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Papanikolaou, Nikolaos I.

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Nikolaos I. Papanikolaou*

Bournemouth University

Department of Accounting, Finance and Economics

Abstract

In the recent crisis, the U.S. authorities bailed out numerous banks, while let many others to fail as going concern entities. Even though both interventions fully protect depositors, a bail out represents an implied subsidy to shareholders, which is not yet the case with closures where creditors are not subsidised. We investigate this non-uniform policy, demonstrating that size and not performance is the decision variable that endogenously determines one threshold below which banks are treated as 'Too-Small-To-Survive' by regulators and another one above which are considered to be 'Too-Big-To-Fail'.

JEL Classification: G01; G21; G28

Keywords: Distressed banks; Too-Big-To-Fail; Too-Small-To-Survive; bank size; threshold estimation.

*Bournemouth University, Faculty of Management, Business School, Department of Accounting, Finance & Economics, Executive Business Centre, 89 Holdenhurst Road, Bournemouth, BH8 8EB, United Kingdom.
Tel: +44 (0) 1202 968769; *E-mail address:* npapanikolaou@bournemouth.ac.uk

1. Introduction

In the global financial crisis, the U.S. regulatory authorities bailed out numerous distressed banks, while at the same time let several others to go bankrupt as going concern entities via FDIC-backed failures. Even though under both interventions small retail depositors do not lose a penny, bailouts represent an implicit subsidy to shareholders, which is not yet the case with assisted failures where shareholders and other creditors are not subsidised.

This paper focuses on size and the performance of distressed banks with the purpose to shed light on the decision of authorities to choose between a bailout and an assisted failure. In this context, two threshold sizes are endogenously determined: one for the 'Too-Small-To-Survive' (TSTS) banks and a second one for the 'Too-Big-To-Fail' (TBTF) banks.

The paper proceeds as follows. Section 2 presents the data set. The multivariate threshold model is developed in Section 3. Section 4 focuses on the econometric results and discusses the policy and business implications. Section 5 concludes.

2. Data

We collect quarterly data for U.S. banks that filed a Report on Condition and Income (Call Report). Data period extends from the beginning of 2002 to the end of 2012 when the crisis in the U.S. is considered to have come to a halt.

We identify all the distressed banks, i.e., the banks which either failed as going concern entities during the crisis requiring disbursements by the FDIC or were bailed out. Acquired banks as well as those which were merged with some other institution not at the initiative of regulators are excluded from our sample.

In total, 449 FDIC-backed failures are identified.[1] Bailed out banks are those that received capital injections under the Capital Purchase Program (CPP) of the Troubled Asset Relief Program (TARP). We obtain all TARP/CPP recipients from the U.S. Treasury and trace all banks which participated in the program either directly, or through their parent holding companies. Our final list consists of 824 bailed out institutions.[2]

[1] The relevant data are collected from the FDIC web site. The names of banks, their distribution across the U.S. states and cities, the date that every failed institution ceased to exist as a privately-held going concern entity, the estimated assets and deposits of each institution at the time of failure, and the cost of every individual failure for FDIC are all available upon request.

[2] The detailed list of bailed out banks is available upon request.

3. Multivariate threshold regression analysis

We follow Hansen (1999)'s panel threshold technique, which allows us to divide our sample of failed and bailed out banks into zero, one, two or more regimes based on the threshold values of size. The single threshold model is:

$$y_{it} = a_i + \beta'_1 x_{it} I(q_{it} \leq \gamma) + \beta'_2 x_{it} I(q_{it} > \gamma) + \delta' w_{it} + \varepsilon_{it} \quad (1)$$

or:

$$y_{it} = \begin{cases} a_i + \beta'_1 x_{it} + \delta' w_{it} + \varepsilon_{it}, & q_{it} \leq \gamma \\ a_i + \beta'_2 x_{it} + \delta' w_{it} + \varepsilon_{it}, & q_{it} > \gamma \end{cases} \quad (2)$$

where *i*=1, 2,…, *N* (*N*=1273) distressed banks, i.e., 449 failed and 824 bailed out banks, and *t*=1, 2,…, *T* (*T*=44) quarters over the period 2002-2012; y_{it} is a binary scalar, which equals to 1 if bank *i* failed as a going concern entity at *t* and 0 if it was bailed out; x_{it} is a *k*-dimensional vector; w_{it} is a *m*-dimensional vector; the threshold variable q_{it} is a scalar; γ stands for the threshold; a_i reflects individual fixed-effects; ε_{it} is the error term; $I(\cdot)$ is an indicator function that equals to 1 or 0 depending on whether q_{it} falls short of or exceeds γ.

Observations are divided into two distinct regimes depending on whether q_{it} is smaller or larger than γ. The two regimes are characterised by different regression slopes, β_1 and β_2.[3]

Setting $x_{it}(\gamma) = \binom{x_{it} I(q_{it} \leq \gamma)}{x_{it} I(q_{it} > \gamma)}$ and $\beta = (\beta'_1, \beta'_2)'$, Eq. (1) is rewritten:

$$y_{it} = a_i + \beta' x_{it}(\gamma) + \varepsilon_{it} \quad (3)$$

After eliminating a_i, β can be estimated for any given γ by OLS:

$$\hat{\beta}(\gamma) = (X^*(\gamma)' X^*(\gamma))^{-1} X^*(\gamma)' Y^* \quad (4)$$

[3] If q_{it} is either below or above a certain value of γ, then x_{it} has a different impact on the dependent variable of the model, y_{it}, with $\beta_1 \neq \beta_2$.

where $X^*(\gamma)$ and Y^*denote the data stacked over all banks. The vector of residuals is:

$$\hat{\varepsilon}^*(\gamma) = Y^* - X^*(\gamma)'\hat{\beta}(\gamma) \tag{5}$$

Hence, the sum of squared errors is:

$$S_1(\gamma) = \hat{\varepsilon}^*(\gamma)'\hat{\varepsilon}^*(\gamma) = Y^{*\prime}(I - X^*(\gamma)'(X^*(\gamma)'X^*(\gamma))^{-1}X^*(\gamma)')Y^* \tag{6}$$

We estimate γ by minimising the concentrated sum of squared errors:

$$\hat{\gamma} = argmin_\gamma S_1(\gamma) \tag{7}$$

We can now estimate the slope coefficient for $\hat{\beta} = \hat{\beta}(\gamma)$. The residual vector is $\hat{\varepsilon}^* = \hat{\varepsilon}^*(\gamma)$ and the residual variance is:

$$\hat{\sigma}^2 = \frac{1}{N(T-1)}\hat{\varepsilon}^{*\prime}\hat{\varepsilon}^* = \frac{1}{N(T-1)}S_1(\hat{\gamma}) \tag{8}$$

We test the hypothesis of no threshold effect H_0: $\beta_1 = \beta_2$. Under H_0, we obtain:

$$\mathrm{y}_{it} = a_i + \beta'{}_1 x_{it} + \varepsilon_{it} \tag{9}$$

or:

$$y_{it}^* = \beta'{}_1 x_{it}^* + \varepsilon_{it}^* \tag{10}$$

The OLS estimator of $\beta_1$is $\tilde{\beta}_1$, the residuals are$\tilde{\varepsilon}_{it}^*$, and the sum of squared errors is $S_0 = \tilde{\varepsilon}_{it}^{*\prime}\tilde{\varepsilon}_{it}^*$. The likelihood ratio test of H_0 is based on:

$$F_1 = \frac{S_0 - S_1(\hat{\gamma})}{\hat{\sigma}^2} \tag{11}$$

We follow a bootstrap methodology to simulate the asymptotic distribution of the likelihood ratio test. We create a bootstrap sample, which is used to estimate Eq. (1) under H_0 and H_1 and to calculate the bootstrap value of the likelihood ratio statistic F_1.[4]

In case of a threshold effect, $(\beta_1 \neq \beta_2)$, $\widehat{\gamma}$ is consistent for the true value of γ, say γ_0. The null is now H_0: $\gamma = \gamma_0$ and the likelihood ratio statistic is:

$$LR_1(\gamma) = \frac{S_1(\gamma) - S_1(\widehat{\gamma})}{\widehat{\sigma}^2} \tag{12}$$

The test rejects H_0 at the asymptotic level α if $LR_1(\gamma_0)$>0. The asymptotic (1 - α) confidence interval for γ is the set of values of γ with $LR_1(\gamma) \leq c(\alpha)$.

We can extend Eq. 1 to its double threshold counterpart:

$$y_{it} = a_i + \beta'_1 x_{it} I(q_{it} \leq \gamma_1) + \beta'_2 x_{it} I(\gamma_1 < q_{it} \leq \gamma_2) + \beta'_3 x_{it} I(\gamma_2 < q_{it}) + \delta' w_{it} + \varepsilon_{it} \tag{13}$$

The two thresholds, $\gamma_1$and γ_2, are ordered so that $\gamma_1 < \gamma_2$. Eq. (13) is also estimated by OLS. The sum of squared errors $S(\gamma_1, \gamma_2)$ is calculated based on Eq. (6) and the joint estimates of (γ_1, γ_2) minimise $S(\gamma_1, \gamma_2)$.

Let $S_1(\gamma)$be the single threshold sum of squared errors as defined in Eq. (6) and $\hat{\gamma}_1$ be the threshold estimate that minimises $S_1(\gamma)$. Fixing $\widehat{\gamma}_1$, the criterion for the second stage is:

$$S_2^r(\gamma_2) = \begin{cases} S(\hat{\gamma}_1, \gamma_2) & if\ \hat{\gamma}_1 < \gamma_2 \\ S(\gamma_2, \hat{\gamma}_1) & if\ \gamma_2 < \hat{\gamma}_1 \end{cases} \tag{14}$$

Hence:

$$\hat{\gamma}_2^r = argmin_{\gamma_2} S_2^r(\gamma_2) \tag{15}$$

Holding $\hat{\gamma}_2^r$ fixed, we obtain:

[4] This procedure is frequently repeated and the bootstrap estimate of the asymptotic *p*-value for F_1under H_0 is the percentage of draws for which the simulated likelihood ratio statistic exceeds the actual statistic.

$$S_1^r(\gamma_1) = \begin{cases} S(\gamma_1, \hat{\gamma}_2^r) & if\ \gamma_1 < \hat{\gamma}_2^r \\ S(\hat{\gamma}_2^r, \hat{\gamma}_1) & if\ \hat{\gamma}_2^r < \hat{\gamma}_1 \end{cases} \quad (16)$$

$$\hat{\gamma}_1^r = argmin_{\gamma_1} S_1^r(\gamma_1) \quad (17)$$

We can now determine the number of thresholds in Eq. (13): there will be no thresholds, one threshold, or two thresholds.[5] The minimised sum of squared errors form the second stage threshold estimate is $S_2^r(\hat{\gamma}_2^r)$ with variance estimate:

$$\hat{\sigma}^2 = \frac{S_2^r(\hat{\gamma}_2^r)}{N(T-1)} \quad (18)$$

The likelihood ratio statistic for a test of one versus two thresholds is:

$$F_2 = \frac{S_1(\hat{\gamma}_1) - S_2^r(\hat{\gamma}_2^r)}{\hat{\sigma}^2} \quad (19)$$

F_2 is calculated from the bootstrap sample and this procedure is repeated multiple times for the bootstrap *p*-value to be obtained. The single-threshold hypothesis is rejected in favour of two thresholds when F_2 is large.

To construct the confidence intervals for (γ_1, γ_2), we let:

$$LR_2^r(\gamma) = \frac{S_2^r(\gamma) - S_2^r(\hat{\gamma}_2^r)}{\hat{\sigma}^2} \quad (20)$$

and

$$LR_1^r(\gamma) = \frac{S_1^r(\gamma) - S_1^r(\hat{\gamma}_1^r)}{\hat{\sigma}^2} \quad (21)$$

[5] Like we did in the single threshold case, we resort to F_1 as given by Eq. (11) to test the null of no threshold. If the null is rejected, we need an additional test to distinguish between one or two thresholds.

where $S_2^r(\gamma)$and $S_1^r(\gamma)$are defined in Eqs. (14) and (16), respectively. The asymptotic (1 - α) confidence intervals for the threshold estimates are the set of values of γ with $LR_2^r(\gamma) \leq c(\alpha)$ and $LR_1^r(\gamma) \leq c(\alpha)$.

To avoid violating the exogeneity assumption of the regressors (Hansen, 1999), we apply the Akaike Information Criterion to Eq. (13), which specifies a 4-quarter lag structure:

$$y_{it} = a_i + \beta'_1 x_{it-4} I(q_{it-4} \leq \gamma_1) + \beta'_2 x_{it-4} I(\gamma_1 < q_{it-4} \leq \gamma_2) + \\ + \beta'_3 x_{it-4} I(\gamma_2 < q_{it-4}) + \delta' w_{it-4} + \varepsilon_{it} \quad (22)$$

where x_{it} contains the six components of the CAMELS ratings: Equity-to-assets ratio measures capital strength (*CAP*); asset quality is reflected in the ratio of non-performing to total loans (*ASSETQLT*); management expertise (*MNGEXP*) is proxied by managerial efficiency as calculated by the input-oriented Data Envelopment Analysis model based on two outputs (total loans and leases; total deposits), and three inputs (price of borrowed funds; price of labour; price of physical capital);[6] 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 the 3-month T-bill rates divided by earning assets.[7] w_{it} contains the control variables: *POLCON* accounts for bank connections with policy-makers; *FEDCON* indicates if a bank executive has been on the board of directors of one of the U.S. Federal Reserve Banks;[8] *MA* captures if a bank is involved in a M&A transaction as acquirer; *MSA* shows if a bank is located in a Metropolitan Statistical Area;[9] *DENOVO* accounts for banks which are less than five years old; and, *PUBLIC* captures all listed banks. The size threshold variable (q_{it}) is measured by the book value of bank assets (*SIZE*).

[6] For the calculation of managerial efficiency, the interested reader can refer to Coelli et al. (2005).
[7] Accounting data are at the bank-level and are collected from Call Reports. Interest rates are obtained from the Federal Reserve Board and the U.S. Department of Treasury.
[8] 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.
[9] *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.

4. Econometric results

We follow Hansen (1999) and apply 300 bootstrap replications for each bootstrap test. The single threshold F_1 and double threshold F_2 tests are highly statistically significant with bootstrap p-values of 0.002 and 0.010, respectively as shown in Table 1. However, the test for a third threshold F_3 is not significant.

Table 1
Tests for determining the number of thresholds

H_0: no threshold vs one threshold	
F_1	27.581
p-value	0.002
(10%, 5%, 1% critical values)	(10.84, 14.32, 29.04)
H_0: one threshold vs two thresholds	
F_2	23.192
p-value	0.010
(10%, 5%, 1% critical values)	(11.99, 15.26, 30.11)
H_0: two vs three thresholds	
F_3	7.884
p-value	0.517
(10%, 5%, 1% critical values)	(9.12, 10.85, 19.44)

As Table 2 displays, two size thresholds are endogenously specified: one for the TSTS banks which is equal to \$0.387bn, and a second one for the TBTF banks that equals to \$2.961bn. Hence, banks are allocated to the following three regimes: a TSTS regime that contains all distressed banks with assets up to \$0.387bn; an intermediate regime that consists of all banks with assets between \$0.387bn and \$2.961bn; and a TBTF regime, which includes all institutions with more than \$2.961bn of assets. In the TSTS regime, it is only the insured depositors and, in some cases, a part of uninsured depositors and debtholders who are bailed out. In the TBTF regime, on the other hand, all the stakeholders and shareholders are fully bailed out.[10]

Table 2
Threshold estimates

	Estimate	95% confidence interval
$\hat{\gamma}_1$	\$0.387bn	[0.312, 0.469]
$\hat{\gamma}_2$	\$2.961bn	[2.598, 3.147]

[10] The asymptotic 95% confidence intervals for each threshold shown in Table 2 are tight, reflecting little uncertainty about the nature of this clustering.

Table 3
Threshold estimation results

Variable	TSTS regime $SIZE \leq \$0.387$bn	Intermediate regime $\$0.387\text{bn} < SIZE \leq \$2.961$bn	TBTF regime $\$2.961\text{bn} < SIZE$	
CAP	-0.043** (0.020)	-0.046*** (0.009)	-0.065** (0.028)	
ASSETQLT	0.125** (0.060)	0.127*** (0.035)	0.080** (0.038)	
MNGEXP	-0.039** (0.018)	-0.036** (0.015)	-0.055** (0.025)	
EARN	-0.098** (0.041)	-0.092*** (0.020)	-0.139** (0.064)	
LQDT	-0.029* (0.016)	-0.030** (0.013)	-0.064** (0.030)	
SENSRISK	0.095** (0.043)	0.091*** (0.019)	0.044* (0.024)	
POLCON				-0.091*** (0.018)
FEDCON				-0.120*** (0.032)
MA				-0.020* (0.011)
MSA				-0.068*** (0.018)
DENOVO				0.030* (0.016)
PUBLIC				-0.049*** (0.007)
R^2		0.17		

White heteroskedasticity-robust standard errors are reported in parentheses.
***, **, * correspond to 1%, 5%, and 10% level of significance respectively for a two-tailed distribution

We estimate Eq. (22) by linear probability OLS regression. As Table 3 demonstrates, all coefficients on CAMELS components are statistically significant and their signs remain unchanged across the three regimes. The TSTS banks experience higher coefficients on the components which are positively related with the failure probability (*ASSETQLT* and *SENSRISK*) compared to TBTF banks, and lower coefficients on those components which are negatively linked to failure (*CAP*, *MNGEXP*, *EARN*, and *LQDT*). Hence, a TSTS bank which has exactly the same performance with a TBTF bank based on the CAMELS system is more likely to fail due to the different weights put on each CAMELS component and which are in favour of TBTF banks.

Accordingly, it is in the interest of bank managers to adopt strategies that focus on the aggressive size growth of their banks knowing that the bigger a bank becomes the more likely is to receive a TARP-style and not an FDIC-backed assistance and, therefore, not to lose its charter. These results suggest regulators to revise their implied weighting scheme on the ratings system they utilise to evaluate bank performance so as to push banks above the TSTS threshold and below the TBTF threshold in order to avoid implementing the respective resolution practices which are both costly.[11]

A bank's political connections (*POLCON*) significantly reduce the failure probability. Similarly, when a bank is closely linked to regulators (*FEDCON*) then failure is less likely. Banks which are either publicly traded (*PUBLIC*), or involved in a M&A transaction (*MA*) as acquirers, or located in a MSA, are less likely to fail. Newly-chartered banks (*DENOVO*), on the other hand, are linked to a higher failure likelihood.

5. Conclusions

We document that size is the key determinant that classifies distressed banks into three distinct regimes. Regulators appear to be reluctant to assist the TSTS distressed banks to survive as going concern entities. In contrast, they assist the TBTF distressed banks to remain afloat even though their performance may be relatively worse compared to that of their TSTS counterparts. This is in line with Goodhart and Huang (2005), who show that it is optimal for authorities to rescue banks whose size is above some threshold level.

[11] On the one hand, the U.S. Treasury invested up to $250 billion in the preferred equity of banks to enhance their capital ratios through TARP/CPP. On the other hand, The FDIC was appointed receiver of the bankrupt institutions and this inflicted a total loss of $76 billion on the system.

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