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Too-Big-To-Fail: Bank Failure and Banking Policy in Jamaica

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Abstract

Research on the causes of bank failure has focused on developed countries, particularly the United States of America. Relatively little empirical work has examined developing countries. We examine the total population of banks in Jamaica between 1992 and 1998 and find that real GDP growth, size, and managerial efficiency were the most significant factors contributing to the failure of banks. Bank failure is defined to include bailout and regulator-induced or supervised merger. Our results suggest that there were implicit 'Too-big-to-Fail' policies during this period.

Keywords: Bank failures, Too-big-to-Fail, developing economies, Jamaica

JEL Codes: G21, G28

We are grateful without implication to the Editor and an anonymous referee. All remaining errors are ours entirely.

1. Introduction

The last decade of the twentieth century was unprecedented in Jamaica's financial history. Of a population of thirty-seven banks, twenty-one were classified as failed, with fourteen being so classified in one year - 1998. However, few outright closures occurred. Most problem banks were merged with other banks, or continued to operate through financial support from the government. More than a half of domestic banks received some kind of financial support from the government, initiated voluntary bankruptcy proceedings or surrendered their licences.

Explanations for such banking problems vary. Empirical research on bank failures separates the causal factors into bank-specific, industry-specific, macroeconomic and other. However, much of the debate on developing countries has neglected banks at the individual level, and has focused on the problems faced at sector or industry level. Moreover, the (often conflicting) results of existing studies do not offer inferences about the factors that are particularly significant in developing countries, or to those that are significant to the failure of individual banks, or to the fate of problem banks. This paper addresses the following questions: what factors were significant in the banking crisis in Jamaica? What factors influenced how the crisis was handled and was there an implicit Too-Big-to-Fail (TBtF) policy? What are the lessons for bank regulators in developing economies that can assist in better preparedness for the future?

To address these questions, the within-sample performance of a panel of Jamaican banks is examined. Some of the factors identified as contributing to failure include deterioration in the macroeconomic environment, rapid expansion and weakness in a range of bank-specific factors: capital, management, and liquidity. The size results are particularly significant and point to the operation of implicit 'TBtF' policies. Larger banks are more likely to fail, but are also more likely to be bailed out rather than closed.

The next section discusses the banking crisis in Jamaica. Section 3 reviews the literature on bank failures. Section 4 discusses data and methodology. Sections 5 and 6 present the results, and Section 7 concludes.

2. Bank failure in Jamaica

The term 'bank failure' has been interpreted varyingly. The more precise definitions have focused on accounting factors (for example, Martin, 1977 and Benston and Kaufman, 1995), economic factors (Bell, Ribar, and Verchio 1990 and González-Hermosillo, Pazarbasioglu and Billings 1997), or legal factors (Meyer and Pifer, 1970). Conversely, more general definitions have attempted to be all-inclusive and have applied a 'catch-all' combination of specific definitions (for example, Thomson, 1992). Using a general definition of 'bank failure' embracing closure, bankruptcy, supervised merger, or direct government assistance, we assess the population of banks in Jamaica over the period 1992 to 1998.[1] Table 1 shows a comparative profile of the Jamaican banking sector before and after the crisis.

INSERT TABLE 1 HERE

Three banks that had been subject to regulator-induced cessation saw the government discharging the liabilities to their depositors within the context of *de facto* deposit insurance; ninety per cent of the deposits in one case and one hundred per cent for the others. The majority of bank failures occurred in 1997 and 1998. Four banks failed in 1997, and 14 failed in 1998.

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[1] An involuntary merger initiated by a central bank or other regulatory authority may be considered evidence of failure if the merged bank was seen as unable to survive on its own (see, for example, Martin, 1977; Altman, Avery, Eisenbeis and Sinkey 1981). Moreover as noted by Altman *et al*. (1981), to ignore such mergers could result in bank groups that are not entirely discrete and may result in misspecification of the results of predictive models.

However, even in those years when a relatively greater number of banks failed, there were survivors.

3. Bank failure literature

Studies attempting to empirically identify the causes of bank failures in developing countries have focused mainly on macroeconomic factors (Rojas-Suárez 1998, Bongini, Claessens and Feri, 2000). It is common for banking crises to occur in periods of macroeconomic downturn (Benston and Kaufman, 1995; Gavin and Hausmann, 1996; González-Hermosillo *et al*., 1997; Demirgüç-Kunt and Detragiache, 1998; Hardy and Pazarbasioglu, 1998; Brownbridge and Kirkpatrick, 1999). Some observers find that credit expansion is strongly associated with banking crises (Gavin and Hausmann, 1996; Hardy and Pazarbasioglu, 1998; Kaminsky and Reinhart, 1999; Dermirgüç-Kunt and Detragiache, 1999). In contrast, other observers note that the link between lending booms and banking crises is weak, particularly outside Latin America (Caprio and Klingebiel, 1996; Hanohan, 1997; Gourinchas, Valdés and Landerretche, 2001). While macroeconomic factors are clearly important, bank failures are more likely to occur when banks are both weak <u>and</u> face macroeconomic shocks (IMF, 2000). Bank failure, then, would seem to result from the vulnerability of individual banks; macroeconomic shocks expose the inherent weaknesses of such banks.

The literature on quantitative bank failure studies separates bank-specific effects from common industry or macroeconomic effects.[2] In general, the bank-specific factors to which bank failures have been attributed are the 'CAMELS' variables.[3] Capital adequacy measures have

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[2] For a recent survey see Heffernan (2003)
[3] 'CAMELS' is a mnemonic for a framework adopted by financial regulators by which the following are analysed: capital adequacy, asset quality, management expertise, liquidity and sensitivity to market risk.

been found to be significant predictors in a number of studies (Martin 1977; Lane, Looney and Wansley, 1986; Thomson, 1992; Bongini *et al*., 2000; Estrella, Park and Peristiani 2000). Bongini *et al*. (2000) found that the ratio of loan loss reserves to capital and the rate of growth of loans were good predictors of distress and closure in the East Asian crises. Sheng (1996) cited connected party lending between banks and their shareholder-managers as one of the main factors contributing to the banking problems in Argentina and Chile. The importance of the behaviour and capability of management to the survival of banks has also been emphasised (Meyer and Pifer, 1970; Wheelock and Wilson, 2000).[4] In addition, the source of a bank's earnings (Espahbodi, 1991; Wheelock and Wilson, 2000) and also the level (Martin, 1977; Thomson, 1992; Bongini *et al*., 2000) have been shown to be significant to the probability of failure. Similarly, the likelihood of failure has been shown to be significantly greater when a bank is illiquid (Lane *et al*., 1986; Bell *et al*., 1990).

In addition to the CAMEL components, other non-financial bank-specific factors such as size (Boyd and Gertler, 1993 and Bongini *et al*., 2000 contrast with Thomson, 1992), and the extent of foreign ownership (Goldstein and Turner, 1996) have been suggested to explain bank failures. However, no consensus has emerged as to which indicators are most relevant for assessing bank soundness and stability, or for building effective 'early warning' systems. The statistical significance of individual factors, as well as variables, varies across studies and the results have produced conflicting results. Moreover, an understanding of the interplay between these factors and banking crises in developing countries is still scant. As most of these studies have been conducted in industrialised countries, the efficacy of the factors in developing

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[4] See also Benston and Kaufman (1995), Gavin and Hausmann (1996), Demirgüç-Kunt and Detragiache (1998).

countries remains unproven.

4. Data and Methodology

Given the relatively small number of banks in Jamaica, the full population that existed during the period 1990-1998 was utilised. Data for up to seven years prior to the year of failure were sought to accord with the seven-year review period utilised in 'early warning' models in some US surveillance systems (Sahajwala and Van den Bergh, 2000). To qualify for inclusion, deposit-taking institutions had to be governed by the Banking Act or the Financial Institutions Act.[5] A total of 34 banks was assessed, 18 of which were classified as failed. The sample of failed banks was compiled from public data sources, including financial statements and annual reports, the website of the Central Bank, and media reports. Of the 18 failures, 12 were further classified as distressed-assisted (bailed out); the remaining six were subject to liquidation. Of the total banks, 7 were foreign owned.

Logit regression with financial accounting, other bank-specific and macroeconomic information is used to explain the likelihood of bank failure, bailout or closure. The standard logit model is a binary outcome, where either the bank fails (p_i = 1) or survives (p_i = 0). The conventional function is described by (1).

$$y_i = \ln\left(\frac{p_i}{1-p_i}\right) = \alpha + \beta X + \rho Y + \varpi Z + \varepsilon \qquad (1)$$

where p_i = 1 if $y_i > 0$ and p_i = 0 if $y_i < 0$. The variable y_i is a dichotomous variable indicating whether or not a bank fails, X is a vector of financial characteristics of banks, Y is a vector of

[5] The Banking Act governs the operations of commercial banks while the Financial Institutions Act governs the operations of merchant banks. Merchant banks were established primarily to develop the local capital markets by providing medium and long-term loans to the public (B0J Annual Report 1998 and are formally referred to as Licensees under the Financial Institutions Act. Firms that executed the services performed by banks but were governed instead by the Companies Act have been excluded.

other bank-specific characteristics, Z represents macroeconomic factors affecting all banks, and ε is the disturbance term.

The empirical analyses aim to identify those characteristics within banks and within the wider macroeconomic environment that influence the likelihood of bank failures and, secondly, to test, using multinomial logit, the robustness and comparative performance of the models in ascertaining the factors that discriminate between distressed banks that are bailed out, as distinct from those that are not, and also from those banks that are able to remain 'healthy.'

The trinomial model provides the opportunity to evaluate a third alternative outcome, the distressed-assisted (bailout) alternative, which is concerned with identifying factors that distinguish banks that are bailed out (either through direct liquidity assistance or by a supervised merger) and remain open from those that are allowed to enter into liquidation.[6] It is also concerned with identifying the ability of statistical models to discriminate between distressed banks that had different outcomes. As in the binomial case, the dependent variable is categorical and discrete, but taking one of the following three values: where either the bank ceases operation in a particular year ($p_i = 0$) or the bank is bailed out in a particular year ($p_i = 1$) or otherwise – the bank remains ''healthy'' – ($p_i = 2$). The use of the three outcomes identifies whether the characteristics of banks that were allowed to close differ significantly from those that were assisted, and may shed light on the preferential treatment afforded to some banks.

Financial and other bank-specific data are taken from financial statements and auditors' notes. Macroeconomic data are obtained from the Bank of Jamaica Statistical Digest and from the Inter-American Development Bank (IADB).[7] The data consist of a panel of 34 banks with 243 observations, of which 18 are failures.[8]

The independent variables are financial strength (proxied by capital adequacy, asset quality, earnings and liquidity ratios), the quality of management (proxied by inefficiency ratios), and other variables representing size, audit status, ownership, bank risk and the general macroeconomic state. The appendix highlights each selected concept, its use in previous studies, how it has been measured in the present study and its expected correlation with the likelihood of failure. Multiple measures of a specific dimension of a bank's operation and performance have been avoided in order to reduce the variable set to manageable proportions, to ensure model parsimony, and to control for the effect of multi-collinearity. The financial information is thus summarised into a pool of 22 operating ratios using the year-end balance sheet and income statement information. Data for two dummy variables representing audit status and bank ownership have also been extracted from financial statements.

Independent sample t-tests of the means of these variables (see Table 2) show that, with the exception of liquidity and size, the means of all the variables are significantly different between failed and non-failed banks.

INSERT TABLE 2 HERE

With the exception of the ratio of gross capital to risk assets and the rate of increase of loans

[6] Relatively few studies have focused specifically on banks that cease to exist in their original form. Hardy and Pazarbasioglu, (1998) utilised multilogit models to seek to identify the emergence of various stages of banking sector distress.
[7] http://database.iadb.org/esdbweb/Scripts/80152N23.CSV
[8] The relatively limited number of failure observations in this study suggests caution in the interpretation of the results. Chamberlain (1980) shows that a panel estimation of a multinomial logit where the number of observations per group is small can result in inconsistent estimates caused by omitted variables. Furthermore, a major characteristic overlying the data in this study is that 61% of the failures are grouped in one year suggesting that the macroeconomic element of the data is appropriate in identifying common factors.

relative to GDP, the data support extant theories regarding the expected correlation of the variables with the likelihood of failure.

5. The Likelihood of Failure

The major underlying assumption to the analysis is that financial and economic distress signs appear in the financial statements (and the macroeconomic environment) at least one year before a bank fails. Contemporaneous variables, that have no predictive content, are therefore excluded from the estimated models. The predictive power of the data is explored by lagging the independent variables one, two and three years prior to the dates of failure. For some variables, it is anticipated that movement within the variable from one year to the next may be most relevant to the likelihood of failure.

A sample of results is shown in Table 3 detailing the statistical properties and the classification accuracy of the binomial logit models.[9] All models were significant at the 1% level. These four equations show that the likelihood of failure in any year, t, is significantly related to the change in capital adequacy between t-3 and t-2, the level of efficiency with which management conducts its affairs in t-3 and in t-1, the size of the bank in t-2, the level of real growth in the economy in t-3, and the rate of growth in the economy between t-3 and t-1.

INSERT TABLE 3 HERE

Five variables behaved consistently in all the models; the inefficiency, liquidity, ownership, size and macroeconomic proxies. Coefficients on the ownership proxy, the inefficiency proxy for t-1 and t-3 and macroeconomic variables for t-1 and t-3 always carried the

[9] The full set of results with variable elimination procedure is available from the corresponding author.

expected signs, while coefficients on the liquidity and size proxies carried mixed signs. These same broad conclusions hold for most of the models developed. The sensitivity of the models in general to eliminations, and also of specific variables to the elimination of other variables, is suggestive of high collinearity. This is not necessarily a problem in prediction studies. However, some variables, in particular the inefficiency proxy for t-1, the size proxy for t-2, and the macroeconomic variable for t-3, were robust in this respect.

The equation in column (2) of Table 3 has many parameters and is therefore expected to be unstable. Restricted versions are shown in columns (3) and (4). Column (5) reports results for a parsimonious equation, but that does not result in marked deterioration of the predictive performance.

To make a further assessment about the usefulness of the variables included in the models, some regression tests are performed to support the findings of more comprehensive equations and provide additional information on lead-time. Three sets of logit equations are estimated: a set of observations for failed banks up to and including one year before failure and all observations up to the corresponding financial year-end for non-failed banks, and similar observations for the periods up to two and three years before failure, respectively, with corresponding year-end figures for the non-failed banks. The results of these tests are summarised in Table 4.

INSERT TABLE 4 HERE

All models were significant at the 1% level, and the signs of the coefficients are in accord with theoretical *priors*. There are three key results. First, as macroeconomic conditions improve, the probability of failure falls. Although macroeconomic shocks do not discriminate between banks, the effect on individual banks would correspond to its specific exposure to the shock (González-Hermosillo *et al*., 1997). Impairment in weaker banks is expected to be greater as a result of worsening economic conditions.

Second, the models suggest that larger banks are more likely to fail. An increase in the size variable is a sign of expanding assets (usually loans or investments). The proxies for size, where significant, consistently carried a positive coefficient. The robustness of the positive conclusion was checked and confirmed throughout the modelling process. This result is consistent with the results of Bongini *et al*. (2000) in respect of the East Asian crises.

It is possible that there is a moral hazard associated with an implicit 'TBtF' policy which has led the larger banks in Jamaica to take up riskier loan portfolios. Alternatively, the bank size increase may have resulted from an increased and riskier portfolio. This suggests a possible link between the positive coefficient for the rate of growth in real GDP and the positive size proxy. Consistent real growth in the economy can result in lending booms, *inter alia*, causing banks' assets to grow faster, with a growing portfolio of bad loans.

The third major finding is that the inefficiency and earnings proxies are significant discriminators between banks. The expectation that failed banks would be significantly less efficient than non-failed banks was strongly indicated in the models, consistent with the findings of Bongini *et al*. (2000). The consistently significant and positive coefficient for the management inefficiency proxy indicates that banks that incur excessive operating expenses relative to operating income or show increases in this ratio in period t-1, display a greater likelihood of failure in period t. In addition, there is evidence of a negative association between the return on assets and the likelihood of failure, supporting the findings in several studies that emphasize an important relationship between earnings and failure prediction (González-Hermosillo *et al*.

(1997); Bongini *et al*. (2000).

Much of the results reported here have been confirmed by the recent study of technical bank failure in Central and Eastern European emerging markets by Männasoo and Mayes (2005). Using a sample of 300 banks over 17 countries, Männasoo and Mayes (2005) find strong evidence for the role of GDP growth in reducing the probability of insolvency or distress and higher cost-income (inefficiency) in increasing the probability. Other contributory variables were non-performing loans and capital-to-assets ratio[10].

For Jamaica, the performance of banks, as determined by their operating ratios (the CAMEL factors), is critical to the degree of macroeconomic shocks that they can absorb. Capital adequacy, management expertise and capability, and liquidity are all useful in determining the state of the banks' insulation against adverse macroeconomic conditions as evidenced in their contribution to the various models estimated. A comparison of columns (2) to (5) of Table 3 reveals that failing banks exhibit differing characteristics from healthy ones in terms of the changes in the levels of capital to risk assets, their operating efficiency, and the level of liquid assets held. However, proxies for the various operating variables overlap in terms of their definition, contributing to the level of collinearity among the CAMEL components. Given the level of multicollinearity evident in the models, therefore, it is difficult to isolate the individual contribution of each of the CAMEL components, although the inefficiency variable for t-1 appears quite robust in this respect. Notwithstanding, each individual variable set selected is useful for prediction.

There is no evidence of ownership as an explanatory variable. The fact that all failures have been local banks is possibly due to factors indirectly related to ownership, such as management. However, the importance of the operational, size, and bank risk proxies appears to be intrinsically linked with considerations regarding ownership and the resulting influences of different types of ownership. This was evidenced in the effect on some of the variables of the removal of the ownership proxy from the models. The finding of a statistically insignificant ownership proxy is consistent with that of Bongini *et al*. (2000).

The trade-off between timeliness and accuracy is striking in the models. Clearly, the usefulness of the models depends upon information availability: the explanatory power, although not always the predictive power, of the models decline as the information set becomes more dated. Generally, the predictive power of the models improved in the second year before failure over the third year, while the explanatory power increased as failure approached. The preference for greater classification accuracy or more advanced lead-time depends on the purpose of the user. Policy makers prefer a longer lead-time since many economic decisions take months to implement. More instantaneous decision-makers would prefer more reliable signals, even if there is less time in which to respond.

6. Failure and Bail-Out

This section reports the results of the re-estimation of the equations produced in the previous section using the multinomial logit estimator. If the banks that had different outcomes reflect dissimilar characteristics, then this information could be useful to decision-makers although both outcomes result in potentially significant fiscal costs. If the banks' characteristics are similar,

[10] They also report some evidence that could be interpreted as an indicator of a size effect, whereby size indicates an increased

then this suggests that there are other, non-quantitative, factors that influence the decision to bailout or close a bank. Again, all banks and all periods are included in the pooled sample. Table 5 shows the final multilogit models. These models are significant at the 1% level and are well determined: chi-squared values not less than 70.0, LRI not less than 0.62 and overall classification accuracy not less than 96.4%.

INSERT TABLE 5 HERE

The two sets of equations reflect qualitatively similar results: as in the binomial model, changes in capital adequacy, levels of efficiency, size and the state of the economic environment are statistically significant discriminators between closed and 'healthy' banks, most at the 5% level or better. Larger banks are more likely to be bailed out than closed, while banks with larger increases in capital and that are less efficient in an environment of rapidly improving economic conditions are more likely to be closed than to remain 'healthy.' Nevertheless, one statistically significant difference emerges - larger banks are more likely to be bailed out than they are to be closed. One strong implication of this finding is that there are either implicit or explicit 'TBtF' policies in effect in Jamaica that constrain the authorities from allowing larger banks that are distressed to be closed. Table 6 below shows the size distribution of the banks between those that failed, were 'bailed out' or survived. {JENIFER CAN YOU DO THE TABLE AND SEND BACK TO ME FOR COMMENT OR PUT IN YOUR COMMENT – THE REFEREE HAS SPECIFICALLY ASKED FOR THIS.}

probability of distress or technical insolvency. They find that the ratio of assets to gross income is a significant contributory factor in predicting bank insolvency or distress.

Table 6
Size Distribution of Banks

$ Assets (Current)	Failed	Bailed Out	Survived
Mean			
Standard Deviation			
Maximum			
Minimum			
Number of Banks			

The second implication is that, since there are financial and non-financial characteristics other than size in t-2 that discriminate between ‘healthy’ banks and the broader category of ‘failed’ banks, bailed out banks exhibit financial and other characteristics that are similar to the broader group of ‘failed’ banks. These findings suggest that some banks that were bailed were probably as acutely distressed as those that were closed. Clearly, there are other non-quantitative factors that influence regulators’ decision to close a bank (or to allow it to be closed) or to provide assistance to enable it to remain open.

Because of the economic influence of large banks, and the potential systemic financial disruption, governments tend to bear the cost than lose large banks to closure (Goodhart, Hartmann, Llewellyn, Rojas-Suárez and Weisbrod, 1998; Mishkin, 2000b). However, the presence of ‘TBtF’ policies generates moral hazard incentives. Furthermore, connections with government or political power often influence why some banks are rescued.

7. Conclusion

This paper has estimated a bank failure model for Jamaica. The results show that factors typically used in developed economies to predict distress and failure also apply to Jamaica. An ‘early warning’ system may therefore be developed as an effective complement to supervisory mechanisms. However, the econometric model is open to the so-called 'Lucas Critique', in that the results could be conditioned by the moral hazard implications of an implicit 'TBtF' policy.

Overall, the findings of the binomial and multinomial models are mutually supporting. The results of this paper also demonstrate the potential use of econometric models to pinpoint the source of developing problems in banks, from one to three years in the future. Several indicators – particularly inefficiency, size and the proxy for the macroeconomic state – discriminate between failed and non-failed banks very well. In addition to the general causes of banking failures in Jamaica, this paper sheds light on the closure policies of regulators. In respect of the causes, weaknesses in individual banks contributed significantly to the crisis. The significant weaknesses highlighted are delays in addressing capital requirements resulting in rapid expansion shortly before failure, inefficiency, and rapid expansion in assets at the expense of quality. In respect of the regulator's closure policies, the findings also suggest that the resolution processes of regulators were possibly influenced by concerns of 'Too-Big-to-Fail'.

These findings raise some important questions for the banking regulators in Jamaica, in respect of how policies regarding banks are made and executed, forbearance in respect of distressed banks, and the methods employed to identify weakness in individual banks. To some extent, these questions will intensify the pressure that has been brought to bear on regulators following the banking crises. On the basis of the empirical evidence, the variables significant to discriminating between failed and non-failed banks in Jamaica warrant further attention and study. While the empirical results cannot be considered definitive, given the sample size, they are indicative and warrant further investigation.

Appendix I Pool of Variables

Variable/Ratio	Construct	Definition	Exp. Sign
Capital/total assets	Capital Adequacy	LT Debt + Equity /Total Assets	-
Gross capital/risk assets	Capital Adequacy	LT Debt + Equity/Loans + Leases	-
Total loans/total capital	Capital Adequacy	Loans + Leases/LT Debt + Equity	+
Loan loss Reserves/Gross Loans	Asset Quality	Reserve for loan loss/Loans + leases	+
Provision for Loan loss/Net Loans	Asset Quality	Provisions for loan loss/(Loans + leases) – provision	+
Non-performing loans/Gross loans	Asset Quality	Non-performing loans/ loans + leases	+
Loans to insiders/Net loans	Asset Quality	(Staff loans + loans to connected parties)/(loans + leases) – loan loss reserves	+
Loans + Leases/Total sources of funds	Earnings	Loans + leases/Total deposits + borrowings	+/-
Net Income/Total Assets (Return on assets)	Earnings	Profit after tax/Total Assets	-
Return on Equity	Earnings	Profit after tax – Preference dividend/Total Equity	-
Net interest margin	Earnings	Net interest revenue/Total earning assets	-
Loan revenue/Total operating income	Earnings	Loan + lease income/Net interest revenue + other operating Income	+
Liquid Assets/Total Assets	Liquidity	(Cash + Dep. with other banks + Deposits with central bank)/Total Assets	-
Total loans/total deposits	Liquidity	Total loans/total deposits	+
Net Loans/Total Assets	Liquidity	(Loans + leases) - provision/Total assets	+/-
Liquid assets/Total sources of funds	Liquidity	(Cash + Dep. With other banks + Deposits with central bank)/(Total deposits + borrowings)	-
Total Op. Expenses/Operating Revenue	Man. Capability/ Inefficiency	Total Operating Expenses/(Net int. rev. + other Op. Inc)	+
Loan revenue/Net loans	Man. Capability/ Inefficiency	Interest on loans + leases/Net loans (i.e. less loan loss reserves)	-
Interest on Deposits/Time + Savings deposits	Man. Capability/ Inefficiency	Interest on Deposits/Time + Savings deposits	+
Overheads/Total assets	Man. Capability/ Inefficiency	Overheads/Total assets	+
Total Assets	Size	Total Assets	-
%Δ Loans/GDP	Bank Risk	%Δ Individual bank's Loans /GDP at current market prices	+
Accounts qualification going concern	Audit Status	Dummy variable: 1 for qualified, 0 for unqualified	+
Local/Foreign ownership	Ownership	Dummy variable: 1 for foreign, 0 for local ownership	-
Real GDP growth	Macroeconomic Environment	GDP growth in constant J$ 1986 prices	-

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TABLES

Table 1

Banking System Profile: pre and post banking crisis

Jamaican Banking Sector	**1993**	**1998**
Number of Banks:*	37 (37)	27 (17)
Jamaican	30 (30)	21 (11)
Foreign	7 (7)	6 (6)
Total Assets	J$73.2bn	J$181.6bn
Total Loans:	J$29.1bn	J$70.3bn
Performing	N/a	59.6bn
Non-performing	N/a	10.7bn
Total Deposits	J$52.7bn	J$119.8bn

Notes: * Total banks arrived at by taking *de facto* failures. Figures in brackets indicate totals arrived at taking theoretical failures.
N/a = Not available.
J$ (Jamaica Dollar) is the unit of currency in Jamaica.
Source: Bank of Jamaica Annual Report, 1998; Bank of Jamaica Statistical Digest, 1999.

Table 2

Mean of Selected Variables, Non-Failed and Failed Banks compared 1992-1998

Variables	Non-failed	Failed	t-statistic
Gross Capital/Risk Assets	18.69	-18.46	1.8*
Loan loss reserve/Gross Loans	6.78	17.78	-3.1**
Total operating expenses/Total Operating Revenue	96.87	152.65	-2.9***
Return on Assets	-0.03	-8.28	2.0**
Liquid Assets/Total Assets	40.34	45.20	-0.8
SIZE (Total Assets deflated)	0.53	0.43	0.2
%ΔLoans/GDP	0.02	-0.16	2.7***

Note: All variables are ratios in percentages except for SIZE, which is the log of total assets deflated by the CPI. ***, **, * shows significance level at 1%, 5%, and 10%, respectively.

Table 3
Binomial Logit Models of Bank Failure Prediction

(1)	(2)	(3)	(4)	(5)
COEFFICIENTS				
Constant	-5.22 (-1.0)	-6.76* (-1.7)	-7.05* (-1.8)	1.01 (0.2)
CAMEL				
Gross capital/risk assets$_{t-1}$	-0.05 (-1.2)	-	-	-
Gross capital/risk assets$_{t-2}$	0.38** (2.2)	-	-	-
Gross capital/risk assets$_{t-3}$	-0.33** (-2.2)	-	-	-
Δ GCRA $_{t-2}$	-	0.08** (2.0)	0.07* (1.8)	0.1** (2.1)
Inefficiency $_{t-1}$	0.1** (2.1)	0.05*** (2.9)	0.05*** (2.9)	0.05*** (2.7)
Inefficiency $_{t-3}$	0.16*** (2.5)	0.10*** (2.6)	0.10*** (2.5)	0.04 (0.9)
Liquid assets/ total Assets $_{t-1}$	-0.1** (-1.9)	-0.02 (-0.9)	-	-
Liquid assets/ total Assets $_{t-3}$	0.10 (1.4)	-	-	-
BANK-SPECIFIC				
Ownership: foreign = 1 Local = 0	-	-	-	-14.55 (-0.1)
Size $_{t-1}$	-4.93** (-1.9)	-	-	-
Size $_{t-2}$	12.00** (2.0)	1.18*** (2.6)	1.06*** (2.6)	1.36*** (2.7)
Size $_{t-3}$	-5.12* (-1.6)	-	-	-
%Δ Loans/GDP $_{t-2}$	1.47 (1.2)	-	-	-
%Δ Loans/GDP $_{t-3}$	-0.84 (-0.5)	-0.88 (-0.8)	-0.86 (-0.8)	0.51 (0.2)
MACROECONOMIC				
Real GDP growth $_{t-1}$	3.15** (2.1)	-	-	-
Real GDP growth $_{t-3}$	-20.44*** (-2.5)	-7.79*** (-2.9)	-	-10.15*** (-2.9)
Real GDP growth $_{t-1}$ - $_{t-3}$	-	0.86 (1.4)	-7.37*** (-2.9)	1.24* (1.7)
McFadden's LRI	0.65	0.58	0.59	0.63
Chi Squared	59.42	52.90	52.00	55.34
No. of Observations	101	101	101	100
Classification Accuracy (% correct)				
Failure	82.3	82.3	64.7	81.2
Non-failure	97.6	96.4	96.4	97.8
Total	95.0	94.1	92.1	96.0

***, **, * Significant at 1, 5 and 10 *per cent* level, respectively. t-statistics in brackets.

Table 4
Binomial Logit Models of Bank Failure Prediction (one, two and three years before failure).

(1)	(2)	(3)	(4)
COEFFICIENTS			
Constant	-3.72*** (-5.1)	-6.22*** (-3.3)	0.04 (0.0)
CAMEL			
Inefficiency	-	0.04*** (2.6)	0.04* (1.8)
Return on Assets	-0.10*** (2.4)	-	-
BANK-SPECIFIC			
Ownership: foreign = 1 Local = 0	-12.88 (-0.1)	-13.35 (-0.1)	-13.55 (-0.1)
Size	0.76*** (2.7)	0.89*** (3.0)	0.91*** (2.7)
MACROECONOMIC			
Real GDP growth	-1.36*** (-3.4)	-1.60*** (-4.2)	-5.63*** (-3.7)
McFadden's LRI	0.55	0.51	0.49
Chi Squared	62.49	54.4	45.50
No. of Observations	183	149	115
Classification Accuracy (% correct)			
Failure	57.8	57.8	56.2
Non-failure	97.2	97.2	96.0
Total	94.5	93.3	90.4

***, **, * Significant at 1, 5 and 10 *per cent* level, respectively. t-statistics in brackets.

Table 5
Multilogit Models

(1)	(2) BAILOUT	(3) 'HEALTHY'	(4) BAILOUT	(5) 'HEALTHY'
COEFFICIENTS				
Constant	-20.89	11.86**	-27.68	4.51
	(-0.3)	(2.1)	(-0.1)	(0.6)
CAMEL				
ΔGross capital/risk assets$_{t-2}$	-0.05	-0.08*	-0.06	-0.09*
	(-0.8)	(-1.7)	(-0.9)	(-1.7)
Inefficiency $_{t-1}$	-0.01	-0.06***	-0.01	-0.06***
	(-0.6)	(-3.1)	(-0.7)	(-2.8)
Inefficiency $_{t-3}$	-0.02	-0.11***	0.01	-0.06
	(-0.3)	(-2.4)	(0.1)	(-0.9)
BANK-SPECIFIC				
Ownership: foreign = 1	-	-	-1.76	13.17
Local = 0			(-0.0)	(0.0)
Size $_{t-2}$	1.88**	0.18	2.01**	0.01
	(2.3)	(0.3)	(2.2)	(0.0)
Δ% Loans/GDP$_{t-3}$	-4.86	-0.95	-3.84	-2.88
	(-0.7)	(-0.2)	(-0.5)	(-0.6)
MACROECONOMIC				
Real GDP growth $_{t-3}$	1.31	5.31**	1.76	6.97**
	(0.1)	(2.0)	(0.0)	(1.9)
ΔReal GDP growth $_{t-1} - _{t-3}$	-9.12	-1.85**	-10.59	-1.96**
	(-0.4)	(-2.1)	(-0.1)	(-2.1)
McFadden's LRI	0.62		0.65	
Chi Squared	70.05		69.60	
No. of Observations	101		100	
Classification Accuracy (% correct)				
Total	93.1		94.0	
Closure	66.7		60.0	
Bailout	81.8		81.8	
'Healthy'	96.4		97.6	

***, **, * Significant at 1, 5 and 10 *per cent* level, respectively. t-statistics in brackets.