Monitoring Banking Sector Soundness in the Eastern Caribbean Currency Union: A Multivariate Data Analysis Approach

Tracy Polius
& Leah Sahely[1]

Abstract

Using a combination of multivariate data analysis techniques, the paper seeks to identify key variables which can be used to monitor commercial bank performance in the context of the Eastern Caribbean Currency Union. The paper takes a step away from the development of an Early Warning System. Rather, it attempts to establish benchmarks or thresholds for financial system indicators that will signal the need for action on the part of the regulatory authorities; whether in the form of enhanced monitoring such as onsite visits, offsite analysis, institutional dialogue or intervention.

[1] Tracy Polius is a Research Fellow at the Caribbean Centre for Money and Finance, UWI, St. Augustine and *Leah Sahely is a Deputy Director in the Monetary and Financial Statistics Unit within the Statistics Department of the Eastern Caribbean Central Bank.*

Section I: Introduction

A significant portion of the work on the financial sector in recent times has been geared to the etiology of financial sector distress, and the development of systems which can be used to assess financial sector vulnerability or to predict financial sector crises. The emphasis has largely been on the identification of factors which influence or cause banking sector difficulties and the development of Early Warning Systems (EWS) which can be used to predict such crises. These EWS have been successful in some limited measure in predicting financial crises in some countries. However, the literature and experience has demonstrated that for a significant number of financial crises including, the US subprime and global financial crises, the EWS was not very effective in anticipating these events. For the most part, the literature identifies changing etiology of the different crises for the failure of EWS to predict such crises. Additionally EWS models can be described as data hungry and the informational requirements may be too significant in the context of developing economies.

In response to the failure of EWS models to predict some episodes of currency and banking crises authors such as Grabel (2004) have proposed alternative approaches to monitoring and managing risks within the financial sector. The Grabel (2004) trip wire and speed bump approach focuses less on predicting the occurrence of a crisis and more on identifying potential risks to facilitate the implementation of corrective measures. This paper is therefore cast in the spirit of Grabel (2004) and seeks to identify variables which suggest increasing risk within the banking system thus affording regulatory and other authorities the opportunity for remedial action.

This paper evaluates the performance of the banking sector which serves the Eastern Caribbean Currency Union, and seeks to isolate indicators which can identify weaker banking institutions. Moreover; these factors are grouped to determine which have the largest impact on the health of individual financial institutions. In so doing, we develop an approach to monitoring the performance of the banking system which is not as data intensive as an Early Warning System, yet will allow for improved monitoring and regulatory outcomes, and therefore reduce the probability of a crisis.

Development of this approach will allow for more effective monitoring of commercial banks within the Eastern Caribbean Currency Union and is consistent with the Central Banks objective of maintaining financial stability. However, with the exception of the failure of Bank of Montserrat and the recent run on the Bank of Antigua, precipitated by the US charges against the major shareholder, Sir Allen Stanford, the ECCU can be broadly classified as a non crisis area. In light of this, the approach focuses on indentifying factors which can weaken individual banks and possibly compromise the wider banking system. Developing such an approach in a non crisis territory can therefore be challenging as “actual” evidence for that jurisdiction cannot be used to point the main causes. We therefore take our cue mainly from the literature on the causes of banking crisis and from the limited research which has been conducted in the context of the Caribbean.

The rest of the paper is divided as follows; In Section II we include a discussion of the characteristics of the banking system in the ECCU. A summary of the literature of indicators of financial sector soundness, and early warning systems is highlighted in Section III. The methodology is detailed in Section IV and the results are presented in Section V. Brief conclusions are outlined in Section VI.

Section II: Overview of the ECCU Banking System

2.1 Financial Infrastructure

The Eastern Caribbean Currency Union (ECCU) has forty banks, 18 foreign branch banks and 22 locally incorporated banks. Of the 21 locally incorporated banks, eight are foreign owned, eleven are private owned and three are state-owned. The ECCU also has 88 off-shore banks, 7 development banks, 68 credit unions, 164 insurance companies/agencies, 7 national development foundations, 15 finance companies and 4 building and loan associations. About 70 per cent of the total assets of the financial system are held by commercial banks. The ECCB regulates all commercial banks and the 15 finance companies, inclusive of mortgage companies.

Table I: Number of Financial Institutions in the ECCU as at December 2009

Number of Institutions	ANG	ANU	DOM	GDA	MON	SKN	SLU	SVG	Total
Commercial Banks [1]	4	8	4	5	2	7	6	4	**40**
ODCs	0	7	18	20	1	4	21	9	**80**
Credit Unions [3]	0	5	17	19	1	3	16	7	**68**
Mortgage & Finance [2]	0	2	1	1	0	1	5	2	**12**
Finance Co	1	1	2	3	1	1	3	2	**14**
Finance/Microfinance [2]	0	0	0	1	0	0	2	0	**3**
Building and Loan [3]	0	0	1	1	1	0	0	1	**4**
Development Banks [3]	1	1	1	1	0	1	1	1	**7**
Insurance Co [3]	22	26	19	24	7	17	26	23	**164**
Total	**27**	**42**	**43**	**52**	**11**	**29**	**56**	**38**	**298**
Regulators									
[1]ECCB: Banks	4	8	4	5	2	7	6	4	**40**
[2]ECCB: NBFI	0	2	1	2	0	1	7	2	**15**
[3]SRUs*	23	32	38	45	9	21	43	32	**243**

During the year 2009, the assets of the domestic banking system increased by 3.2 per cent to $24.7m; deposits grew by 2.7 per cent to $16.4m. The branches of the international banks accounted for 56.7 per cent of the banking system's assets and 53.6 per cent of total deposits. These banks also control 94 per cent of the liquid assets in the banking system. Deposits account for 66.4 per cent of total liabilities and loans 69.2 per cent of assets.

2.2 Trends in Financial Indicators

Liquidity

The liquidity position in the ECCU banking system has been deteriorating over the last 5 years. As at December 2009, the ratio of liquid assets to total deposits plus liquid liabilities (LAR) stood at 29.6 per cent, compared to 29.8 a year prior (Chart 1). Liquidity during 2000 to 2004 was high, reflecting a larger rate of increase of deposits relative to the growth in credit. Between 2000 and 2004 deposit liabilities grew at an annual average rate of 8.9 per cent, while loans and advances rose on average by 5 per cent. Following that period, the LAR continuously fell to 29.6 per cent. The loans to deposits ratio increased from 90.7 per cent, a 0.16 percentage point increase from the year prior, but stood at a 6.2 percentage point increase from 2000 (Chart 2).

Chart 1: Liquid Assets to Liquid Liabilities plus Deposits

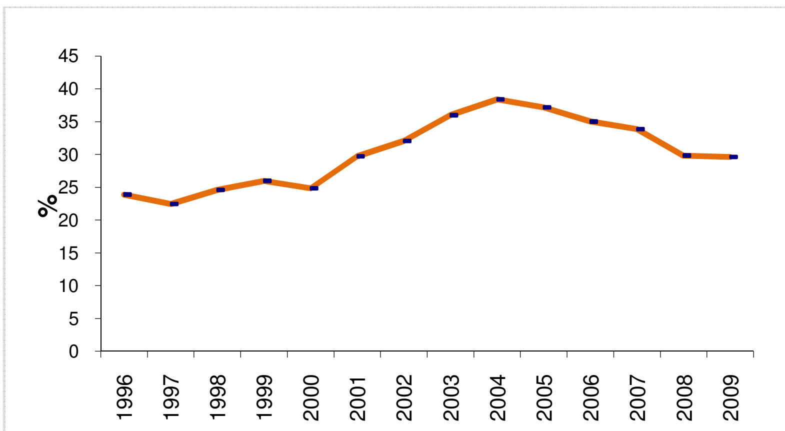
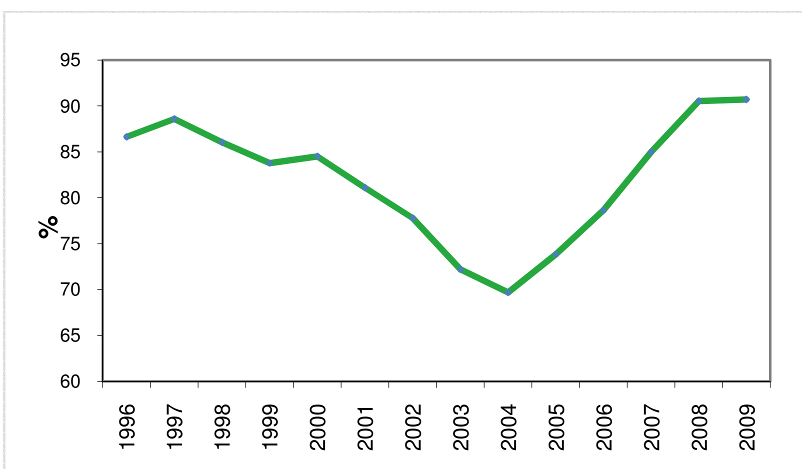


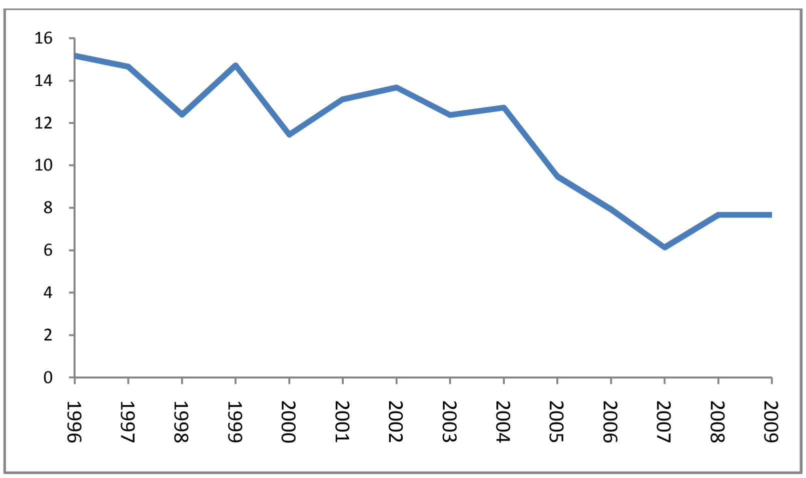
Chart 2: Loans to Deposits Ratio



Credit Quality

Credit risk exposure, the risk of customer or counterparty default, is one of the more significant risks within the ECCU financial sector. Commercial banking assets are predominantly loans and advances. As at 31 December 2009, loans constituted 60.2 per cent of the total assets of the commercial banking system and should commercial bank investments be included, credit exposures would constitute 71.7 per cent of total assets. Further, unsatisfactory assets (excluding impaired investments) as a percentage of total loans (NPL) stood at 7.7 per cent for the ECCU. Notwithstanding, there has been an overall declining trend in the ratio of non-performing loans over the period 1996 to 2007, but increased thereafter as depicted in chart 3. The main contributors to non-performing loans were natural disasters, reduced economic activity at the territory level, and weaknesses in credit administration weakness at the individual bank level.

CHART 3: NPL'S to Total Loans in the ECCU



A number of locally incorporated banks are highly exposed to the public sector. The implication is that deterioration in the fiscal positions of member governments would be reflected in the banks' performance. Banks are also vulnerable to non-bank financial institutions, such as insurance companies. The increasing existence of interrelationships between commercial banks and other non bank financial institutions also has implications for credit exposure of the banks. Commercial banks are exposed through holding financial products from with insurance companies who also hold deposits for the banks and provide property and life insurance as collateral for loans and advances.

Earnings

Earnings performance weakened as evidenced by the Return on Average Equity and Return on Average Asset ratios. The ECCU recorded a decline in pre-tax income compared to the corresponding period of the previous year; there was an overall decline of 18.1 per cent or $109.7m in the level of pre-tax profit generated. Decline in profits for the year were driven by deterioration in loan quality. Return on Average Assets declined by 0.52 percentage points to 2.0 per cent, while Return on Average Equity declined by 8.9 percentage points to 11.4 per cent (Charts 4 and 5).

Chart 4: Return on Average Assets

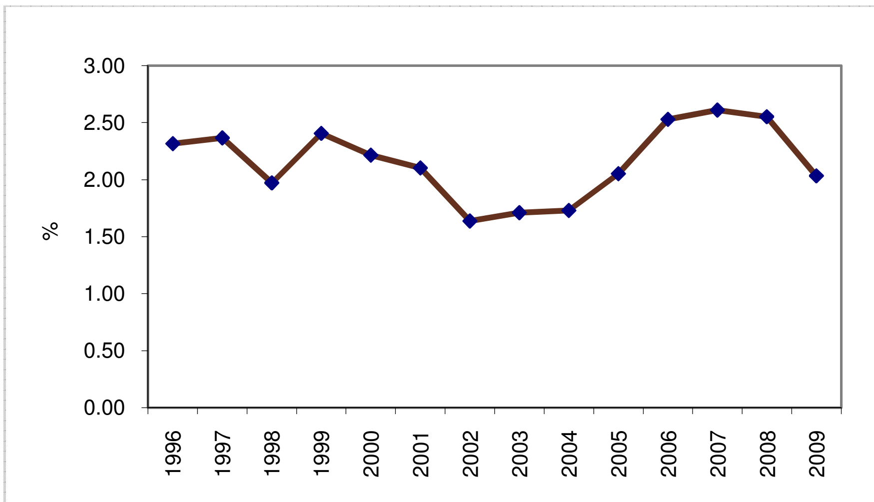
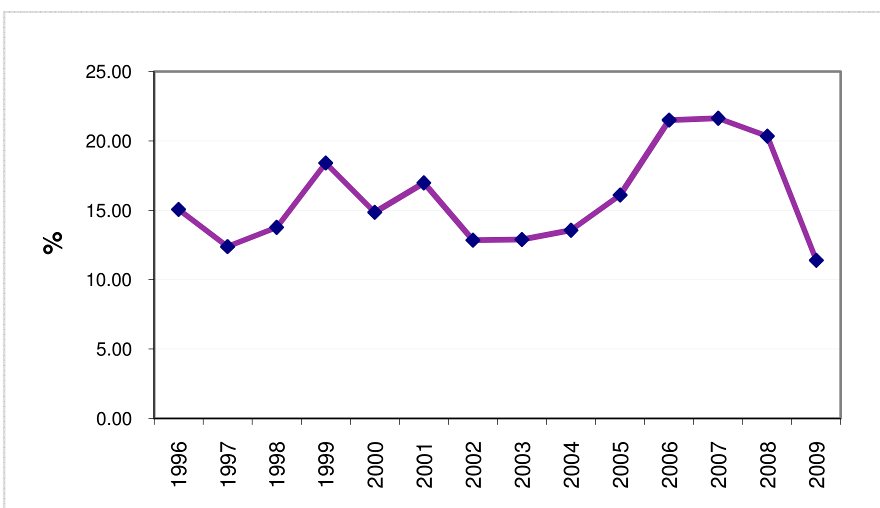


Chart 5: Return on Average Equity

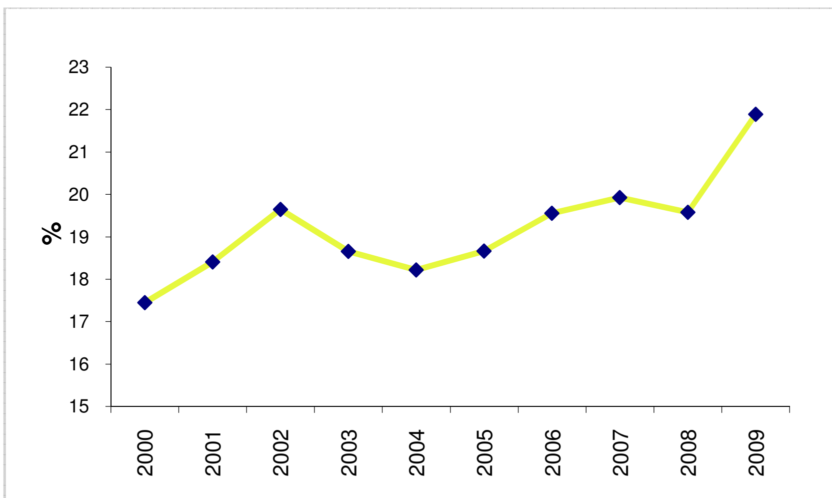


Capital Adequacy

The capital adequacy ratios (CARs) of the locally incorporated banks in the ECCU suggest a sufficiency of capital (Chart 6). Against a minimum regulatory capital adequacy requirement of 8 per cent, the banking sector's capital adequacy ratio stood at 21.9 per cent in December 2009 compared to 19.6 per cent in December 2008.

The high level of NPLs at some commercial banks continues to pose a threat to capital. Further, the reluctance of banks to write-off loans that are fully provided for in accordance with the ECCB's guidelines inflates the level of the capital ratios of banks. The protracted approach to writing off debts could lead to further erosion in the value of the underlying asset, adversely impacting full collectability. The ongoing monitoring and evaluation of its credit and investment portfolios is critical to a bank's assessment of risk, particularly in instances where investments carry a high market risk which could adversely affect capital.

Chart 6: Capital to Adjusted Risk Weighted Assets



Section: III Literature Review

The literature on factors which cause banking sector crisis and bank failures can be classified into two related groups of empirical investigation; the first group takes a strict indicator approach where individual indicators of bank soundness are identified mainly using case analysis, and the second segment of the literature utilizes those indicators to develop early warning systems for financial sector. This section of the paper presents a summary of the work in those areas and in so doing provides some theoretical inspiration for our choice of variables and indicators in the methodology which is detailed later in the paper.

A number of authors have presented analysis on indicator determinants of banking sector crises. These include Demerguc-Kunt and Detragiache (1998), Kaminsky and Reinhart (1999), Hardy and Pazarbasioglu (1998), Garvin and Hausmann (1996) and Lindgren (1996). Hardy and Pazarbasioglu (1998) in an examination of banking crises in 38 countries found that banking crisis tend to be related to large contemporaneous declines in real GDP, boom burst inflation cycles, rapid credit expansion and sharp declines in the real exchange rate among other factors. Demerguc-Kunt and Detragiache (1998) utilized a multivariate logit approach to examine the determinants of banking crises in developed in developing economies over the period 1980 to 1994. They concluded that banking crises are more likely to occur in weak macroeconomic environments characterized by low growth, high inflation and higher real interest rates. They also argued that vulnerability to balance of payments crisis and the presence of deposit insurance may increase the probability of banking sector crises.

The earlier research presented by Garvin and Hausmann (1996) and Lindgren (1996) point to microeconomic causes of banking sector crises. Garvin and Hausmann argue that bank specific factors such as the quality of the loan portfolio, quality of management and the regulatory regime all impact on the soundness of the financial sector. Lindgren in an IMF survey of worldwide banking sector problems posits that a significant number of these crises showed evidence of high non performing loans, connected lending and undercapitalization. He also pointed to regulatory failure as a contributory factor to the occurrence of banking sector crises.

In the Caribbean, research on the causes of banking crisis has been conducted by Polius and Craigwell (1997), Polius (1998) and Duttagupta and Cashin (2008). Duttagupta and Cashin used a Binary Classifcation Tree (BCT) model to analyze banking crises in 50 emerging markets and developing countries. Their study revealed three conditions which may facilitate the occurrence of banking crises; very high inflation, highly dollarized bank deposits combined with nominal depreciation or low liquidity and low profitability. They also concluded that one of the main factors underpinning the resilience of banking systems in the Caribbean is exchange rate stability offered by the fixed exchange rate regime.

The earlier analysis of determinants of banking crises or financial distress in the late 1990's have morphed into the development of models which will serve as Early Warning Systems (EWS) to signal the occurrence of banking sector crises. Kamisnksy, Lizondo and Reinhart (1998) proposed an EWS which focused on monitoring changes in a certain economic indicators that are done to behave differently prior to a crisis. Warning signals are generated by the system when indicators exceed the established threshold values. This EWS signal approach found that deviations of the real exchange rate from trend, exports, output, equity prices and the ratio of broad money to gross international reserves were the leading indicators which worked best in terms of anticipating financial sector crises.

Reinhart, Goldstein and Kaminsky (2000) utilized a data set for the period 1970 to 1995 to examine a sample of 87 currency crises and 29 banking crises which occurred in smaller industrial countries. They adopt a non parametric signals approach which was developed in earlier work by Kaminsky and Reinhart (1996). This approach is predicated on the assumption that the economy behaves in a different manner on the eve of a crisis; for instance banking crisis usually occur after periods of declines in asset prices. They concluded that the best high frequency leading indicators of currency crises are the appreciation of the real exchange rate, decline in equity prices, a fall in exports, a high ratio of broad money to international reserves and low or declining international reserves. The best leading predictors for banking crises were an appreciation of the real exchange rate, a decline in equity prices, a rise in the money multiplier, a decline in real output, a fall in exports and a rise in the real interest rate.

Kaminsky and Reinhart (1999) examined the causes of banking and balance of payments problems. They studies 76 currency crises and 26 banking crises for the period 1970 to 1995, as well as the out of sample case of the Asia financial crisis of 1997. Their results point to common causes of balance of payments and banking crises including economic recessions or below normal economic growth, worsening terms of trade, an overvalued exchange rate, rising cost of credit, rapid growth in credit and weak economic fundamentals.

In response to the failure of EWS models to predict various episodes of banking crises, Grabel (2004) developed a trip wire and speed bump approach to managing financial risk and reduce the potential for financial crises in developing economies. Her approach details trip wires and speed bumps for identifying currency risk, fragility risk, cross border contagion, lender flight risk. Trip wires in her analysis are indicators which can signal potential difficulties in the financial system and therefore have no value in reducing financial risks. Grabel defines speed bumps as narrowly targeted changes in policies and regulations which are activated once trip wires reveal potential problems. Some of the trip wires include the ratio of official reserves to current account deficit, the ratio of short term debt to long term debt and the ratio of official reserves to private and bi/multilateral foreign currency denominated debt. Grabel presents speed bump options such as restrictions on currency convertibility, selective currency convertibility and implementation of tax measures which discourage the incurrence of new foreign debt obligations. The paper argues that speed bumps that govern inflows are preferable to those which govern financial outflows, and speed bumps should generally be automatic and transparent in their operations.

Section IV: Data and Methodology

The paper uses annual banking sector and macroeconomic data for all eight countries within the Eastern Caribbean Currency Union.[2] Higher frequency quarterly banking sector data is utilized for some of the analysis. Given the limited availability of macroeconomic data on a quarterly basis, we could not have provided a full analysis using quarterly data. However, we felt that high frequency analysis was sufficiently important to warrant some investigation using the available quarterly banking sector data. The sample therefore runs on a quarterly or annual basis from 1996 to 2008 and includes data on thirty eight commercial banks which operate in the various jurisdictions within the ECCU.[3]

Choice of Variables

The dependent variable; watch list was based on the ECCB Bank Supervision Department 2003 classification. This watch list is constructed on the basis of the results of onsite and offsite supervision.[4] The choice of independent variables was informed by the results from empirical research as outlined in the literature review and the experience of the bank supervision staff.

Methodology

Our approach involved the application of three multivariate data analysis techniques; discriminant analysis, cluster analysis and classification trees. The main benefit of utilizing the three techniques is the ability to check for consistency of results and for cross checking of cases. The use of the various methodologies allows for choosing the best variables that can be utilized for the purposes of monitoring the performance of the banking sector.

In the ECCU, only locally incorporated banks are required to hold capital, as foreign branch banks form part of an international network and rely on their parent institutions to provide liquidity and capital buffers. In light of this, we conduct our analysis using two data sets; one which covers the full sample of banks and one which contains data only on locally incorporated banks. This was done in an effort to determine whether capital and solvency ratios played any role in classification of observations.

Classification Trees

Classification tree analysis is one of the main techniques used in data mining when the goal is to generate rules for sorting that are easily understood and explained. Classification tree methods (also called decision trees) are used to predict membership of cases, observations or objects in classes of categorical dependent variables, using the measurement of cases on various explanatory or predictor variables. Classification tree analysis possesses some similarities with techniques such as dicriminant and cluster analysis, non parametric statistics and non linear estimation.

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[2] The member territories of the ECCU include Anguilla, Antigua and Barbuda, Dominica, Grenada, Montserrat, Saint Kitts-Nevis, St. Lucia, and St. Vincent and the Grenadines.

[3] Our data set excludes two commercial banks which commenced operations within the last three years.

[4] The criteria for watch listing banks would have changed over the sample period. However, our sample reflects an application of the 2003 criteria.

A classification tree is built through a process of binary recursive partitioning, where the data is split into initial partitions and those partitions are split further on each of the branches. The recursive partitioning process essentially amounts to a hierarchical decision making process. The analysis starts with a set of pre classified records; in this case a group of watch listed and non watch listed observations, with the goal being to build a tree that effectively distinguishes between the two classes. However, the splitting criterion can be used to distinguish between more than two classes and multi way partitioning can be accomplished through recursive binary splitting. In order to choose the best splitter at the initial and every other node, the algorithm considers the measurements for the predictor variables for all cases and sorts them. All possible splits are considered, and the best split at each node is chosen. The best splitting variable at each node will be the one which maximizes the difference on cases within the partitions.

One unique advantage associated with classification tree analysis, is the ability of the method to isolate and examine the effect of one predictor variable at a time (hierarchical approach), rather than examine the effects of all the variables at once.

Discriminant Analysis

Discriminant analysis is data analysis technique which uses the measurements of independent predictor variables to classify observations into mutually exclusive and exhaustive groups. The independent variables are used so that the researcher can determine the dimensions on which the groups differ. These variables are then used to predict group membership. Computationally discriminant analysis is similar to a multiple one way analysis of variance problem (MANOVA). The research question is whether the two or more groups of observations are significantly different from each other based on the means of a set of independent variables. In the case where more than two independent variables are included in the study to determine which ones best distinguish between the groups, there will be a matrix of total variances and covariances, and a matrix of polled within group variances and covariances. These two matrices can then be compared using multivariate F tests in order to determine whether these variables discriminate between the groups.

The technique is predicated upon a few assumptions; the independent variables must have multivaraiate normal distributions and the variance-covariance matrix of independent variables in each of the groups must be the same. Sharma(1996) notes that the technique is quite robust to violations of these assumptions. Discriminant functions can be computed using two approaches. With the stepwise approach, independent variables enter the model one at a time based on their discriminatory strength. The Strongest discriminatory variable is entered first, thereafter the variable which best improves the discriminating power of the model is entered and the process continues. At each step all variables are evaluated to determine which one can contribute most to the difference between the groups. The simultaneous method involves entering all the independent variables into the model at the same time and therefore the resulting discriminant function is based on the discriminating power of the entire set of independent variables, rather than the strength of individual variables.

Cluster Analysis

Cluster analysis is an exploratory data analysis tool which aims to sort different objects or observations into groups using the data or measurements associated with those observations. The objective of cluster analysis is to ensure that the groups that are derived from the process ensure a significant level of homogeneity across observations within the same group, but allow for maximum difference if observations are members of different groups. Cluster analysis can therefore be used to examine the underlying structure in a data set without providing explanations about why those structures exist. Cluster analysis unlike discriminant analysis techniques, does not require the researcher to have a priori classifications or hypotheses related to the observations under study.

The most common distinction used to distinguish between types of clusterings is whether a set of clusters is hierarchical or partitioned. Partitional clustering relates to the situation where observations are classified into groups with no overlapping clusters or subsets. In the context of hierarchical clustering; clusters can have subsets resulting in a set of nested clusters organized as a tree. Nodes (clusters) in the tree are therefore the aggregation of sub clusters, while the root is the cluster consisting of all observations. There are a number of clustering techniques including; K means clustering, agglomerative hierarchical clustering and density based clustering algorithm (DBSCAN).

K means clustering, the approach used in this paper, is a partitioning clustering technique which classifies observations into a user specified number of groups or clusters using the centroids associated with the measurements on those observations. Agglomerative hierarchical clustering as the name implies is a hierarchical approach which starts of with singleton clusters and merges clusters as the process advance (based on similarity of data measurements) to form larger clusters. The density based clustering algorithm (DBSCAN) method produces partitional clusters in which the final number of cluster is automatically determined by the algorithm.

Section V: Results

5.1 Discriminant Analysis

Full Sample

The variables enter the discriminant function in a stepwise manner using the Wilks lambda criterion. For each given independent or predictor variable, the Wilks lambda is computed as the ratio of the within group sum of squares to the total sum of squares.

The results from the discriminant analysis for the full sample of banks suggest that loan quality, liquidity, earnings, growth in imports and the ratio of domestic credit to gross domestic product (GDP) best determine whether a bank should be watch listed. For the full sample of banks, the predictor variable with the greatest influence was liquidity as measured by the loans to deposit ratio. Loan quality and growth in the banking sector relative to the economy were also found to be strong predictor variables.

As indicated in table 2 below, one canonical discriminant function which accounts for all the between groups variability was generated from the analysis. In investigating the canonical discriminant function, the Wilks' lambda indicates the level of between group variability with smaller values of lambda indicating greater levels of between group variability. A Wilks' Lambda of 0.74 was generated suggesting a moderate level of between group variability; and is presented in the table below with its associated significance level. The significance level of the lambda statistic is based on a chi-square transformation of the statistic.

Table 2: Canonical Discriminant Function for Full Sample of Banks

Function	Eigen value	% Var.	Cum%	Canonical correlation	Wilks L	Chi Square	DF	Significance
1	.355	100	100	0.512	.738	68.94	6	0.000

The standardized canonical function coefficients indicate the relative contribution of the predictor variables to the discriminant function. The larger the standardized canonical function coefficient the greater the discriminating power of the associated variable. Thus, our results suggest that liquidity, asset quality and growth of the banking sector relative to the economy are the strongest variables in terms of distinguishing between watch listed and non watch listed banks. The results are presented in table 3 below.

Table 3: Full Sample Standardized Canonical Discriminant Function

Total loans/ Total deposits	0.587
Net Interest Income to total income	-.350
Growth rate in Imports	-.373
Unsatisfactory assets/total loans	.503
Domestic Credit to GDP	.502
Operating expenses/total expenses	-.386

The structure coefficients or discriminant loading represent the correlation between a predictor variable and the discriminant scores produced by the discriminant function. The higher the absolute value of the coefficient, the stronger the distinguishing impact of the independent variable on the dependent variable; watch listed/non watch listed banks. Table 4 below presents those coefficients. Again liquidity and asset quality are among the variables with the largest absolute values associated with their coefficients.

Table 4: Structure Coefficients for the Full Sample of Banks

Structure Matrix

	Function
	1
Total Loans/Total Deposits	.563
Volatile Deposits/Total Deposits [a]	.494
Unsatisfactory Assets/Total Loans	.474
Interest Expense/Avg Interest Bearing Liabilities [a]	.464
Investments/Earning Assets [a]	-.450
Net Liquid Assets/Total Deposits [a]	-.412
Growth rate in Imports	-.337
Net Interest Income to Total Income	-.308
Net Foreign Currency Exposure to Total Capital [a]	-.280
M2/Imputed Reserves [a]	-.273
Domestic Credit/GDP	.268
Govt Consumption/GDP [a]	-.203
Growth rate of GDP at Market Prices [a]	-.175
Operating Expenses/Total Expenses	-.165
Current Account Balance/GDP [a]	.162

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions
Variables ordered by absolute size of correlation within function.
a. This variable not used in the analysis.

Table 5 below presents the classification results. The hit ratio is 71.9 percent suggesting that approximately 71.9 percent of the originally grouped cases were correctly classified. Correctly classified watch listed observations stood at 89 percent, while correctly classified non watch listed observations stood at 38.3 percent.

Table 5: Classification Results for Full Sample of Banks

Classification Results [a]

			Predicted Group Membership		Total
		Watchlist	Watchlist	Non-Watchlist	Total
Original	Count	Watchlist	284	35	319
		Non-Watchlist	100	62	162
	%	Watchlist	89.0	11.0	100.0
		Non-Watchlist	61.7	38.3	100.0

a. 71.9% of original grouped cases correctly classified.

Local Banks

For the sample of locally incorporated banks we found that the solvency ratio and the ratio of unsatisfactory assets net of provision for loan loss to total capital were significant predictor variables (see tables 6 and 7 below). This result is consistent with what obtained for the full sample, where liquidity emerged as the strongest predictor variable. The results presented in the table with the standardized canonical discriminant coefficients (table 7) show that asset quality emerges as the strongest predictor variable for the sample of local banks followed by liquidity.

Table 6: Canonical Discriminant Function for Local Banks

Function	Eigen value	% Var.	Cum%	Canonical correlation	Wilks L	Chi Square	DF	Significance
1	.442	100	100	0.554	0.693	82.975	7	0.000

Table 7: Standardized Canonical Discriminant Function for Local Banks

Total loans/ Total deposits	0.864
Net Interest Income to total income	-0.338
Growth rate in Imports	-0.296
Unsatisfactory assets/total loans	1.236
Domestic Credit to GDP	0.470
Tier I Capital to Total Deposits (solvency ratio)	0.640
Unsats net of PLL to Total Capital	-0.948

The structure coefficients or discriminant loading represent the correlation between a predictor variable and the discriminant scores produced by the discriminant function. The higher the absolute value of the coefficient, the stronger the distinguishing impact of the independent variable on the dependent variable; watch listed/non watch listed bank. For the sample of locally incorporated banks, liquidity (proxied by the loans to deposit ratio and net liquid assets to total deposits) emerges as the strongest predictor variable. Efficiency of earning assets ranks second in terms of discriminating ability. Asset quality features in the top three predictor variables in similar manner to the results obtained for the full sample of banks (see table 8).

Table 8: Structure Coefficients for Locally Incorporated Banks

Structure Matrix

	Function 1
Total Loans/Total Deposits	.504
Investments/Earning Assets [a]	-.470
Net Liquid Assets/Total Deposits [a]	-.449
Unsats net of PLL to Total Capital	.434
Unsatisfactory Assets/Total Loans	.425
Interest Expense/Avg Interest Bearing Liabilities [a]	.413
Volatile Deposits/Total Deposits [a]	.356
Growth rate in Imports	-.302
Net Foreign Currency Exposure to Total Capital [a]	-.285
Net Interest Income to Total Income	-.276
Govt Consumption/GDP [a]	-.274
Tier 1 Capital to Total Deposits (Solvency Ratio) 1:	.244
Total Capital/Risk Weighted Assets [a]	-.241
Domestic Credit/GDP	.240
Growth rate of GDP at Market Prices [a]	-.217
Current Account Balance/GDP [a]	.151

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions
Variables ordered by absolute size of correlation within function.
a. This variable not used in the analysis.

Table 9 presents the classification results for the sample of locally incorporated banks. The hit ratio is 94.4 percent suggesting that approximately 94.4 percent of the originally grouped cases were correctly classified. Correctly classified watch listed observations stood at 94.5 percent, while correctly classified non watch listed observations stood at 94.1 percent. These results together with the results for the full sample of banks suggest that the criteria for classifying watch listed banks is more effective in the context of the sample of locally incorporated banks.

Table 9: Classification Results for Locally incorporated Banks

Classification Results [a]

			Predicted Group Membership		
		Watchlist	Watchlist	Non-Watchlist	Total
Original	Count	Watchlist	205	12	217
		Non-Watchlist	1	16	17
	%	Watchlist	94.5	5.5	100.0
		Non-Watchlist	5.9	94.1	100.0

a. 94.4% of original grouped cases correctly classified.

5.2 Classification Trees

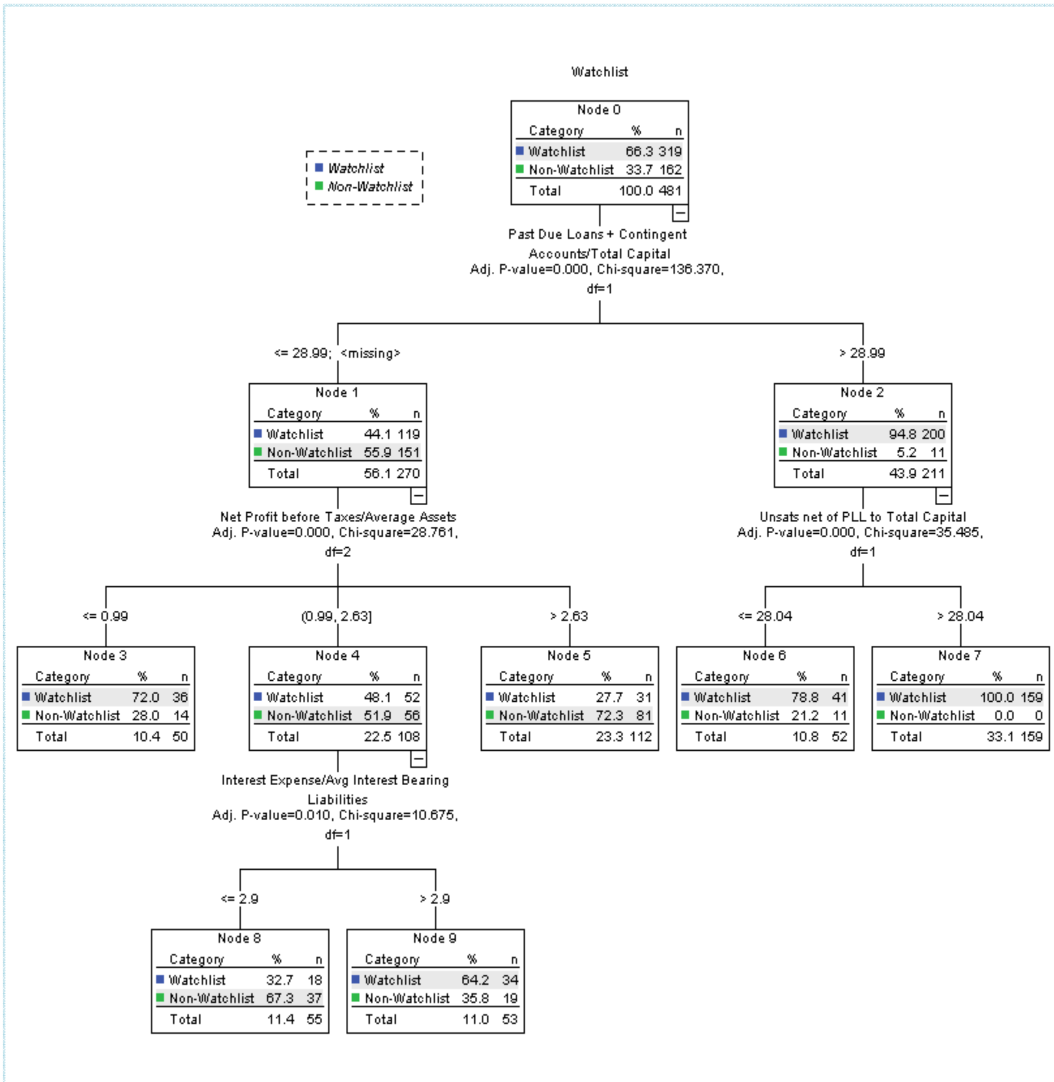
Full Sample

The estimation of the classification trees for the full sample of commercial banks yields 9 nodes six of which are terminal nodes (nodes 3 &5 and nodes 6 through to node 9). These terminal nodes emerge from the classification power of two variables namely; operational efficiency as proxied by interest expense to average interest bearing liabilities and asset quality measured by the ratio of unsatisfactory assets net of provision for loan loss to total capital. Commercial bank profitability (return on assets) and capital adequacy also featured as distinguishing variables between watch listed and non-watch listed banks.

The root node (node 0) utilizes the independent variable asset quality (past due loans plus contingent accounts/ total capital) as the first splitting or classification variable. This splits the observations into two possible nodes associated with values of the variable; *past due loans plus contingent accounts/ total capital* less than or equal to 28.99 or greater than 28.99. Thus the root node suggests that both asset quality and capital are important factors in determining whether a bank is watch listed or not.

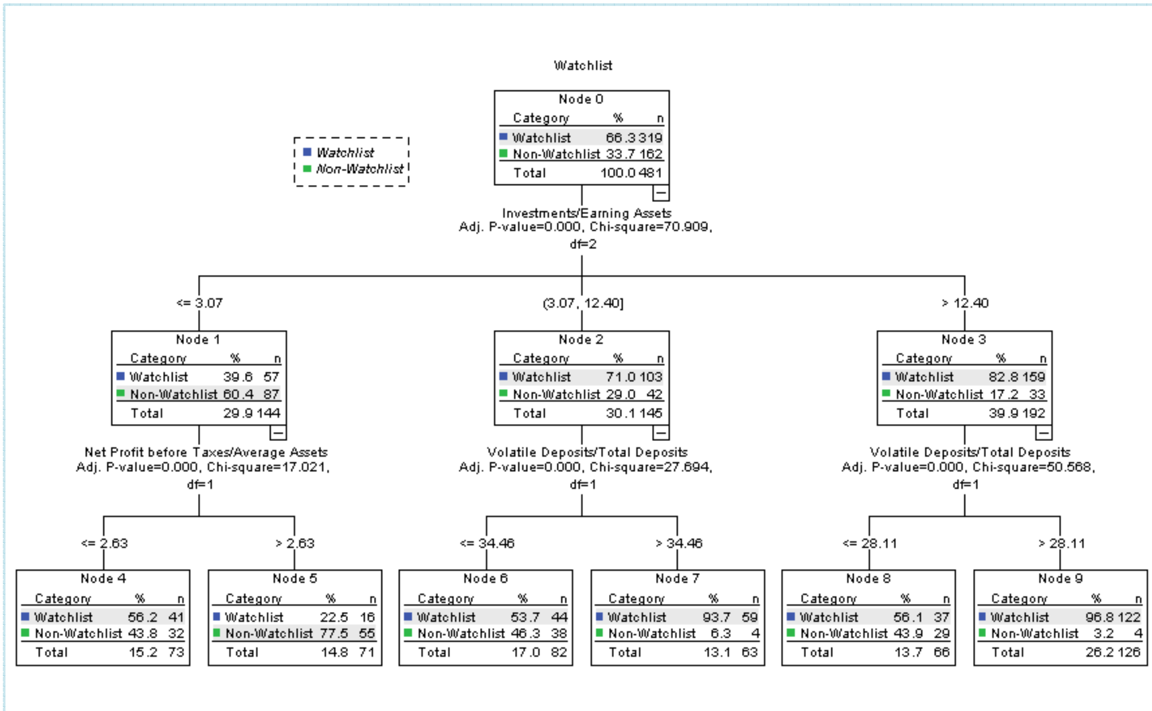
In subsequent steps other split variables emerge; profitability as proxied by net profit before taxes/average assets and unsatisfactory assets net of provision for loan losses to total capital, again reflecting the influence of asset quality, capital and profitability. From the profitability variable emerge three nodes (nodes 3through 5), two of which are terminal. These nodes are based on values of the profitability variable in the following manner; observations less than or equal to 0.99, between 0.99 and 2.63(Node 4) and observations with values on the profitability variable that are greater than 2.63. The results suggest that banks which are more profitable are less likely to be classified as watch listed banks. From node 4, the splitting variable is a proxy for operational efficiency (interest expense or average interest bearing liabilities) and it yields two terminal nodes(less than or equal to 2.0 or greater than 2.9). The results from nodes 8 and 9 indicate that operationally efficient banks are less likely to be placed on a regulator's watch list. The ratio of unsatisfactory assets net of provision for loan losses to total capital (node 2) yields two terminal nodes (less than or equal to 28.04 or greater than 28.04) suggesting the higher the proportion of unsatisfactory assets in total capital the greater the probability of classification as a watch listed bank.

Figure 1: Classification Tree for Full Sample of Banks



Local Banks

Figure 2: Classification Tree for Locally Incorporated Banks



The root node for the classification tree for the sample of locally incorporated banks is defined by the ratio of investments to earning assets. This ratio measures the extent to which banks move away from traditional intermediation activities in their income earning profile. This node is further split resulting in three nodes (nodes 1 through 3). These nodes are based on values of the root predictor variable in the following manner; less than or equal to 3.07, between 3.07 and 12.4 and greater than 12.40. This suggests that the greater the proportion of investments in total earning assets (greater the movement from traditional intermediation), the more likely that the observation can be classified as watch listed. Node 1 is further split into two terminal nodes (4&5) defined by profitability (net profit before taxes on average assets), with higher profitability associated with lower probability of being placed on the watch list. Nodes 2 and 3 both produce two terminal nodes based on the predictor variable liquidity proxied by volatile deposits to total deposits. The classification tree suggests that higher ratios of volatile deposits to total deposits are associated with a greater possibility of observations classified as watch listed.

5.3 Cluster Analysis

The results from the cluster analysis for the full sample of banks suggest the occurrence of two clusters of commercial banks within the ECCU. The cases are fairly evenly distributed across the two clusters (cluster 1: 255 cases, cluster 2: 223 cases). Table 10 below presents the final cluster centers for the explanatory variables that were used in determining those clusters. The final cluster centers reveal the characteristics of the typical case for each cluster. Observations in cluster I are characterized by a higher level of unsatisfactory assets to total assets, lower liquidity, lower provisioning and greater leverage.

Table 10: Final Cluster Centers for Full Sample of Banks

	Cluster	
	1	2
Unsatisfactory Assets/Total Loans	12.07	10.61
Total Loans/Total Deposits	90.70	64.34
Net Interest Income to Total Income	47.84	47.88
Domestic Credit/GDP	84.15	70.35
Growth rate in Imports	7.12	8.44
Investments/Earning Assets	10.00	16.60
Net Profit before Taxes/Average Assets	2.38	1.71
Interest Earned on Loans/Total Income	74.32	60.32
Operating Expenses/Total Expenses	92.64	94.26
Cash and Liquid Investments/Current Liabilities	9.19	16.76
Liquid Assets/Total Deposits + Total Liabilities	26.07	50.57
Provision for Loans Losses/Unsatisfactory Assets	27.36	52.03
Liquid Assets/Total Assets	22.93	44.22
Long Term Loans/Core Deposits	89.60	34.23
Cash Reserves/Total Deposits	7.84	10.78
Volatile Deposits/Total Deposits	42.83	23.63
Interest Expense/Interest Income	43.43	41.70
Total Loans/Total Assets	70.71	49.53
General Govt Loan/Total Loans	12.29	9.74
M2/Imputed Reserves	16.15	18.63

The ANOVA table (table 11) indicates which variables contribute the most to the clusters that were derived. Variables with the largest associated F values indicate greater distinguishing power between the two clusters. The results for the full sample of banks suggest that liquidity and the measure of the importance of traditional banking activity to income earning potential (interest earned on loans to total loans) were the most important separating variables for the two clusters.

Table 11: Cluster Analysis Results for Full Sample of Banks

ANOVA

	Cluster		Error		F	Sig.
	Mean	df	Mean	df		
Long Term Loans/Core Deposits	364.719	1	1203.314	476	303.10	0.00
Liquid Assets/Total Assets	53.928	1	194.6689	476	277.03	0.00
Liquid Assets/Total Deposits + Total Liabilities	71.437	1	276.4385	476	258.42	0.00
Total Loans/Total Assets	53.341	1	209.0675	476	255.14	0.00
Total Loans/Total Deposits	82.673	1	404.9656	476	204.15	0.00
Volatile Deposits/Total Deposits	43.841	1	267.8329	476	163.69	0.00
Interest Earned on Loans/Total Income	23.295	1	184.6183	476	126.18	0.00
Cash Reserves/Total Deposits	1,032	1	19.0501	476	54.15	0.00
Provision for Loans Losses/Unsatisfactory Assets	72,406	1	1824.641	476	39.68	0.00
Cash and Liquid Investments/Current Liabilities	6,810	1	180.8803	476	37.65	0.00
M2/Imputed Reserves	733	1	22.21541	476	33.01	0.00
Investments/Earning Assets	5,195	1	178.3193	476	29.13	0.00
Domestic Credit/GDP	22,637	1	909.4292	476	24.89	0.00
Net Profit before Taxes/Average Assets	53	1	3.294442	476	16.09	0.00
General Govt Loan/Total Loans	773	1	185.4714	476	4.17	0.04
Interest Expense/Interest Income	353	1	96.53469	476	3.66	0.06
Unsatisfactory Assets/Total Loans	254	1	100.3999	476	2.53	0.11
Operating Expenses/Total Expenses	313	1	199.2474	476	1.57	0.21
Growth rate in Imports	209	1	173.568	476	1.20	0.27
Net Interest Income to Total Income	0	1	90.01646	476	0.00	0.97

The F tests should be used only for descriptive purposes because the clusters have been chosen to maximize the differences among cases in different clusters. The observed significance levels are not corrected for this and thus cannot be interpreted as tests of the hypothesis that the cluster means are equal.

Figure 3: Diagnostic Plot for Full Sample

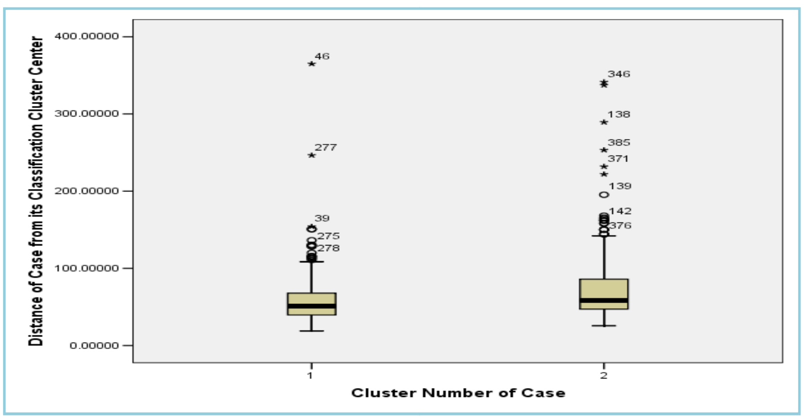


Figure 3 above presents the diagnostic plot associated with our cluster analysis results. The plot essentially shows the distance of outliers within the cluster from the cluster centre. An examination of the plot reveals fewer outliers in cluster 1 than cluster 2. In cluster two (non watch listed cluster) the number of outlier cases is larger. This result suggests that although some of the cases within cluster 2 may not have been classified as watch listed, their measurements on some of the important indicator variables may mean that they may be susceptible to be so classified if the "cases' are subject to any unfavorable developments.

The results for the sample of local banks are consistent with that for the full sample, reflecting the occurrence of two clusters, one with 143 cases the other with 90 cases. The final cluster centers suggest that observations in cluster 1 register higher levels of unsatisfactory assets, lower liquidity, lower provisioning. However for the sample of local banks, the F values provided in the ANOVA table indicate that asset quality is the strongest separating variable followed by liquidity. The variable measuring the importance of traditional intermediation activity to income of the banks is also a strong separating variable. The diagnostic box plot for cluster two shows that like the results for the full sample, we have more outliers within that cluster showing a greater divergence from the cluster centers associated with the predictor variables. This can reflect the likely prospects of such cases to move to a "watch listed" category if an adverse event occurs.

Table 12: Final Cluster Centers for Locally Incorporated Banks

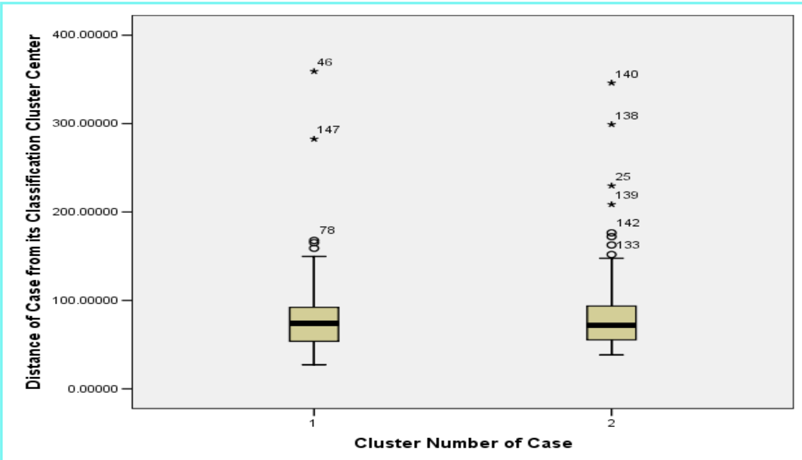
	Cluster	
	1	2
Unsatisfactory Assets/Total Loans	20.45	11.23
Total Loans/Total Deposits	81.68	66.58
Net Interest Income to Total Income	44.94	48.55
Domestic Credit/GDP	85.86	78.29
Growth rate in Imports	6.66	9.35
Investments/Earning Assets	15.65	25.24
Net Profit before Taxes/Average Assets	1.49	2.04
Interest Earned on Loans/Total Income	74.02	59.57
Operating Expenses/Total Expenses	89.37	93.13
Cash and Liquid Investments/Current Liabilities	14.05	23.85
Liquid Assets/Total Deposits + Total Liabilities	31.10	48.84
Provision for Loans Losses/Unsatisfactory Assets	22.15	48.76
Liquid Assets/Total Assets	26.06	39.58
Long Term Loans/Core Deposits	98.51	51.85
Cash Reserves/Total Deposits	7.83	8.30
Volatile Deposits/Total Deposits	50.24	35.28
Interest Expense/Interest Income	48.55	42.61
Total Loans/Total Assets	66.36	51.10
General Govt Loan/Total Loans	17.33	13.96
M2/Imputed Reserves	15.46	18.07
Tier 1 Capital to Total Deposits (Solvency Ratio) 1:	10.79	8.69
Unsatisfactory Loans net of Specific Provisions to Total Capital	114.91	34.77
Total Capital/Risk Weighted Assets	16.06	22.28

Table 13: ANOVA Table for Locally Incorporated Banks

ANOVA	Cluster		Error		F	Sig.
	Mean	df	Mean	df		
Unsatisfactory Loans net of Specific Provisions to Total Capital	354,789	1	1,783	231	198.98	0.00
Total Loans/Total Assets	12,859	1	172	231	74.94	0.00
Long Term Loans/Core Deposits	120,283	1	1,656	231	72.64	0.00
Interest Earned on Loans/Total Income	11,529	1	185	231	62.19	0.00
Unsatisfactory Assets/Total Loans	4,699	1	78	231	60.63	0.00
Volatile Deposits/Total Deposits	12,363	1	209	231	59.22	0.00
Liquid Assets/Total Assets	10,091	1	177	231	56.91	0.00
Liquid Assets/Total Deposits + Total Liabilities	17,373	1	316	231	54.93	0.00
Total Loans/Total Deposits	12,603	1	286	231	44.00	0.00
Investments/Earning Assets	5,072	1	183	231	27.78	0.00
Provision for Loans Losses/Unsatisfactory Assets	39,131	1	1,640	231	23.85	0.00
Cash and Liquid Investments/Current Liabilities	5,305	1	234	231	22.68	0.00
Interest Expense/Interest Income	1,953	1	91	231	21.53	0.00
Total Capital/Risk Weighted Assets	2,135	1	106	231	20.07	0.00
Tier 1 Capital to Total Deposits (Solvency Ratio) 1:	244	1	14	231	17.90	0.00
M2/Imputed Reserves	377	1	24	231	15.73	0.00
Net Profit before Taxes/Average Assets	17	1	1	231	14.16	0.00
Net Interest Income to Total Income	720	1	113	231	6.35	0.01
Operating Expenses/Total Expenses	777	1	143	231	5.44	0.02
Domestic Credit/GDP	3,164	1	1,124	231	2.81	0.09
General Govt Loan/Total Loans	628	1	305	231	2.06	0.15
Growth rate in Imports	400	1	200	231	2.01	0.16
Cash Reserves/Total Deposits	12	1	7	231	1.78	0.18

The F tests should be used only for descriptive purposes because the clusters have been chosen to maximize the differences among cases in different clusters. The observed significance levels are not corrected for this and thus cannot be interpreted as tests of the hypothesis that the cluster means are equal.

Figure 4 Diagnostic Box Plot for Locally Incorporated Banks



5.4 Comparison of the Results for the Three Methods

Table 14 below presents a summary of results across all three methods. The results presented show that the asset quality variables unsatisfactory assets to total loans and unsatisfactory assets net of provision for loan losses to total capital were important predictor variables across all three methods. Liquidity measured by the loans to deposit ratio was also found to be an important predictor variable across the methods. The following variables were significant predictor variables across two methods; investments/earning assets, net interest income to total income, net profit before taxes to average assets, operating expenses to total expenses, interest expenses to average interest bearing liabilities and liquidity measured by the ratio of volatile deposits to total deposits . This provides some comfort in the terms of the validity of the results and the ability of the selected variables to assist in distinguishing between watch listed and non watch listed observations.

Table 14: Summary of Results Across Methods

	Discriminant Analysis	Cluster Analysis	Classification Trees
Past due loans +contingent accounts/total capital			*
Unsatisfactory assets/Total loans	*	*	*
Domestic Credit/GDP	*	*	
Unsatisfactory net of PLL to total capital	*	*	*
Provision for loan losses/Unsatisfactory assets		*	
Investments/Earning Assets		*	*
Net interest income to Total income	*	*	
Operating Expenses/Total expenses	*	*	
Interest expenses/Average interest bearing liabilities		*	*
Net Profit before taxes/Average Assets		*	*
Volatile Deposits/Total Deposits		*	*
Liquid Assets/Total assets			*
Long term loans/Core deposits			
Total loans/Total deposits	*	*	*
Tier 1 Capital/Total deposits	*	*	

5.5 Benchmarking the Indicators

We seek to establish benchmarks or ranges for some of the indicators for some of the important predictor variables. These benchmarks and ranges will then be incorporated into the existing stress testing and monitoring framework for the regulatory authority and help signal when there is a need for greater monitoring, analysis or action when values of predictor variables approach these benchmarks or fall within a particular range.

Two of the methods presented in this research exercise (classification trees and cluster analysis) present estimates or ranges of the predictor variables associated with the various clusters or nodes. Discriminant analysis however, does not present any ranges or benchmarks. The benchmarks are therefore derived using discriminant analysis and then compared to the ranges presented from the classification tree analysis and the cluster centers derived from the cluster analysis. We determine the benchmarks through recursive estimation of discriminant functions until we find the point at which a predictor variable ceases to distinguish between watch listed and non watch listed observations.

Table 15 presents the benchmarks and range values associated with significant predictor variables for the full sample of banks from the various methods.

Table 15: Benchmarks and Value Ranges from Estimation Process

	Discriminant Benchmark	Watch list center Cluster centers	Classification Tree node Splits
Total Loans/Total Deposits	< 55.2	90.93	<=72.36
Net Interest Income to Total Income	<=51.9	47.54	
Growth rate in Imports	<=15.9	7.36	
Unsatisfactory Assets/Total Loans	>=5.5	12	> 8.66
Domestic Credit/GDP	>=71.9	84.41	
Operating Expenses/Total Expenses	>=94.7	92.81	
Unsats net of PLL to total capital			> 28.04
Volatile deposits to total deposits		43.85	> 28.11
Net profit before taxes/average assets		2.36	> 2.63
Investments/earning assets		10.02	3.07-12.40

Section VI: Conclusion

The paper sought to determine the variables which are best predictors of whether a bank within the ECCU should be closely monitored. We found that factors such as asset quality, liquidity, the degree of movement away from traditional banking business and profitability are all indicators which can we used for the purposes of monitoring. We establish benchmarks which can be incorporated into the stress testing and monitoring framework for the bank in an effort to develop signals that can be used for more effective monitoring. The next step of the research process will involve use of the standardized canonical discriminant function coefficients and the benchmarks to develop a scoring model for banks. This will allow for the introduction of an additional tool for monitoring of the banking system.

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