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# A Cross-Country Bank Failure Prediction Model

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**Abstract:** This paper empirically investigates the causes of bank failures in Japan and Indonesia. Using logistic regression analysis of financial ratios, we explore the usefulness of domestic bank failure prediction models with a cross-country model that allows for cross-correlation of the error terms.

Our results suggest that loans, both as a ratio to total assets, deposits and in some cases the ratio of non-performing loans, are the most significant predictors of bank failure in both Japan and Indonesia. Regulatory capital ratios, on the contrary, do not seem to be significant indicators of failure. In addition to the domestic models, we explore the usefulness of a cross-country model of bank failure prediction and find that this model outperforms the domestic models on several diagnostic tests.



**Keywords:** Bankruptcy, logistic regression, early warning, logit, bank failure, bank crisis



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## I. Introduction

The Asian Crisis of 1997 brought calls to strengthen monitoring of financial markets in the region. In light of academic research on crisis "contagion" during the 1997 crisis, not only domestic regulatory agencies in Asia, but regional bodies as well, have devoted increased resources to early warning systems to monitor the likelihood of systemic crisis or instability in their own economies and regionally as well.

This study proposes an early warning model for predicting bankruptcy of commercial banks and investigates the usefulness of regional cooperation in designing such models and monitoring the sector.

We hope that this study will serve as a reference to domestic regulators designing early warning monitoring systems for their banking sector and encourage regional cooperation in the design and monitoring of such systems.

## II. Methodology

Our study uses logit analysis[1] on financial ratios[2] of commercial banks in Indonesia and Japan to compare the two domestic models with a cross-country model of bank failure prediction.

### A. Data

Our data on financial ratios is drawn from the balance sheets and income statements for the entire population of commercial banks in Indonesia and Japan. In Indonesia, the sample includes state-owned banks, private national foreign exchange and non-foreign exchange banks, regional development banks, joint-venture banks, and foreign banks for fiscal years 1997-2003. The population of Japanese commercial banks includes city banks, long-term credit banks, trust banks and regional I and II banks for fiscal years 1978-2001[3].

We investigate the failure prediction value of 17 financial variables that proxy for the fundamental condition and performance of the banks'under analysis.

The variables are as follows:

1. CaD = Capital to Deposits
2. EtD = Equity to Deposits
3. LtE = Loans to Equity
4. LtC = Loans to Capital
5. FAE = Fixed Assets to Equity
6. FAC = Fixed Assets to Capital
7. ETA = Total Equity Capital to Assets
8. ROE = Return on Equity

[1] Beaver (1966) and (1968) was a pioneer in this approach. Altman (1968) proposed an alternate approach, multiple discriminant analysis (MDA), but later studies, such as Martin (1977) concluded that the distribution assumptions of the logit model are more reasonable.

[2] Meyer and Pifer (1970) found that financial variables are good predictors of failure even when the cause of failure is embezzlement or other financial irregularities. Recent work by Hillegeist, Keating, Cram and Lundstedt (2003) recommends including market based measures in addition to financial variables, but this is not feasible here as most Indonesian banks do not have real market data available for analysis: there are only 26 banks listed on the Indonesian Stock Market and of these only 8 are actively traded.

[3] Consolidation in the Japanese banking sector since 2001 means that it is not possible to construct a consistent sample of banks extending beyond 2001.

9. ROA = Return on Assets
10. LAD = Liquid assets-short term borrowing to total deposits
11. ERA = Equity to risk assets (= assets - cash – CB DD - government securities)
12. LTA = Loans to Assets
13. STA = Treasury Securities to Assets
14. OTA = Other Securities to Assets
15. CTA = Capital to Assets
16. CDL = Core deposits to Total Liabilities
17. NPL = Non Performing Loans to Total Loans
18. LtD = Total Loan to Total Deposit

**B. The Logistic Function**

The logistic function, given as $f(\theta) = e^{\theta} / (1 + e^{\theta})$, varies from 0 to 1 as $\theta$ varies from $-\infty$ to $+\infty$[4]. Replacing $\theta$ with an index of bank characteristics *xb*, the logistic model can be used to express the likelihood of bankruptcy (Y=1) or survival (Y=0) as follows:

$$P_{it} = E\langle Y=1 \mid X_{i.t-k}\rangle = \frac{1}{1+e^{-(\beta_0+\beta_i X_{i.t-k})}} \qquad (1)$$

or $P_{it} = \dfrac{1}{1+e^{-Z_{it}}}$ ; and $Z_{it} = \beta_0 + \beta_1 X_{i.t-k}$

where: $P_{it}$ : probability that $i^{th}$ bank will fail (Y=1); $0 \le P_i \le 1$
$X_i$ : predictor variable for $i^{th}$ bank
$Z_i$ : linear function from predictor variable; $-\infty \le Z_i \le +\infty$
t : time
k : period (yearly) before bank goes bankrupt
e : natural logarithm; e = 2,7182
β : regression coefficients

After estimating the logistic model with the full set of financial data, we do a stepwise logistic regression that uses factor analysis[5] to reduce the number of independent variables in the regression by identifying those variables which are most informative in predicting bankruptcy.
In the logistic estimation, we also employ maximum likelihood technique as an approach to calculate the intercept and coefficient parameters. We
$P_i$ is the probability of $Y_i = 1$ given $X_i$ ($P_i = P(Y_i=1/X_i)$
$P$ is the probability of $Y_i = 0$ given $X_i$ ($P = P(Y_i=0/X_i)=1- P_i$
The probability of N values of sample *Y* given all N sets of values $X_i$ is calculated by multiplying the N probabilities:

$$P\ (Y/X) = \prod_{i=1}^{n} P_i^{Y_i}(1-P_i)^{1-Y_i}$$

The maximum likelihood estimation (MLE) chooses estimates of the intercept and coefficients of parameters from a set of K independents variables (i.e. $\tilde{b}$ ) which

[4] The logistic function looks very much like the cumulative normal function but is much easier to calculate as is does not require evaluating an integral.
[5] See Santoso (2004), Rencher (1995) and Qurriyani (2000) for a detailed description of this method.

would make the likelihood produces estimate of Y as large as possible. The likelihood function is:

$$\underset{b}{Max}\, L(Y/X, b)$$

Intercept and coefficient of b's are solved from the following method:
Recall the following equation:

*L(Y/X, b) = P(Y/X)*

*Log L P (Y/X, b) =*

$$= \sum_{i=1}^{n} Y_i \log\left[\frac{\exp \sum b_k X_k}{1+\exp \sum b_k X_k}\right] + (1-Y_i)\log\left[\frac{1}{1+\exp \sum b_k X_k}\right]$$

$$\text{Log L} = \sum_{i=1}^{n_i} \log P_1 + \sum_{i=n_{i+1}}^{n} \log(1-P_1)$$

To obtain the slope estimates of $\tilde{\alpha}$ and $\tilde{\beta}$ we differentiate log L with respect to $\alpha$ and $\beta$, set the result to zero and solve:

$$\frac{\partial(\log L)}{\partial\alpha} = \sum_{i=1}^{n_1} \frac{\partial P_1/\partial\alpha}{P_1} - \sum_{i=n_1+1}^{N} \frac{\partial P_1/\partial\alpha}{1-P1}$$

$$\frac{\partial(\log L)}{\partial\beta} = \sum_{i=1}^{n_1} \frac{\partial P_1/\partial\beta}{P_1} - \sum_{i=n_1+1}^{N} \frac{\partial P_1/\partial\beta}{1-P1}$$

### C. Diagnostic Tests

After estimating both the full logistic model and the stepwise logistic model, we conduct some diagnostic tests on the appropriateness of the three prediction models: the domestic models for Japan and Indonesia and the cross-country model. A goodness of fit test is conducted using the likelihood ratio statistics as proposed by Aldrich and Nelson (1984) and McFadden (1973), which measures the difference between observed value and predicted value of dependent variable (the probability of bankruptcy) and tests the null hypothesis that there is no statistically significant difference between actual observed bank failure and classification using the bank failure prediction model.

We also look at the predictive power of our models. This is a test of the power of the model to predict bankruptcy or survival of the population of banks. Our bankruptcy prediction model generates a number between 0 (zero) and 1 (one) representing the probability of bankruptcy. Depending on the set cut-off-point for classification, the predictive power of the model can be expressed by four ratios: accurate estimation of bankruptcy, accurate estimation of survival, false classification of a surviving bank as a bankruptcy (type I error) and false classification of a failed bank as a survivor (type II) error (refer to Santoso (1996)). The cut-off-point represents the probability level where a bank is classified as signaling bankruptcy or not and therefore plays a critical role in determining the predictive power of the model. We follow the suggestion of Santoso (1996) suggests the use of the proportion of bankrupt and

non-bankrupt bank in the sample (or in our case actual population) as the idea cut-off-point.
Finally, we include some graphical representations of the specificity, the fraction of observed survivals that are correctly classified by the model, and sensitivity, the fraction of observed bankruptcies that are correctly classified, of the prediction models and compare these for the three models.

## III. Empirical Results

### A. Logistic and Stepwise Logistic Models

Tables 3A-3B report the results of the first logistic regression, incorporating all available financial ratios in domestic bankruptcy prediction models for Japan and Indonesia and a cross-country model taking advantage of information from both.
Tables 4A-4C report the results of the second step, where we have used factor analysis to narrow the range of variables used in the prediction model considerably. In all tables, rather than the coefficient estimates, we report the log of the odds ratio, which is derived from the coefficient estimates[6] and represents the increased odds of bankruptcy for each unit increase in the independent variable.
In the stepwise regressions, for both domestic prediction models, the behavior of loans, in particular the ratio of loans to deposits or loans to equity, are significant indicators of bankruptcy. In Indonesia the ratio of loans to total assets and non-performing loans are also significant indicators of bankruptcy. This is perhaps not surprising, as troubled banks may increase lending in the face of financial difficulty as a way of bringing in revenue and this lending may in fact tend to go to riskier borrowers who can pay higher interest rates. For the domestic Japanese model, the fact that OTA (ratio of other securities to assets) and ROA (return on assets) enter positively is contrary to our expectations but neither odds ratio is significantly different from 0[7]. In the case of ROA, this may be signaling increasing risk, requiring higher return on assets.
The cross-country stepwise regression results, reported in table 4C, also suggest that loan behavior is very significant in predicting bankruptcy. The loan to equity ratio and ratio of non-performing loans for Indonesian banks enter statistically significantly in the cross-country model. The ratio of securities to total assets and for Indonesian banks and equity to total assets for both Indonesian and Japanese banks (STA and ETA) also enter significantly positive, and the odds ratio for STA is particularly large. This is contrary to our expectations, but may reflect depositor flight prior to bankruptcy, which would reduce short-term liabilities, thereby increasing the ratio or equity to assets in the short-run, as longer-term assets were fixed. The same phenomenon may be reflected in the very large positive odds ratio on capital to deposit ratios for Japanese banks.

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[6] If the probability of survival, or non-bankruptcy is $1-P_{it} = \frac{1}{1+e^{Z_{it}}}$, then the ratio of the probability of bankruptcy to survival, $\frac{P_{it}}{1-P_{it}} = \frac{1+e^{Z_{it}}}{1+e^{-Z_{it}}} = e^{Z_{it}}$, is the odds ratio. The log of the odds ratio $\ln\left(\frac{P_{it}}{1-P_{it}}\right) = Z_{it}$ is not only linear in X, but also (from the estimation view point) linear in the parameters. Thus the relationship between the logistic coefficients and the odds ratios can be expressed as odds ratio = exp(logistic coefficients).
[7] Note that although the odds ratio may be negligible, it can still be statistically significant, as the coefficient estimates from which the odds ratios were derived was statistically significantly different from 0

### B. Goodness of Fit

Goodness of fit test for all three bank failure prediction models – Japan, Indonesia and the Cross-Country Model – display good fit with actual observed bankruptcy (table 5). Using the Hosmer and Lemeshow (2000) test[8], we cannot reject the null hypothesis that there is no difference between observed bankruptcy and bankruptcy predicted by our model.

### C. Predictive Power

Table 6 reports the predictive power of all three models. All three models correctly classified over 90% of the outcomes.

Negative predictive power, the probability of a bank surviving given that our model had classified it as a survivor, was highest for the model using only Japanese data, at 99.47%, but negative predictive power was fairly high in all cases, 97% for the cross-country model and 93% for the Indonesian model.

Perhaps more important to regulators is positive predictive power, the probability of a bank actually going bankrupt given that the model classifies it as such. Positive predictive power was highest for the cross-country model at 32.41%, and significantly lower for the two domestic country models at around 22% for Japan and 26% for Indonesia.

Type I and type II error are also reported in table 6. Type I error, the percentage of surviving banks that were incorrectly predicted to fail by the model, was below 5% in all cases, and lowest at 0.20% for the domestic Japan model. Perhaps more significant for regulators, type II error, the percentage of failed banks that were incorrectly predicted to survive by the prediction model, was substantially higher even for the cross-country model, which at 51% displayed the lowest type II error.

### D. Sensitivity and Specificity

Table 6 and graphs 1A-1C display the sensitivity and specificity of the prediction model.

Specificity, the fraction of observed survivals that are correctly classified by the model, was fairly high – over 95% - for all the models, and highest for Japan at 99%, followed by the Indonesian model at 97%.

Sensitivity, the fraction of observed bankruptcies that are correctly classified, was significantly lower for all three models and for the two domestic models was even below 10% (9.5% for Japan and 8.7% for Indonesia. Of the three, the cross-country model performed best on sensitivity, with 49% of observed bankruptcies correctly classified.

Graphs 1A, 1B, and 1Cdisplay graphically the ROC curve, the trade-off between sensitivity and 1-specificity as the cutoff point is varied between 0 and 1. A model with no predictive power would display a straight 45 degree line (50% of the graph beneath the curve) and in general the more bowed the line is and the larger the area beneath the curve, the better the performance of the model. Our cross-country model displays the best performance, with 92% of the area under the ROC curve. This is higher than the single country curves for either Japan (88%) or Indonesia (78%)

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[8] Since the number of covariate patterns in our data set is equal to the number of observations, the Hosmer and Lemeshow test is preferred to the Pearson chi-square goodness of fit test.

## IV. Conclusions

Our domestic bank failure prediction models highlight the importance of monitoring banks' loan behavior in monitoring bankruptcy or financial weakness. In both Japan and Indonesia ratios such as loans to deposits and loans to total assets entered statistically significantly with odds ratios generally higher than 1. The ratio of non-performing loans also entered significantly statistically and quantitatively for Indonesia. This contrasts with other studies on corporate bankruptcies in the region, which find liquidity and profitability ratios to be the most important indicators of failure (see for example Shirata (1998)).

Surprisingly, we do not find regulatory capital ratios to be important predictors of bank failure for the period under study. This contrasts with other studies and may be due to the inaccuracy of regulatory capital measures during the period, or to unique domestic regulations, such as the inclusion of latent capital gains on equity to count toward tier II capital for Japanese banks.

The main goal of this study was to explore the usefulness of cross-country models in monitoring the health of the banking sector or providing early warning systems of systemic crisis. We find that such models hold promise. Our cross-country bank failure prediction model displays high percentage of outcomes to be correctly classified, good goodness-of-fit, and high specificity. On diagnostics likely to be of most concern to regulators and policy makers - sensitivity, positive predictive power and type II error – the cross-country model actually out-performed the domestic models. We hope these findings will stimulate regional cooperation on this issue.

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# TABLES AND FIGURES

**Table 1: Variable Definitions**

| Ratios | | No | Expected. Sign |
|---|---|---|---|
| Capital To Deposit | CaD | 1 | - |
| Equity To Deposit | EtD | 2 | - |
| Loans To Equity | LtE | 3 | + |
| Loans To Capital | LtC | 4 | + |
| Fixed Assets To Equity | FAE | 5 | + |
| Fixed Assets To Capital | FAC | 6 | + |
| Equity To Total Assets | ETA | 7 | - |
| Return On Equity | ROE | 8 | - |
| Return on Assets | ROA | 9 | - |
| (Liquid Assets - ST. Borrowing) / Deposit | LAD | 10 | - |
| Equity / (Asset - Cash – Demand Deposit at CB – Govt Bonds) | ERA | 11 | - |
| Loans To Total Assets | LTA | 12 | + |
| Securities / Total Assets | STA | 13 | - |
| Other securities / Total Assets | OTA | 14 | - |
| Core Deposit/Total Assets | CTA | 15 | - |
| Core Deposit / Total Liabilities | CDL | 16 | - |
| NPL / Total Loans | NPL | 17 | + |
| Total Loan to Total Deposit | LtD | 18 | + |

## Table 2: Summary Statistics

### 2A: Summary Statistics – Japan

| Variable \| | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| CaD | n/a | | | | |
| EtD \| | 3905 | .04253 | .0425743 | -1.129774 | .4915473 |
| LtE \| | 3905 | 21.0785 | 13.6192 | -398.4082 | 522.1701 |
| LTC | n/a | | | | |
| FAE \| | 3904 | .3521111 | .2461225 | -6.827916 | 7.573432 |
| FAC | n/a | | | | |
| ETA \| | 3905 | .0322047 | .0227423 | -.4910522 | .0855581 |
| ROE \| | 3905 | .0196271 | .4614258 | -25.40443 | 5.296004 |
| ROA \| | 3906 | .000111 | .0138895 | -.4509065 | .1532793 |
| LAD \| | 3907 | .0673806 | .0890071 | -.9396967 | 1.62967 |
| ERA \| | 3905 | .0344985 | .0234734 | -.4975088 | .1034907 |
| LTA \| | 3907 | .6528798 | .0853023 | .2711748 | 1.485367 |
| STA \| | 3907 | .1656485 | .0501866 | .008097 | .4299378 |
| OTA \| | 3906 | .1145675 | .0378015 | .0064595 | .3266291 |
| CTA | n/a | | | | |
| CDL \| | 3906 | .5463418 | .122011 | .0331849 | .811878 |
| NPL \| | 1136 | .0093129 | .0077838 | .0003813 | .0868371 |
| LBtA \| | 3907 | .9678085 | .022748 | .9144419 | 1.491052 |
| LtD \| | 3907 | .8512459 | .3454865 | .5336297 | 4.423113 |
| RAtA \| | 3907 | .9335682 | .045114 | .6401036 | .9928454 |

### 2B: Summary Statistics – Indonesia

| Variable \| | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| CaD | 1172 | .4827942 | 13.72192 | -131.163 | 429.0062 |
| EtD \| | 1172 | .5317192 | 14.00255 | -131.163 | 445.0072 |
| LtE \| | 1181 | 2.498564 | 78.61991 | -2399.348 | 442.1502 |
| LTC | 1107 | 3.313105 | 27.35114 | -685.4061 | 254.4361 |
| FAE \| | 1172 | .0535329 | .2350333 | 0 | 7.794224 |
| FAC | 1107 | .2077126 | .8029576 | -7.416095 | 9.786787 |
| ETA \| | 1179 | .0742362 | .3783745 | -5.053132 | .9959792 |
| ROE \| | 1179 | -.0225764 | .3063509 | -5.345872 | 5.688718 |
| ROA \| | 1107 | .1506441 | 2.75549 | -47.69755 | 26.81897 |
| LAD \| | 1172 | .9509131 | 13.84752 | -28.41261 | 464.4332 |
| ERA \| | 1181 | .1918114 | 1.172451 | -5.549695 | 24.08738 |
| LTA \| | 1179 | .5158241 | .3177601 | 0 | 3.960895 |
| STA \| | 1179 | .0523917 | .115531 | 0 | .7639019 |
| OTA \| | 1179 | .008585 | .0354516 | 0 | .641086 |
| CTA | 1178 | 2.078283 | 51.29923 | -11.37069 | 1752.082 |
| CDL \| | 1181 | .3708535 | .292839 | -5.357526 | .9569352 |
| NPL \| | 1136 | .0093129 | .0077838 | .0003813 | .0868371 |
| LBtA \| | 1178 | .1748941 | .2652908 | 0 | 2.500596 |
| LtD \| | 1097 | 3.614599 | 26.74982 | .0076813 | 794.127 |
| RAtA \| | n/a | | | | |

## Table 3 – Logistic Regression Results

## 3A: Logistic Regression Results: Japan

| Dependent Variable: Probability of BANKRUPTCY | ODDS Ratio |
|---|---|
| **lagEtD** | 0.193<br>[1.875] |
| **lagLtE** | 1.019<br>[0.020] |
| **lagROE** | 1.235<br>[0.500] |
| **lagROA** | 0<br>[0.000] |
| **lagLAD** | 0.024<br>[0.062] |
| **lagLTA** | 1.218<br>[3.785] |
| **lagSTA** | 277.45<br>[2,785.808] |
| **lagOTA** | 0<br>[0.000]*** |
| **lagLtD** | 3.33<br>[1.794]** |
| **Observations** | 3589 |

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

## 3B: Logistic Regression Results: Indonesia

| Dependent Variable: Probability of BANKRUPTCY | ODDS Ratio |
|---|---|
| **Dt** | 26.909<br>[15.872]*** |
| **lagEtD** | 1.053<br>[0.062] |
| **lagLtE** | 1.054<br>[0.017]*** |
| **lagROE** | 1.273<br>[0.594] |
| **lagROA** | 1.047<br>[0.073] |
| **lagLAD** | 1.094<br>[0.169] |
| **lagLTA** | 5.992<br>[4.056]*** |
| **lagSTA** | 36.255<br>[84.934] |
| **lagOTA** | 1.627<br>[7.049] |
| **lagLtD** | 0.933<br>[0.029]** |
| **NPL** | 3.644<br>[1.378]*** |
| **Observations** | 885 |

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

## 3C: Logistic Regression Results: Cross Country Model

| Dependent Variable: Probability of BANKRUPTCY | ODDS Ratio |
|---|---|
| Dt | 17.131<br>[10.696]*** |
| lagCaDi | 1.296<br>[0.346] |
| lagEtDi | 0.59<br>[0.194] |
| lagLtEi | 1.022<br>[0.021] |
| lagLtCi | 1.007<br>[0.017] |
| lagFAEi | 1.843<br>[5.052] |
| lagFACi | 0.909<br>[0.377] |
| lagETAi | 1.22E+17<br>[1.635e+18]*** |
| lagROEi | 119.3<br>[269.700]** |
| lagROAi | 0.965<br>[0.104] |
| lagLADi | 1.22<br>[0.203] |
| lagERAi | 0<br>[0.000]*** |
| lagLTAi | 2.319<br>[1.211] |
| lagSTAi | 524.016<br>[1,396.394]** |
| lagOTAi | 108.656<br>[574.804] |
| lagCDLi | 0.866<br>[0.678] |
| NPLI | 3.097<br>[1.209]*** |
| lagEtDj | 0<br>[0.000] |
| lagLtEj | 0.002<br>[2.447] |
| lagLtCj | 2.082<br>[4,224.480] |
| lagFAEj | 5.14E+237<br>[0.000] |
| lagFACj | 0<br>[0.000] |
| lagETAj | 0<br>[0.000] |
| lagROEj | 0<br>[0.000] |
| lagROAj | 0<br>[0.000] |
| lagLADj | 0<br>[0.000] |
| lagSTAj | 0<br>[0.000] |
| lagOTAj | 0<br>[0.000] |
| lagCDLj | 0<br>[0.000] |
| lagNPLj | 0<br>[0.000] |
| Observations | 1505 |

Standard errors in brackets: * significant at 10%; ** significant at 5%; *** significant at 1%

## Table 4 – Stepwise Logistic Regression Results

### 4A: Stepwise Logistic Regression Results: Japan

| Dependent Variable: Probability of BANKRUPTCY | ODDS Ratio |
|---|---|
| **lagOTA** | 0<br>[0.000]*** |
| **lagLtE** | 1.009<br>[0.004]** |
| **lagLtD** | 3.013<br>[0.859]*** |
| **lagROA** | 0<br>[0.000]*** |
| **Observations** | 3589 |

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

### 4B: Stepwise Logistic Regression Results: Indonesia

| Dependent Variable: Probability of BANKRUPTCY | ODDS Ratio |
|---|---|
| **lagLtD** | 0.948<br>[0.024]** |
| **lagLtE** | 1.035<br>[0.016]** |
| **NPL** | 11.197<br>[4.216]*** |
| **lagLTA** | 2.709<br>[1.326]** |
| **Observations** | 885 |

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

## 4C: Stepwise Logistic Regression Results: Cross Country Model

| Dependent Variable: Probability of BANKRUPTCY | ODDS RATIO |
|---|---|
| **Dt** | 8.695<br>[4.032]*** |
| **lagETAj** | 0.644<br>[0.087]*** |
| **lagCaDj** | 9,353.57<br>[26,414.599]*** |
| **lagLtEi** | 1.033<br>[0.014]** |
| **lagETAi** | 3.85E+14<br>[3.883e+15]*** |
| **lagROEi** | 7.171<br>[5.292]*** |
| **lagERAi** | 0<br>[0.000]*** |
| **lagSTAi** | 99.127<br>[216.712]** |
| **NPLI** | 2.991<br>[1.106]*** |
| **Observations** | 1505 |

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

**Table 5 – Goodness of Fit Test**

**5A: Goodness-of-Fit Test: Logistic model for bankruptcy - Japan**

number of observations = 3589

number of covariate patterns = 3589

Pearson chi2(3584) = 2674.05

Prob > chi2 = 1.0000

**5B: Goodness-of-Fit Test: Logistic model for bankruptcy - Indonesia**

number of observations = 885

number of covariate patterns = 885

Pearson chi2(880) = 808.96

Prob > chi2 = 0.9577

**5C:Goodness-of-Fit Test: Logistic model for bankruptcy – Cross Country Model**

number of observations = 1505

number of covariate patterns = 1505

Pearson chi2(1495) = 1405.13

Prob > chi2 = 0.9521

**Table 6 – Predictive Power**

**6A: Predictive Power: Logistic model for bankrupt - Japan**

| | True Bankrupt (1) | True Survivor (0) | Total |
|---|---|---|---|
| Classified Bankrupt (+) | 2 | 7 | 9 |
| Classified Survivor (-) | 19 | 3561 | 3580 |
| Total | 21 | 3568 | 3589 |

Classified as Bankrupt (+) if predicted Pr(D) >= .13
True Bankrupt defined as bankrupt = = 1

--------------------------------------------------

| | | |
|---|---|---|
| Sensitivity | Pr( +\| 1) | 2/21 = 9.52% |
| Specificity | Pr( -\|0) | 19/21 = 99.80% |
| Positive predictive value | Pr( 1\| +) | 2/9 = 22.22% |
| Negative predictive value | Pr(0\| -) | 3561/3580 = 99.47% |

--------------------------------------------------

Type I Error:
False + rate for true Survivor Pr( +|0) 7/3568 = 0.20%
Type II Error:
False - rate for true Bankrupt Pr( -| 1) 19/21 = 90.48%

--------------------------------------------------

Correctly classified 99.28%

**6B: Predictive Power: Logistic model for bankrupt - Indonesia**

| | True Bankrupt (1) | True Survivor (0) | Total |
|---|---|---|---|
| Classified Bankrupt (+) | 6 | 17 | 23 |
| Classified Survivor (-) | 63 | 799 | 862 |
| Total | 69 | 816 | 885 |

Classified as Bankrupt (+) if predicted Pr(D) >= .29
True Bankrupt defined as bankrupt = = 1

--------------------------------------------------

| | | |
|---|---|---|
| Sensitivity | Pr( +\| 1) | 6/69 = 8.70% |
| Specificity | Pr( -\|0) | 799/816 = 97.92% |
| Positive predictive value | Pr( 1\| +) | 6/23 = 26.09% |
| Negative predictive value | Pr(0\| -) | 799/862 = 92.69% |

--------------------------------------------------

Type I Error:
False + rate for true Survivor Pr( +|0) 17/816 = 2.08%
Type II Error:
False - rate for true Bankrupt Pr( -| 1) 63/69 = 91.30%

--------------------------------------------------

Correctly classified 90.96%

**6C: Predictive Power: Logistic model for bankrupt – Cross Country Model**

| | True Bankrupt (1) | True Survivor (0) | Total |
|---|---|---|---|
| Classified Bankrupt (+) | 35 | 73 | 108 |
| Classified Survivor (-) | 37 | 1360 | 1397 |
| Total | 72 | 1433 | 1505 |

Classified as Bankrupt (+) if predicted Pr(D) >= .23
True Bankrupt defined as bankrupt = = 1

--------------------------------------------------

| | | |
|---|---|---|
| Sensitivity | Pr( +\| 1) | 35/72 = 48.61% |
| Specificity | Pr( -\|0) | 1360/1433 = 94.91% |
| Positive predictive value | Pr( 1\| +) | 35/108 = 32.41% |
| Negative predictive value | Pr(0\| -) | 1360/1397 = 97.35% |

--------------------------------------------------

Type I Error:
False + rate for true Survivor Pr( +|0) 73/1433 = 5.09%
Type II Error:
False - rate for true Bankrupt Pr( -| 1) 37/72 = 51.39%

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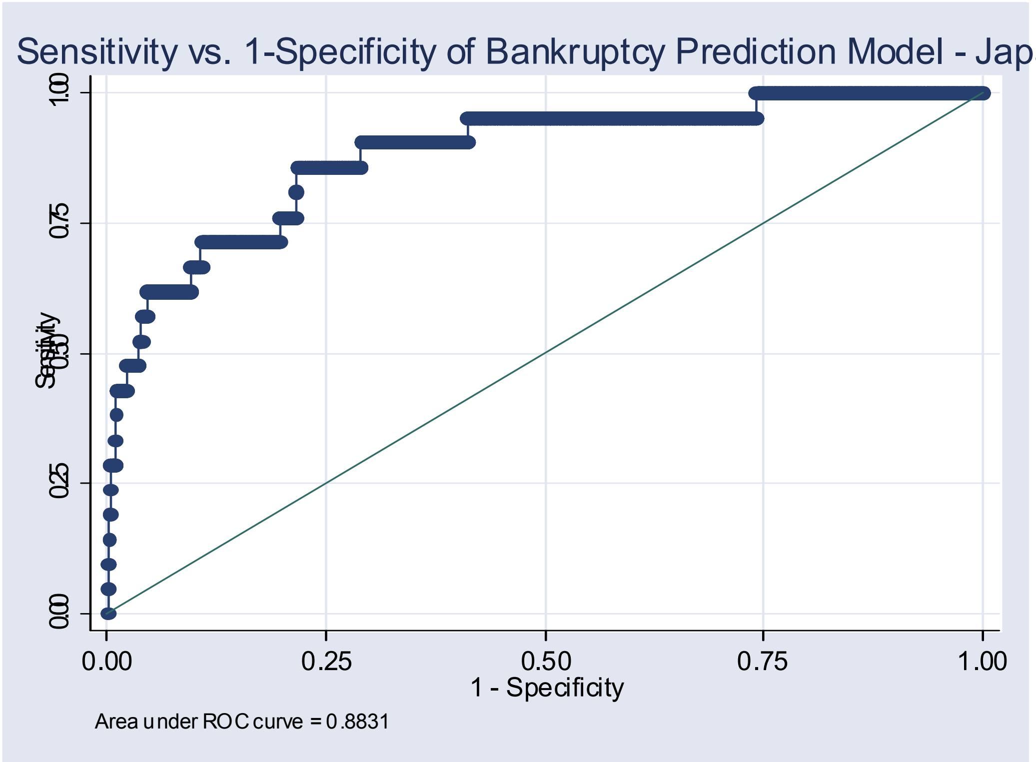
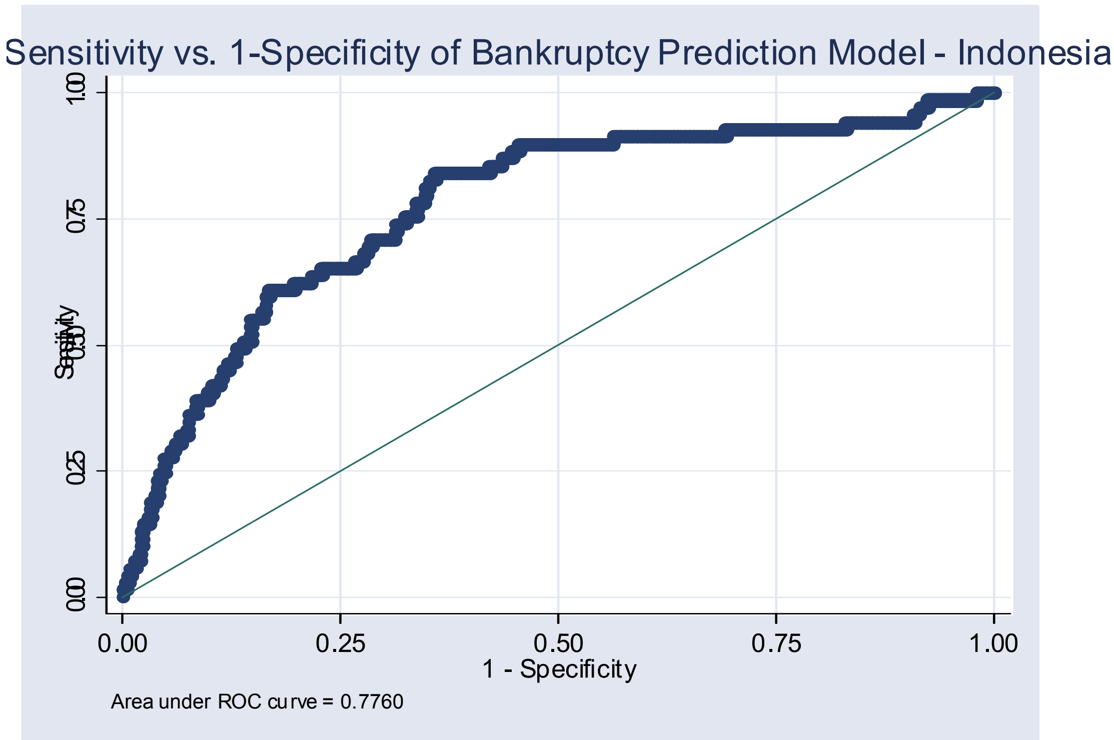
Correctly classified 92.69%

**Graph 1: LROC – Sensitivity vs. Specificity**

**1A: LROC Graph: Japan**




**1B: LROC Graph: Indonesia**



**<u>1C: LROC Graph: Cross Country Model</u>**