An Early Warning Model of Bank Failure in Jamaica: An Information Theoretic Approach

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Abstract

In this paper, an early-warning bank failure model **(EWM)** is designed to capture the dynamic process underlying the transition of the banks from financial sound to closure utilizing a transition probability matrix **(TMP)**. Specifically, Instrumental Variables-Generalized Maximum Entropy **(GME-IV)** formalism by Golan et al. (1996) is used to assess the likelihood of the banking sector experiencing distress via the evaluation of banking crisis probabilities. The framework is also used to assess the impact of hypothetical but plausible macroeconomic and bank-specific shocks on the stability of the commercial banking sector over the medium-term. The informational approach performs well even when data are limited, ill-conditioned, or when explanatory variables are highly correlated, making it an appropriate framework for the evaluation of bank-failure dynamics.

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[1] The views expressed in this paper are those of the author and do not necessarily reflect the view of the Bank of Jamaica.

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I. Introduction

The last two decades have seen a proliferation of systemic banking crises, as documented by the studies of **Lindgren, Garcia, and Saal (1996)** and **Caprio and Klingebiel (1996),** among others. The spread of banking sector problems and the difficultly of anticipating their occurrence has highlighted the need to improve the monitoring capabilities of bank supervisors. To date, bank crisis research has focused on identifying potential indicators of vulnerability, synthesizing the information from these indicators and assessing their predictive performance **(IMF: Research Bulletin, 2003)**. These studies, by and large, have conducted statistical analysis of past banking crises to identify a set of indicators linked to the likelihood of future problems. Some research studies have, for example, used large panel data of countries which have experienced banking sector distress to estimate multivariate logit models. These studies have shown that there is a group of variables that are robustly correlated with the emergence of banking sector crises.

This paper applies a semi-parametric technique to estimate the probability of a banking crisis conditional on bank-specific characteristics. In addition, the impact of exogenous macroeconomic effects and changing financial market conditions on the transition probabilities are estimated. Using the information provided by this framework, estimated probabilities can be used to make a quantitative assessment of fragility. More specifically, these probabilities could trigger a supervisory action such as gathering more information on the risk exposure, scheduling on-site bank inspections or taking other preventative regulatory measures. Secondly, the framework could be used to objectively assess the fragility of the banking system as well as forecast the fragility/robustness of the sector over the medium term.

II. Literature Review

The literature on banking crises has sought to examine the developments leading up to the crisis as well as the policy response before, during and in the aftermath of the crisis. In these studies some key macroeconomic parameters have been cited as key indicators of an impending banking crisis. For example, *credit growth*, *equity price declines*, as well as the *ratio of broad money to foreign exchange reserves* have been identified as critical variables in the evaluation of banking sector vulnerabilities (see for example, **Gavin and Hausman (1996)** and **Sachs, Tornell, and Velasco (1996)**). **Honohan (1997)** use event –study analysis to determine the importance of key factors in the predictions of an impending banking crisis. The study revealed several bank specific factors which preceded banking crises. In particular, he showed that banking crises were associated with *higher loan-to-deposit ratio*, a *higher foreign borrowing-to-deposit ratio*, and *higher growth rate of credit*. Also, a high level of lending to government and of central bank lending to the banking system were associated with crises related to government intervention.

After a set of useful indicators have been identified, the information contained in the indicators need to be combined in an objective manner. The seminal frameworks in the literature to accomplish this task are the indicators approach type models of **Kaminsky and Reinhart (1998)** and limited dependent variable probit/logit models (see, for example **Caprio, Gerry, et. al 1996)**. These papers have sought to use variables which are highly correlated with banking crises to develop statistical and empirical models to predict the likelihood of future banking crises. The basic premise of the nonparametric 'signals' approach is that the economy behaves differently on the eve of a financial crisis and that this aberrant behavior has a recurrent systemic pattern. The signals approach is given diagnostic and predictive content by specifying what is meant by an ‘early’ warning, by defining an ‘optimal threshold’ for each indicator, and by choosing one or more diagnostic status to measure the probability of experiencing a crisis. Furthermore, the indicator methodology takes a more comprehensive approach to the use of information without imposing too many a priori restrictions that are difficult to justify. However, these indicators have a large incidence of type I error as they fail to issue a signal in 73.0 per cent to 79.0 per cent of the observation during the 24 months preceding a crisis. The incidence of type II error, on the other hand, is much lower, rating between **8.0 per cent** and **9.0 per cent**.

On the other hand, multivariate logit models of banking crisis have been used to monitor banking sector fragility. These frameworks use historical incidents of previous crises over a cross-section of countries and time to identify a set of indicators which would signal the likelihood of future problems. By and large, the research shows that there is group of variables, including macroeconomic variables, characteristics of the banking sector, and structural characteristics of the country, that are robustly correlated with the emergence of banking sector crisis. **(Demirguc-Kunt, Ash et. al. (1998a)**. However, at best these models have been found to have real but limited out-of-sample predictive power.

Several factors can be put forward as limiting the performance of these empirical frameworks as early warning systems. Supervisors are usually constrained to make the determination of the health of the financial system using a relatively small number of observations of crises from the total population of the healthy banks. Secondly, the bank specific data sets used in the evaluation of the soundness of the system, generally obtained by extracting information from balance sheets and income statements, involve a large number of variables that are in most cases highly correlated. Thus, traditional maximum likelihood (ML) as well as the Bayesian approaches often fail to yield stable estimates. Without stability (low variances) of the estimates, it is extremely hard to draw inferences from the data. Further, in most cases the underlying distribution that generated the data is unknown. When the underlying distribution is unknown (a realistic assumption for relatively small data sets), the maximum likelihood approaches may yield poor estimates. Likewise, traditional estimation techniques like OLS fail, or require strong restrictions, because the estimated parameters must satisfy probability assumptions. **Mac Rae (1977)** suggested a logit transformation, which automatically satisfied the probabilistic constraints (see **Zepeda 1995a, b** for applications). However, there often is still a degrees of freedom problem which restricts the researcher to the choice of a limited number of explanatory variables. Even if sufficient degrees of freedom are available there can be problems with the convergence of the estimation algorithms. Because most data sets collected by bank examiners or banks suffer from some or all of these data problems, the more traditional estimation methods may fail to provide stable and efficient estimates.

The relatively small number of bank failures in large measure has encouraged researchers to use pooled, over several years and several countries, cross-section estimation frameworks in the bank-failure literature. However, models developed on cross-section data, by design, omit time-varying factors and as result fail to capture the underlying dynamics of the failure/survival process. That is, it does not capture the process by which banks reposition their portfolios and lending strategies to correspond to contemporaneous economic and industry conditions/shocks. Also, the conventional EWM design for bank failure which has a binary formulation (i.e. fail/ non-fail) is not able to capture the underlying dynamics of the failure/survival process. As such, although these models tend to perform well at classifying banks within sample, they generally perform poorly out of sample. Furthermore, not all methods or techniques that are used with cross-section data work well with time-series/cross section data.

This paper utilizes an informational-based approach known as Generalized Maximum Entropy **(GME)** to assess the risk profile of the banking sector.[2] The informational based approach performs well even when the data are limited or ill-conditioned, or when the covariates are highly correlated. Furthermore, using a Markov process to characterize the health of the banking system facilitates the assessment of changes in the quality or robustness of the banking sector over time. A stationary Markov model approach is used, where the transition probabilities from one Markov state *(e.g. healthy)* to another *(e.g. unhealthy)* are explained by a set of exogenous macroeconomic variables as well the portfolio decisions of banks over time.[3] This approach has the advantage that it relies on aggregated data of finite size categories - the so-called Markov states -- at given discrete time intervals. The approach thus obviates the requirement of longitudinal time-ordered

[2] For a review of the both the classical ME and the GME approaches, see Golan, Marsha Courchane, Amos Golan, and David Nickerson

[3] See **(Lee 1977)**, **Zepeda (1995a, b)** for a list of general Markov related studies.

micro data describing movement between different states, data which are only sparsely available. The multistage design combined with the information theoretic approach has several advantages over the more conventional binary-state approach generally found in the bank-failure literature (**Altman, et al., 1981; Fissel, et. al., 1996; Looney, et al., 1989; and Kolari, et al., 2001**).

i) This approach captures the problem-bank/failure transition process over several states of financial distress; a model design that better serves the bank supervisor's early intervention objectives. Moreover, rather than being binary, it differentiates between banks that remain healthy, those that exhibit distress but recover and those that eventually fail.

ii) The GME is a semi-parametric, robust estimator that is based on fewer distributional assumptions than conventional maximum likelihood (or full information maximum likelihood) methods.

iii) The GME procedure can incorporate bank-specific time-series, cross -section data as well as time-varying macroeconomic and financial market variables directly into estimation of the transition probabilities

The paper is organized as follows. Section III discusses the data used in the estimation process and describes trends in risk factors within the banking sector. Section IV discusses the results obtained from estimating the model based on data from Jamaica between 1996 -2006. Finally, Section V closes with some concluding statements and qualifying remarks.

III. Data

Bank specific data was collected for 44 quarters for all commercial banks between 1996Q1 and 2006Q3. Failed and merged banks were identified distinctly for purposes of the analysis.

Bank-Specific Covariates and Macroeconomic Variables

Several bank-specific ratios based on publicly available data that reflect credit, interest rate, and liquidity risks were identified. In addition, several institutional-type variables were selected to capture their dynamic effect on banks' transition to alternative states. Finally, a set of macroeconomic variables that may, a priori, have an impact on the stability of the financial sector were also selected. These indicators reflected both the general state of the economy as well as time-varying monetary policy. The initial selection of bank-specific and macroeconomic variables was consistent with those generally found in the bank-failure literature or commonly identified as indicators of a fragile/strong banking system.

Banks are assumed to continually reposition their portfolios and redevelop their intermediation strategies in response to changes in both current and anticipated market conditions. Table 2 presents the average value (on a pooled basis) for each bank-specific covariate included in the model for both the full sample and three sub-periods.

TABLE 2

Bank-Specific Summary Statistics

Category	Description of Measure	Average Values			
		1996Q1 -2006Q3	1996Q1 -1998Q4	1999Q1 -2002Q4	2003Q1 -2006Q4
Credit Risk	Asset Growth (percentage change)	3.23	6.08	-0.05	4.36
	Non-performing Loans/ Loans	11.58	22.17	12.43	2.21
	Income Earned but Not Received/ Loans	3.54	11.62	0.49	0.33
	Net Interest Income/ Loans	71.26	188.42	41.34	9.45
Market Risk	Liquid Assets/ Liabilities	44.46	45.30	48.83	39.13
	Net Loans/ Deposits	48.24	68.66	34.25	46.83
	Securities / Assets	29.15	20.48	27.79	37.55
Institutional	Regulatory Capital/RWA	14.43	1.54	17.04	21.97

The trend in the average values across sub-periods suggests that, as a group, banks adjusted their behaviour quite extensively to changes in market conditions over the sample period. This was reflected in the pronounced change in the average values of the covariates between the 1996-1999 and 2000 – 2003 sub-periods.

In **Table 3**, the average values of the bank-specific covariates by failure status are shown.[4] There are significant differences in the average (pooled) values of bank-specific covariates by failure status over the full sample; a result that suggests that all banks did not correctly position themselves to survive credit, interest rate, and liquidity shocks.

TABLE 3[5]

Bank-Specific Summary Statistics by Failure States

Category	Description of Measure	Average Values (Per cent)							
		1996Q1 -2006Q3		1996Q1 -1998Q4		1999Q1 -2002Q4		2003Q1 -2006Q4	
		Non-Failed	*Failed*	*Non-Failed*	*Failed*	*Non-Failed*	*Failed*	*Non-Failed*	*Failed*
Credit Risk	Asset Growth (percentage change)	4.53	1.86	5.50	7.96	3.98	-0.84	4.36	NA
	Non-performing Loans/ Loans	8.74	17.21	13.56	30.99	11.17	33.45	2.29	NA
	Income Earned but Not Received/ Loans	1.32	11.75	3.65	15.60	0.48	0.80	0.33	NA
	Net Interest Income/ Loans	7.65	270.44	6.97	279.15	7.97	244.29	7.84	NA
Market Risk	Liquid Assets/ Deposits*	46.84	30.03	53.88	41.41	48.79	49.65	39.13	NA
	Net Loans/ Deposits	38.92	39.04	41.12	89.90	29.85	54.54	46.83	NA
	Securities / Assets*	30.51	13.46	21.34	20.40	30.79	30.34	37.55	NA
Institutional	Regulatory Capital/RWA	17.90	1.91	9.81	-4.95	20.16	12.88	21.97	NA

[4] Banks that failed are labeled as 'failed' for the full sample period. That is, a bank that fails at any time during the sample period is classified as a failed bank.

[5] The period of 1996-1999 captures the banking sector distress and precedes the implementation of significant regulatory reform to militate against credit, counterparty and, to a lesser extent, market risk. The large number of bank failures during this period reflected the general state of the banking sector which was affected by the liberalization of the economy in the early 1990's, underdeveloped risk management systems within banks as well as significant fluctuations in macroeconomic variables. A relatively small number of failures occurred in the post 1999 sub-period. This sub-period is used to generate prior transition probabilities in the model.

For example, failed banks over the full sample period had higher rates of asset growth, held lower quality loans and maintained lower levels of liquid assets to liabilities.

Table 3 also shows the average values of the covariates by failure/survive status for each of the three-sub-periods in which there were large (1996 – 1999), moderate (1999 – 2003), and small (i.e., 2003 – 2006) number of failures. These results show that the relationship between non-failed and failed banks continues to hold over time, even as banks, as a group, adjust to changes in the market. The average values by failure status are significantly different for each sub-period, except for asset growth.

The macroeconomic variables used in the model as well as the average values over the full sample and the sub-periods are shown in **Table 4**. These results show that the macroeconomic conditions have changed significantly over time – with lower unemployment and interest rates in the later period of the sample. The sub-periods were defined with respect to the volume of bank failures and tended not to correspond directly to the business cycle. However, the relatively large difference in the average values of the macroeconomic variables across the sub-periods suggests that macroeconomic conditions contributed to the overall condition of the banking system. This implies that traditional bank-failure of EWM models that omit macroeconomic variables are underspecified.

TABLE 4

Macroeconomic Variables

Variables	**Source**	**Summary Statistics**			
		1996Q1 -2006Q3	1996Q1 -1998Q4	1999Q1 -2002Q4	2003Q1 -2006Q4
Real GDP Growth	STATIN	0.19	-2.73	1.07	1.68
Unemployment Rate	STATIN	14.35	16.00	15.28	11.84
Tbills (6 - Months)	BOJ	20.52	27.64	17.43	17.62
Oil Prices	BOJ	30.90	18.69	26.71	47.03
Wieghted Average Loan Rates	BOJ	24.29	34.33	21.70	18.08

IV. Methodology:

i. A Markov Transition Model Early Warning System

Various states are defined (e.g. financially sound, distressed, insolvent/failure, and closure) in terms of the regulatory capital- risk weighted assets measure. Specifically, the binary random variable y_{itj} is classified as 1 if the i[th] bank (i=1, 2,…,n) is in state j (j=1,2,…,K) at time t (t=1,2, …,T), and y_{itj} is classified as 0 for other K-1 states. The resulting transition probabilities measure the probability that a bank with regulatory capital $y_{t,j}$ (state j, in time t) will have regulatory capital $y_{t+1,k}$ (state k, in time t+1) in the next period. These transition probabilities capture the likelihood that a bank will exhaust or increase its regulatory capital in period t+n conditional on its initial state and that of the macro economy, in time t.

Table 5, shows the nine states as defined within the EWS framework using the Bank of Jamaica's regulatory minimum as a standard benchmark of **10.0 per cent** as indicative of banks which are sufficiently capitalized (CAP).

Table 5

Transition States

States	Label/Zone	Short Name	Criteria
1	Insolvent (Book-Value)	INSOL	Capital/RWA < 0%
2	Near Failure	NFAIL	0% < Capital/RWA < 7%
3	Critically Undercapitalized	CUNDER	7% < Capital/RWA < 8 %
4	Significantly Undercapitalized	SUNDER	8% < Capital/RWA < 9%
5	Undercapitalized	UNDER	9% < Capital/RWA < 10 %
6	Capitalized	CAP	10 % < Capital/RWA < 15 %
7	Well Capitalized	WCAP	15 % < Capital/RWA < 20 %
8	Significantly Capitalized	SCAP	Capital/RWA > 20 %
9	Failure	FAIL	Closed by Supervisor

States 9 is an absorbing state; banks never leave these states once they enter. For example, banks that fail in time t remain in that state in time t+1. Banks that begin the period in state 9 are censored and remain in that state in $t+\tau, \quad \tau = 1,2,...,\infty.$

The objective is to estimate the K x K Markov transition probabilities, p, using information contained over the full sample period. Specifically, the stationary Markov process to be modeled by:

$$y_{t+1,j} = \sum_{k=1}^{K} p_{kj} y_{tk} \,, \qquad \text{(1a)}$$

where y_{t+1} is a K-dimensional vector of *proportions* representing the fraction of banks in the jth Markov state in period t+1, p_{kj} are the stationary Markov probabilities over the relevant periods and y_t is a K-dimensional vector of *proportions* in the kth Markov state in period *t*. The parameter, y_{tk} , represents the fraction of banks in the kth Markov state in period t. The stationary Markov probabilities are defined as probabilities by imposing the restriction in equation 1b.

$$\sum_{j=1}^{K} p_{kj} = 1 \qquad \text{for j, k = 1,2,3, …, K,} \qquad \text{(1b)}$$

The model depicted by equations (1a) and (1b) is underdetermined as there are infinitely many stationary Markov solutions that satisfy this basic relationship.[6] Hence, a maximum entropy (ME) decision criterion is used to select one of the infinitely many solutions.

To provide a basis for understanding the philosophy for the ME approach, consider the following example. Let $\Theta = \{\phi_1, \phi_2 ..., \phi_M\}$ be a finite set and p be a probability mass function of Θ. The **Shannon's (1948)** information criterion, called entropy, defined as $H(p) = -\sum_{i=1}^{M} p_i \log p_i$ with $0 \log 0 \equiv 0$. This *H (p)* information criterion measures the uncertainty or informational content in Θ which is implied by p. The entropy-uncertainty measure H (p) reaches a maximum when $p_1 = p_2 = ... p_M = 1/M$ and a minimum with a point mass function. Given the entropy measure and structural constraints in the form of

[6] That is, the number of unknowns exceeds the number of data points if the number of periods T is small as thus the solution is indeterminate and/or the data sample used is noisy.

moments of the data distribution, **Jaynes (1957a)** proposed the maximum entropy (ME) method, which is to maximize H (p) subject to structural constraints.[7]

To relate the ME formalism to the stationary Markov process with no noise considered in equations (1a) and (1b) the ME formulation is shown in equation (2a)

$$ME = \begin{cases} \hat{p} = \arg\max\left\{ -\sum_{k,j} p_{kj} \log p_{kj} \right. \\ s.t \\ y_{t+1,j} = \sum_{p} p_{kj} y_{tk} ; \quad and \quad \sum_{j} p_{kj} = 1 \end{cases} \tag{2a}$$

The solution to the ME problem in equation (2a) is

$$\hat{p}_{kj} = \frac{\exp\left(-\sum_{t} y_{tk} \hat{\lambda}_{tj} \right)}{\sum_{j} \exp\left(-\sum_{t} y_{tk} \hat{\lambda}_{tj} \right)} \tag{2'}$$

where $\hat{\lambda}$ is the vector of K Lagrange multipliers associated with equation (2a).

However, the solution (2') may be underspecified as the formulation ignores the impact that micro-specific bank data as well as macroeconomic variables may have on the failure outturn or stability of a bank in time t+1. Instrumental Variable Generalized Maximum Entropy **(GME-IV)** formalism by **Golan, Judge and Miller (1996a)** is employed so as to incorporate the impact of the information contained in the balance sheets and income statements as well as the macroeconomic variables on the estimation of $\hat{p}$. The GME- IV formalism is used to recover coefficients on the effects of exogenous bank-specific and macroeconomic variables on the individual transition probabilities when a specific (linear) functional restriction is imposed. This method allows the use of an extensive set of explanatory variables.

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[7] If constraints are not imposed, H (p) reaches its maximum value and the distribution of the p's is a uniform one.

GCE- IV formalism is derived as follows. Let z_{ti} be a G-dimensional vector of bank-specific covariates (e.g., asset quality, liquid asset-to deposits, etc.) with individual elements z_{gti}. In addition, for each period t, let s_t be an L-dimensional vector of macro-level variables. The bank-specific covariates vary by both state and time. However, the macro-level variables vary only with time. These bank-specific and macroeconomic variables can be represented as X= [Z,S] with elements $x_{nti}(n = 1,2,..., N; N = G + L)$ and L macro variables held constant across states. **Golan, Judge and Miller (1996a)** show that given that the exact functional relationship describing the effect of Z and S on the transition probabilities is unknown, an instrumental variables approach, shown in equation (3a), can be used to capture the information related to these variables via the cross moments:

$$\sum_{t-2}^{T}\sum_{j} y_{tj}\, x_{ntj} = \sum_{t-1}^{T-1}\sum_{k=1}^{K} p_{kj}\, y_{tk}\, x_{ntk} + \sum_{t=1}^{T-1}\sum_{i} e_{tj}\, x_{ntk} \tag{3a}$$

The formulation in equation (3a) incorporates both the bank-specific and macroeconomic data. The formulation also incorporates noise as part of the modelling process via the second term on the right hand side of the equation. The incorporation of the noise term is important given the fact that the bank-specific data is measured at book values rather than market values, subject to measurement error as well as successive revisions. Specifically, e_{tj} is a random error term for each state j and period t, $e_{tj} \equiv \sum_{m=1}^{M} w_{tjm} v_m$, v is a symmetric – around-zero support space for each random error e_{tj}, $\sum_{m=1}^{M} w_{tjm} = 1$ and $M \geq 2$. As such equation (3a) can be re-written as

$$\sum_{t-2}^{T} \sum_{j} y_{tj} x_{ntj} = \sum_{t-1}^{T-1} \sum_{k=1}^{K} p_{kj} y_{tk} x_{ntk} + \sum_{t=1}^{T-1} \sum_{k} \sum_{m} w_{tkm} x_{ntk} v_m \tag{4a}$$

The resulting GME-IV estimation rule for the Markov problem is

$$GME-IV = \begin{cases} \underset{\{p,w\}}{Max} \quad \left\{ -\sum_{k,j} p_{kj} \log p_{kj} - \sum_{t,j,m} w_{tjm} \log w_{tjm} \right\} \\ s.t. \\ \sum_{t-2}^{T} \sum_{j} y_{tj} x_{ntj} = \sum_{t-1}^{T-1} \sum_{k=1}^{K} p_{kj} y_{tk} x_{ntk} + \sum_{t=1}^{T-1} \sum_{k} \sum_{m} w_{tkm} x_{ntk} v_m \\ \sum_{j} p_{kj} = 1; \sum_{m} w_{tjm} = 1 \end{cases} \tag{5a}$$

The solution to the GME-IV problem is

$$\hat{p}_{kj} = \frac{\exp\left(-\sum_{t=1}^{T-1} \sum_{n} y_{tk} x_{ntk} \hat{\lambda}_{jn} \right)}{\sum_{j} \exp\left(-\sum_{t=1}^{T-1} \sum_{n} y_{tk} x_{ntk} \hat{\lambda} \right)} \equiv \frac{\exp\left(-\sum_{t=1}^{T-1} \sum_{n} y_{tk} x_{ntk} \hat{\lambda}_{jn} \right)}{\Omega_k} \tag{5'b}$$

and

$$\hat{w}_{tjm} = \frac{\exp\left(-\sum_{n} x_{ntk} v_m \hat{\lambda} \right)}{\sum_{m} \exp\left(-\sum_{n} x_{ntk} v_m \hat{\lambda}_{jn} \right)} \equiv \frac{\exp\left(-\sum_{n} x_{ntk} v_m \hat{\lambda}_{jn} \right)}{\Psi_{itj}} \tag{5'c}$$

with

$$\hat{e}_{tj} = \sum_{m} \hat{w}_{tjm} v_m . \tag{5'd}$$

Maximizing equation 5 and solving for λ, yields the estimated $\hat{\lambda}$, which in turn yield the optimal probabilities $\hat{p}_{kj}$ and $\hat{w}_{tjm}$ via equations (5'c) and (5'd). The GME and the GME-IV optimization problem were programmed and solved using GAMS software. [8]

ii. Diagnostics and Model Reliability

a) Sensitivity Analysis

The incremental or marginal effect of a change in bank-specific ((z_{ntk}) or macroeconomic variables (s_{tl})on the transition probabilities (p_{kj}) can be derived from equation (5'b). The marginal effect of each bank-specific covariate and macroeconomic variable on the estimated transition probabilities is derived by differentiating equation (5'b) with respect to x_{ntk}:

$$\frac{\partial p_{kj}}{\partial x_{ntk}} = p_{kj} y_{tk} \left[\lambda_{jn} - \sum_j p_{kj} \lambda_{jn} \right] \tag{6a}$$

and evaluating at the means, or at any other value of interest, to capture the 'dynamic' effects of the market on the transition probabilities. These are used to inform the impact on the stress test scenarios on the probability that a bank transitions to failure from each of the other states as a result of a shock to the macroeconomic environment.

b) Goodness of Fit

The amount of information captured by the GCE-IV model can be measured using a normalized entropy measure $S(\tilde{P})$ defined in equation (6b).

$$S(\tilde{P}) \equiv \frac{-\sum_k \sum_j \tilde{p}_{kj} \ln \tilde{p}_{kj}}{-\sum_k \sum_j \tilde{p}^{o}_{kj} \ln \tilde{p}^{o}_{kj}} \tag{6b}$$

[8] See **Brook et. Al**, (1992) for a further description of this algebraic modelling package.

with the $\tilde{p}_{kj}$ representing estimated transition probabilities under the GCE-IV estimation rule and the $\tilde{p}^{o}_{kl}$ are the prior probabilities. $S(\tilde{P})$ is bounded between 0 and 1, with 1 reflecting complete ignorance of the estimates and 0 reflecting perfect knowledge **(Golan, Judge, and Perloff, 1996b)**. In that way, $S(\tilde{P})$ captures the amount of information in the data relative to the initial knowledge reflected in the priors **(Soofi, 1996)**. The normalized entropy measure, $S(\tilde{P})$ can also be used to derive a pseudo-R^2 measure, a measure of in-sample goodness-of-fit, based on the normalized entropy S **(McFadden, 1974)**:

$$Pseudo \quad R^2 \equiv 1 - S(\tilde{P}); \qquad (6d)$$

c) Entropy Ratio

In addition, a likelihood ratio test of model fit can be constructed which is analogous to that developed under the maximum likelihood (ML) procedure. That is, let I_{Ω} be the value of the optimal GCE objective function where the parameters of interest is equivalent to minimizing (5a) subject to no constraints. Let I_{ϖ} be the constrained GCE-IV model, constrained such that $\beta \neq \lambda \neq 0$. Then, the Entropy Ratio (ER) static is defined in equation (6c).

$$\text{ER} = \quad 2\left|I_{\Omega} - I_{\omega}\right|. \qquad (6c)$$

Under the null hypothesis, ER converges in distribution to $\chi^2_{(K-1)}$. Hence the ER static can be used to evaluate the usefulness of the overall model.

Empirical Results

a) Evaluation of Unconditional and Conditional Transition Probability Matrices

The prior probabilities are derived from the quarterly transition frequencies over the first three years of the sample. They are computed as the mean of the percentage of banks in state i in time t that fall in state j in time $t+1$, $i, j = 1,2,....,9,$ *and* $t = 1,2.....,12.$ These probabilities are estimated based on the mean behaviour of all banks within each state in time t. Therefore this configuration makes the framework suited for identifying systemic fragility which is a critical importance to supervisors. The prior probability matrix is shown in **Table 6**.

Table 6

Unconditional TPM (March 1999 - December 2002)

	SCAP	WCAP	CAP	UNDER	SUNDER	CUNDER	NEARF	INSOL	FAIL	MERG
SCAP	0.900	0.100	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
WCAP	0.000	0.728	0.222	0.000	0.050	0.000	0.000	0.000	0.000	0.000
CAP	0.000	0.067	0.730	0.150	0.000	0.033	0.020	0.000	0.000	0.000
UNDER	0.000	0.000	0.300	0.600	0.100	0.000	0.000	0.000	0.000	0.000
SUNDER	0.000	0.000	0.100	0.000	0.600	0.200	0.000	0.100	0.000	0.000
CUNDER	0.000	0.000	0.100	0.100	0.100	0.700	0.000	0.000	0.000	0.000
NEARF	0.050	0.000	0.100	0.000	0.020	0.020	0.593	0.192	0.025	0.000
INSOL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000
FAIL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000
MERG	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000

SCAP: Significantly Capitalized, **WCAP**: Well Capitalized, **CAP**: Capitalized, **UNDER**: Undercapitalized, **SUNDER**: Significantly Undercapitalized, **CUNDER**: Critically Undercapitalized, **NEARF:** Near Fail, **INSOL:** Insolvent, **FAIL:** Failure, **MERG:** Merged

The application of the GCE-IV procedure based solely on the prior transition probabilities (P^0) and the row shares (Y_t) is shown in **Table 7**. The proportions of banks in the k^{th} Markov state between March 2003 and September 2006 are used to define the row shares Y_t and are incorporated into the analysis via the constraints outlined in equation (2a). The empirical results show a **22.2 per cent** increase in the likelihood that a well capitalized bank in the first period will remain well capitalized in the next period. This is concomitant with a proportionate decline in the probability that a well capitalized bank in the current period will be downgraded to being a capitalized. Additionally, the likelihood that undercapitalized bank remained undercapitalized declined by **2.1**

percentage points to **57.9 per cent**, while the probability of a critically undercapitalized remaining undercapitalized declined by **1.0 percentage point** to **68.0 per cent**.

Table 7

Conditional TPM Using Proportions of Banks in Each State (March 1996 - September 2006)

	SCAP	WCAP	CAP	UNDER	SUNDER	CUNDER	NEARF	INSOL	FAIL	MERG
SCAP	0.900	0.100	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
WCAP	0.000	0.949	0.000	0.000	0.050	0.000	0.000	0.000	0.000	0.000
CAP	0.000	0.067	0.730	0.148	0.000	0.033	0.020	0.000	0.002	0.000
UNDER	0.000	0.000	0.300	0.579	0.100	0.000	0.000	0.000	0.021	0.000
SUNDER	0.000	0.000	0.100	0.000	0.600	0.200	0.000	0.100	0.000	0.000
CUNDER	0.004	0.000	0.100	0.100	0.100	0.686	0.000	0.000	0.010	0.000
NEARF	0.050	0.000	0.100	0.000	0.020	0.020	0.593	0.192	0.025	0.000
INSOL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000
FAIL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000
MERG	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000

SCAP: Significantly Capitalized, **WCAP**: Well Capitalized, **CAP**: Capitalized, **UNDER**: Undercapitalized, **SUNDER**: Significantly Undercapitalized, **CUNDER**: Critically Undercapitalized, **NEARF:** Near Fail, **INSOL:** Insolvent, **FAIL:** Failure, **MERG:** Merged

These results are in line with *a priori* expectations and reflect the marked improvement in the stability of the banking sector following the banking distress of the mid to late 1990s. It should be noted, however, that these results do not reflect the effect of bank-specific or macroeconomic conditions on the estimates of the transition probabilities between December 1999 and December 2005.

The GCE-IV transition probabilities estimated using equation (5a) are shown in **Table 8**. Specifically, lagged values of bank-specific covariates and macroeconomic instruments through the moment constraints derived in equation (5a) are introduced into the estimation process. Closely following the existing literature on bank failure, several bank-specific ratios as well as macroeconomic variables based on publicly available data were selected **(See Table 4 and Table 5).** The information measure, $S(\tilde{P})\big|_{GME-IV}$, is 0.77. The normalized entropy measure that converts to a pseudo-R^2 of 0.33 and a value for the ER statistic of 20.02, exceeds the critical value of $\chi^2_{df=8,\alpha=0.05}(15.51)$. The estimates from the CGE-IV estimation approach capture significant nuances in the likelihood of banks transitioning from one state to another that would be omitted in the approach which uses only proportional state information.

Table 8

Conditional TPM Using Proportions, Bank Specific and Macro Economic Data (March 1996 - September 2006)

	SCAP	WCAP	CAP	UNDER	SUNDER	CUNDER	NEARF	INSOL	FAIL	MERG
SCAP	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
WCAP	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
CAP	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
UNDER	0.0000	0.0000	0.0000	0.5970	0.0960	0.0000	0.0000	0.2860	0.0210	0.0000
SUNDER	0.0000	0.0000	0.0000	0.0000	0.7710	0.1290	0.0000	0.1000	0.0000	0.0000
CUNDER	0.0000	0.0000	0.0000	0.0000	0.8360	0.1290	0.0350	0.0000	0.0000	0.0000
NEARF	0.0500	0.0000	0.1000	0.0000	0.0200	0.0200	0.5933	0.1917	0.0250	0.0000
INSOL	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.9790	0.0210	0.0000
FAIL	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
MERG	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

SCAP: Significantly Capitalized, **WCAP**: Well Capitalized, **CAP**: Capitalized, **UNDER**: Undercapitalized, **SUNDER**: Significantly Undercapitalized, **CUNDER**: Critically Undercapitalized, **NEARF:** Near Fail, **INSOL:** Insolvent, **FAIL:** Failure, **MERG:** Merged

For instance, the GCE-IV identifies the significantly capitalized banks as merely a transitory state with **100.0 per cent** of the banks in the state likely to move to being well capitalized in the next quarter. That is, banks may in one period either to cushion themselves for significant credit or market risk allocate funds to capital well above the required regulatory threshold. However, as this threat passes the banks will reposition their portfolios to the state of being well capitalized. Again, banks that were well capitalized in the first period were found to remain well capitalized in the next. This reflects the marked improvement in the stability of the banking sector following the banking distress of the mid to late 1990s.

The estimates for the Undercapitalized, Significantly Undercapitalized, and Critically Undercapitalized are of particular interest to supervisors because changes in the likelihood of banks entering this state yield significant early warning information. In particular, it is observed that **9.6 per cent** of banks which are undercapitalized in the first period are likely to become significantly undercapitalized in the next. Additionally, **28.0 per cent** are likely to become insolvent and **2.0 per cent** are likely to fail. For significantly undercapitalized banks **13.0 per cent** are likely to become critically undercapitalized and **10.0 per cent** are likely to become insolvent. Finally, for Critically Undercapitalized banks, **3.0 per cent** are likely to become near failed institutions.

Interestingly, for near failed institutions it is estimated that **10.0 per cent** are likely to become capitalized in the next period and **5.0 per cent** significantly capitalized in the next period. This implies that banks can reposition their portfolios after a significant shock to their capital position so as to rebound over the next period. This observation by itself suggests that models which classify the transition process as binary are underspecified. Along the main diagonal it is observed that banks increased the likelihood of remaining well capitalized and significantly undercapitalized by **5.0** and **17.1 percentage points**, respectively.

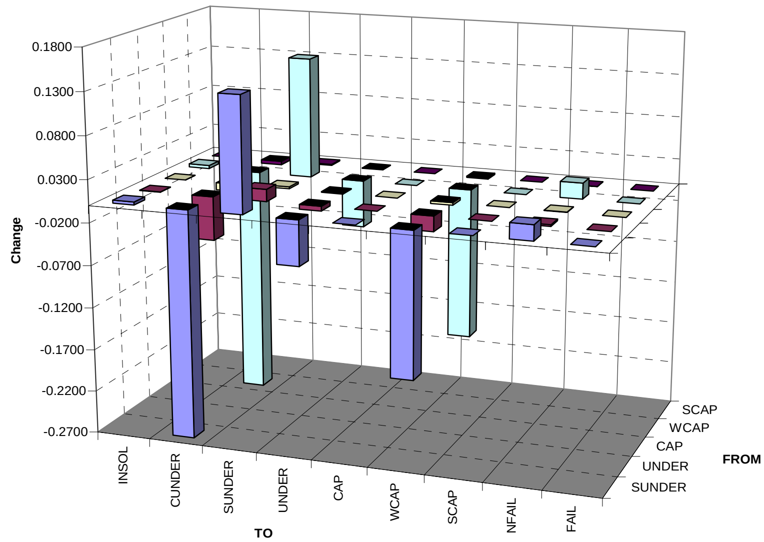
b) Sensitivity Analysis

Figures 1-3 report the marginal effects that selected bank-specific covariates and macroeconomic variables would have on the estimated transition probability estimates. The marginal effects show the direct effect of an increase in the bank-specific factor or macroeconomic variables on each of the transition probabilities.

Incremental Effect of a Change in the Treasury Bill Rate (6-months)

The probability of a bank transitioning from being (WCAP) to being insolvent (INSOL) increased by *0.004* for a **100.0 bps** increase in the Treasury Bill rate. Again, there was a *0.001* increase in probability of a bank transitioning from being significantly capitalized (SCAP) to significantly undercapitalized (SUNDER) for a **100.0 bps** increase in the Treasury Bill rate. On the other hand, the same marginal increase in the rate reduced the probability of banks transitioning from undercapitalized (UNDER) to well-capitalized (WCAP) by *0.018*. These results suggest that, *at least in the short run*, positive interest rate shocks have a measurable destabilizing impact on the financial health of the commercial banking sector in Jamaica. This is likely due to the impact that an instantaneous shock to interest rates would have on the re-pricing and maturity profiles of banks before they had a chance to reposition their portfolios.

Figure 1. Incremental Effect of a Change in Treasury-bill Rate (6-months)

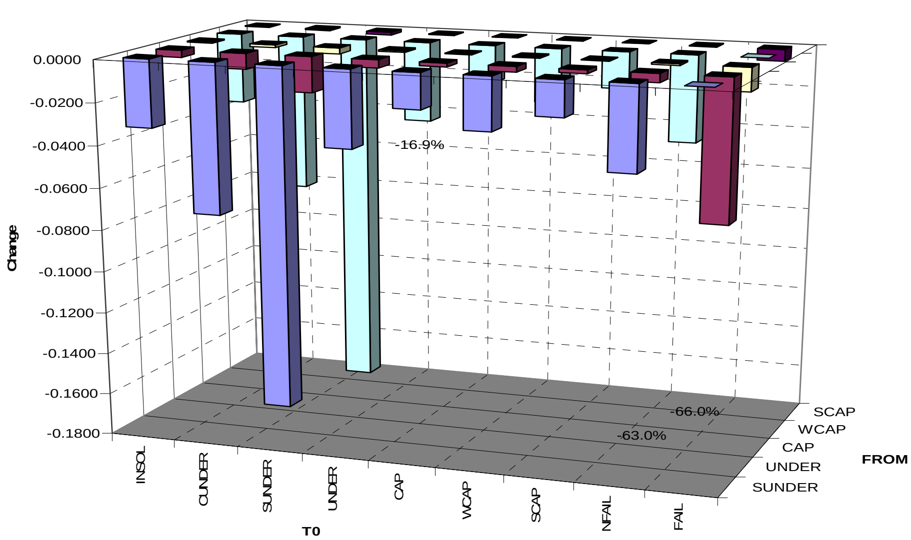


Incremental Effect of a Change in Net Interest Income (NII)

The probability of the representative bank transitioning from being well-capitalized (WCAP) to insolvent (INSOL) decreases by 0.034 for a percentage point increase in net interest income. Similarly, the probability of the representative bank transitioning from well-capitalized (WCAP) to undercapitalized in the next quarter decreases by 0.038 for a unit/percentage point increase in net interest income.

Figure 2.

Incremental Effect of a Change in Net Interest Income (NII)



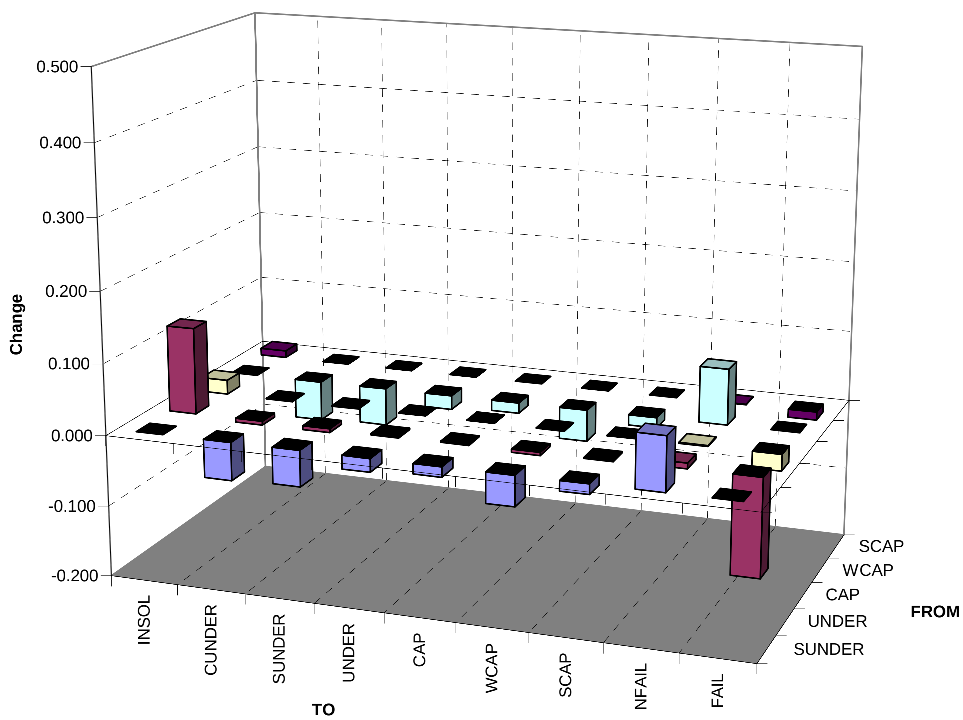
These results are quite intuitive as, *apriori*, one would expect that increases in net interest income of the bank would reduce the likelihood of transitioning from a higher state (e.g. Capitalized) to a lower state (e.g. Insolvent).

Incremental Effect of a Change in the GDP Growth Rate

Positive shocks to GDP generally have a negative impact on the likelihood of transitioning from higher state to a lower state. For example, a one per cent increase in quarter over quarter annual GDP growth rate reduced the likelihood of transitioning from being well capitalized (WCAP) to undercapitalized (UNDER) by *0.02*.

Figure 3

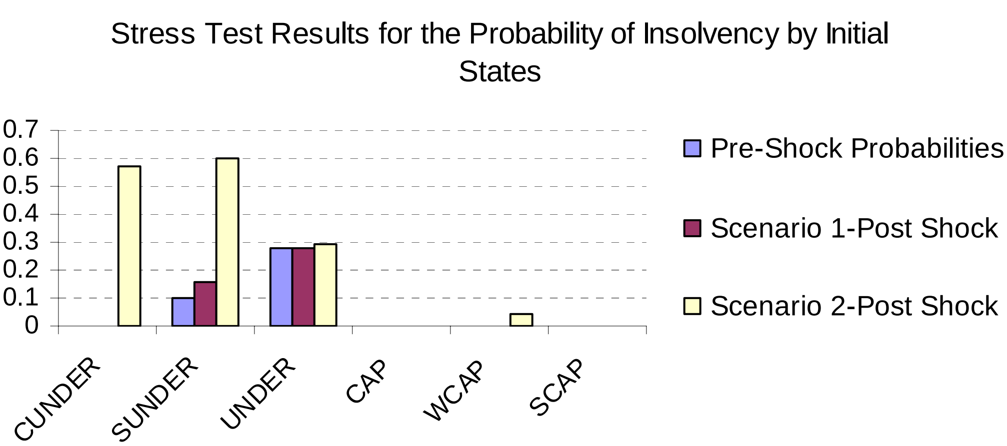
Incremental Effect of a Change in the GDP Growth Rate



c) Stress Test Result of the Commercial Banking Sector

The robustness of the commercial banking system to two hypothetical but plausible combinations of macroeconomic and bank-specific shocks is reported in **Figure 4**. The first scenario (Scenario 1) involves a positive shock of **100.0 bps** on the 6-month Treasury-bill rate, a **1.0 percentage point** decline in the gross domestic product growth rate, and a **2.0 percentage point** decline in the net interest income of commercial banks. The second scenario (Scenario 2) involves a positive shock of **500.0 bps** on the 6-month Treasury-bill rate, a **5.0 percentage point** decline in the gross domestic product growth rate, and a **10.0 percentage point** reduction in the net interest income of commercial banks. The results suggest that banks that had capital adequacy ratios below the **10.0 per cent** regulatory requirement would experience significant increases in the likelihood of becoming insolvent within one-quarter. More specifically, in scenario 2, **57.2 per cent** of critically undercapitalized banks (CUNDER) would become insolvent within one-quarter. The results also point to the robustness of the Jamaica banking sector indicating that even under the extreme shocks contemplated in scenario 2, only **0.04** of well capitalized banks (WCAP) banks would become insolvent within one quarter.[9]

Figure 4.



[9] Most commercial banks in Jamaica fall into the category of being well-capitalized (WCAP) as their initial state in the post- 2000 period evaluated in the paper.

Conclusions

Recent turmoil in the capital markets has highlighted the need for systematic stress testing of the banking sector. Less is known, however, about stress testing the portfolios of banks to evaluate the impact that macroeconomic and bank-specific shocks have on the susceptibility of banks to market and credit risks. The paper highlights the fact that underlying macroeconomic volatility is a key aspect of the assessment of the fragility of the banking sector and models which omit these factors are underspecified. Specifically, sensitivity analysis conducted in the paper confirms that the Jamaican commercial banking sector is bolstered by improvements in the growth of gross domestic product (GDP), increases in the net interest income (NII) and hampered by positive unanticipated shocks to interest rates. Moreover, stress-test analysis of commercials banks in the post 2000 period suggests that they are adequately capitalized to absorb significant adverse combinations of macroeconomic shocks on both their balance sheets and income statements.

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