamic nature of our model provides us with the advantage of examining how distress probability varies over time. This cannot be achieved if discrete choice models like discriminant analysis, probit, or logit models are utilised instead. Moreover, banks' health is measured as a function of a broad set of variables. Overall, we obtain precise parameter estimates and superior out-of-sample forecasts.

5. Concluding remarks

Numerous banking institutions around the globe faced severe liquidity problems and capital shortages after the eruption of the global financial crisis in mid-to-late 2007. National governments in close cooperation with regulatory authorities spent a vast amount of money to keep many of these institutions afloat with the utmost purpose to protect the financial system from a sort of chain domino defaults and to restore the confidence in it. On the other hand, several distressed banks went bankrupt, incurring a large cost to governments, bank customers, bond holders, market participants, and tax payers.

We develop a dual early warning system of distress that offers valuable insights to policy makers on how to better structure the components of the banking industry with the purpose to reduce actions that exert a negative impact on bank soundness and harm the stability of the system. We provide strong evidence that banking organisations with inadequate capital, illiquid and risky assets, poor management, low levels of earnings and high sensitivity to market conditions have a higher bankruptcy probability. However, not all the aforementioned factors play an important role in the probability of a bank to receive assistance in the case of financial debacle. In specific, management quality, as reflected in the ability of managers to create profits for their banks, does not significantly affect the likelihood of a bank to receive financial aid. Further, the quality of bank assets is found not to be relevant to the bailout likelihood.

Our findings also reveal that large and complex financial institutions are less likely to face a licence withdrawal and more likely to be bailed out. Moreover, authorities are found to be more prone to provide support to a distressed institution which is well-connected with politicians and political parties and less prone to let it go bankrupt. Crucially, the effects of an additional set of key bank-specific variables together with a set of environmental variables that we employ in our analysis confirm that, on the whole, the determinants of bank failures and those of bailouts differ from each other to a considerable degree.

Overall, our model is capable of providing the necessary signals to distinguish healthy from distressed institutions and, hence, to work as an effective mechanism for preventing future welfare losses due to failures and bailouts in case of a financial breakdown.

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