A dual early warning model of bank distress

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*Highlights (for review)

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- We develop a dual early warning model of bank distress
- We treat bank failures and bailouts as competing distress events
- We obtain precise parameter estimates and superior in- and out-of-sample forecasts
- The factors that decisively affect bank failures differ from those of bailouts
- We provide a mechanism for preventing welfare losses due to failures and bailouts

*Title Page

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Abstract

We develop a model that estimates the joint determination of the probability of a distressed bank to go bankrupt or to be bailed out. We obtain precise parameter estimates and superior in- and out-of-sample forecasts, which demonstrate that the determinants of failures differ from those of bailouts. Overall, we provide a 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 either failed or received financial assistance thus inflicting substantial losses on the system. The rescue of troubled banks doubled with the cost of failures led to the explosion of public debt in many economies. 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.[1]

We construct a model that estimates the joint determination of the probability of a distressed bank to go bankrupt or to be bailed out. 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 the in- and 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 Federal regulatory agencies are considered to be a third distressed group of 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 regulators. 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.

[1] There is a broad literature on early warning signals of bank failure, which dates back to Meyer and Pifer (1970), Sinkey (1975), and Martin (1977).

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 financial aid, respectively. We define the event-specific hazard function of survival time *T*:

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

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:

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

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

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

The probability density function is:

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

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:

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

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.

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:

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

where $h_{0j}(t)$ reflects the baseline hazard function, which is allowed to differ between the two distress types; β_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:

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

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 assistance, 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 (or less) likely to be closed by regulators.

The patterns of distress are analysed based upon the following covariates *x*. We proxy the components of CAMELS system, which is utilised by regulators 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 (*MNGEXP*) is proxied by managerial efficiency as calculated by the input-oriented Data Envelopment Analysis (DEA) model based on two outputs, namely total loans and leases, and total deposits, and three inputs, namely the price of borrowed funds, the price of labour, and the price of physical capital;[2] the 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 four factors of systemic importance: bank size (*SIZE*) is measured by the logarithm of total assets; organisational complexity (*ORGCOMPL*) is 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 business complexity is captured by the amount of outstanding

[2] For the calculation of managerial efficiency based on DEA, the interested reader can refer to Coelli et al. (2005).

balance of securitised assets divided by total assets (*SECASSET*), and the ratio of the amount of outstanding derivative contracts to equity capital (*DERIV*).[3]

Moreover, *POLCON* accounts for bank connections with policy-makers, and *FEDCON* indicates if an executive at a bank has been on the board of directors of one of the 12 Federal Reserve Banks.[4] Further, we capture if a bank is involved in a M&A transaction as acquirer (*MA*), and if it is located in a Metropolitan Statistical Area (*MSA*).[5] We account for banks which are less than five years old (*DENOVO*) and also for listed banks (*PUBLIC*). 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.[6]

Although x consists of a broad spectrum of bank-specific variables that capture a large portion of heterogeneity amongst banks, we consider the possibility that some piece of information may have been omitted. To address possible unobserved heterogeneity, we introduce a heterogeneity term ε_i in Equation (8):

$$h_j(t; x(t)) = h_{0j}(t) \exp\left[\beta_j' x(t) + v_j + \varepsilon_i\right], \tag{9}$$

4. Results

4.1. In-sample estimation

We estimate Equation (9) using non-distressed banks as the holdout group. The coefficients for failure and bailout hazards are jointly estimated.

[3] Accounting data are at bank-level and are collected from Call Reports. Interest rates are obtained from the Federal Reserve Board and the U.S. Department of Treasury.

[4] 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.

[5] *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 bank through Call Reports; detailed data on Metropolitan Statistical Areas are taken from the U.S. Office of Management and Budget.

[6] Data for *GDP* are obtained from the Bureau of Economic Analysis of the U.S. Department of Commerce; *INF* relies on data from the Bureau of Labor Statistics of the U.S. Department of Labor.

Table 1. In-sample estimation

	Failure	Bailout
CAP	-1.56*** (-3.87)	-1.39*** (-4.30)
ASSETQLT	1.22*** (3.04)	0.72 (1.39)
MNGEXP	-1.94** (-2.51)	1.10 (1.33)
EARN	-1.16*** (-3.79)	-1.44** (-2.11)
LQDT	-1.43*** (-2.72)	-1.14** (-2.27)
SENSRISK	0.76** (2.28)	0.93** (2.39)
SIZE	-1.38*** (-4.83)	1.53*** (4.31)
ORGCOMPL	-0.56** (-1.96)	0.97** (2.21)
SECASSET	-1.98*** (-3.82)	5.68*** (3.20)
DERIV	-2.80*** (-2.66)	5.29*** (3.62)
POLCON	-1.89*** (-4.94)	2.42*** (3.16)
FEDCON	-1.01** (-2.03)	0.89** (2.02)
MA	-0.32*** (-3.31)	-0.20 (-1.31)
MSA	-0.06** (-2.28)	0.10*** (3.75)
DENOVO	0.18** (2.37)	0.37 (1.40)
PUBLIC	-0.10*** (-2.46)	0.09** (2.23)
INF	0.13** (1.96)	-0.18 (-1.09)
GDP	-0.20** (-2.38)	-0.08 (-1.11)
Pseudo R^2 (%)	39.02	
# banks (*n*)	7,602	

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

As shown in Table 1, capital (*CAP*) is beneficial for banks' health, as it reduces both hazards under scrutiny. 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 failure, but has no significant effect on bailout. Profitability (*EARN*) and liquidity (*LQDT*) lower both failure and bailout probabilities. By contrast, sensitivity to market risk (*SENSRISK*) increases both probabilities.

Big (*SIZE*) and complex (*ORGCOMPL*, *SECASSET*, *DERIV*) banks are less likely to face a license withdrawal and more likely to be bailed out, providing support to the Too-Big-To-Fail and the Too-Complex-To-Fail arguments. Moreover, authorities are more prone to bail out a distressed bank that 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 those of macroeconomic factors (*INF*, *GDP*) confirm that, on the whole, the determinants of failures and those of bailouts differ to a considerable extent.

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	61.10	61.10	102	59.50	59.50	490
2	18.00	79.10	30	18.10	77.60	149
3	4.10	83.20	7	4.60	82.20	38
4	3.60	86.80	6	5.00	87.20	41
5	5.40	92.20	9	2.90	90.10	24
6-10	7.80	100.00	13	9.90	100.00	82
			167			824

Table 2 shows that our model classifies 61.10% of failures (102 banks) in the highest probability decile at the quarter in which they declare bankruptcy. It also predicts 18.00% of failures (30 banks) in the second top decile. Overall, it predicts 79.10% of failures (132 banks) in the top two deciles. Similarly, the model classifies 77.60% of bailouts (639 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 in-sample parameter estimates and superior out-of-sample forecasts.

5. Conclusion

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. Our model is capable of providing the necessary signals to distinguish healthy from distressed institutions and, therefore, 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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