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SPECIAL EDITION

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NDIC

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Financial Condition and Performance of Insured Banks in the first and Second Quarters of 2013,
By Research, Policy & International Relations and Insurance & Surveillance Departments

In the first two quarters of 2014, the overall condition of Nigeria's banking industry has witnessed some improvements in both Assets and Liabilities.

The overall banking industry was well capitalized, however, only two banks remained undercapitalized as at the end of March 2014 q while three Banks remained under capitalized as at the end of June 2014. Also, Average Liquidity Ratio remained above the 30% minimum requirement while asset quality and profitability improved significantly during the two quarters under review.

REVIEW OF DEVELOPMENTS IN BANKING AND FINANCE IN THE FIRST AND SECOND QUARTERS OF 2014

BY

RESEARCH DEPARTMENT

1.0 INTRODUCTION

The banking sector witnessed a number of developments during the first and second quarters of 2014. These included CBN New Electronic Transfer Platform; CBN Biometric Registration for Bank Customers; CBN Revokes Licences of 83 Microfinance Banks; CBN Uniform Account Opening Form for Customers; Electronic reference Portal introduced by CBN; CBN Refunds N13bn excess charges to Customers and CBN limits Government stake in banks to 10%.other developments during the period under review included the appointment of new CBN governor; Redeployment of Deputy Governor in CBN; Extension of Parallel Run of Pillar 1 of Basel II Implementation; and CBN Monetary Policy Committee Meeting, which x-rays both the External and Domestic Economies, Inflation, Money Supply, Capital Market, the Naira Exchange Rate and External Sector Developments. Details of this review are presented in the report below:

2.0 CBN New Electronic Transfer Platform

The Central Bank of Nigeria (CBN) had on 9th January 2014, inaugurated a new Real-Time Gross Settlement system, (RIGS) integrated with a Script-less Securities Settlement System. The RTGS is an interbank payment infrastructure that facilitates the real-time (continuous) settlement of electronic fund transfers on gross (individual), final and irrevocable basis.

As part of the execution of the Payment System Vision 2020 strategy, the new RTGS replaced the one that was implemented seven years ago as part of the then CBN transformation programme code-named 'Project EAGLES.

The project is expected to enhance a robust infrastructure to handle faster processing of electronic payments related to banking and financial market services as well as the expansion of the functionality and effectiveness of government securities.

2.1 CBN Biometric Registration for Bank Customers

The Central Bank of Nigeria on February 14, 2014, had inaugurated Bank Verification Number (BVN) to revolutionise banking and payment systems in the country. The BVN is a biometric authentication of bank customers using Point of Sale and Automated Teller Machines. The biometric authentication was meant to address the safety of customers' funds and avoid losses through compromise of Personal Identification Numbers. The initiative represented a major landmark in the Bankers Committee's efforts at promoting financial inclusion drive and to prevent money laundering in the system.

2.2 CBN Revokes Licences of 83 Microfinance Banks

On December 20, 2013, the CBN revoked the operating licenses of 83 Microfinance Banks (MFBs) in the country.

The Nigeria Deposit Insurance Corporation (NDIC) had been appointed the provisional liquidator to the MFBs. This will in no doubt promote financial soundness and also enhances system stability in the country.

2.3 CBN Uniform Account Opening Forms for Customers

The CBN in collaboration with relevant stakeholders in the banking industry had developed uniform account opening forms for customers.

The CBN's action was to ensure that depositors in banks and other financial institutions provide necessary background information for effective Know-Your-Customers' (KYC) due diligence in the industry.

The CBN disclosed this in a circular titled: "Uniform Account Opening Forms and Minimum Information Requirement for Three-tiered KYC for Customers of Banks and Other Financial Institutions in Nigeria" to all banks and other financial institutions,

According to the circular, "Individual prospective customers are required to complete account opening Form A(1), Form A(2) and Form A for accounts in tier one, two and three respectively, while legal entities are to complete Form B.

2.4 CBN Monetary Policy Committee Meeting

The CBN Monetary Policy Committee (MPC) met on March 24 and 25, 2014 to review the economic condition and challenges that confronted the domestic economy against the backdrop of challenging monetary policy environment up to March, 2014 and the outlook for the rest of the year. The CBN decided to:

- Retain the MPR at 12% with a corridor of +/-200 basis points around the midpoint;
- Raise the CRR on private sector deposits by 300 basis points to 15 per cent
- Retain the Cash Reserve Requirement (CRR) on public sector funds at 75%.

2.5 The Electronic Reference Portal Introduced by CBN

As part of efforts to enhance the efficiency of the payment system, the CBN had introduced an electronic reference (e-Reference) portal to fast-track account opening processes of Nigerian banks.

The e-Reference system is a web based automated document management system, designed to process customer account references, and is capable of eliminating the inefficiencies characteristic of the old ways of manual reference processing system. The solution would also ensure that interbank references become faster, more efficient and traceable, by both the presenting and receiving banks.

2.6 CBN Refunds N13bn excess charges to Customers

The CBN had disclosed that it had refunded over N13 billion to bank customers that had suffered excess charges by their financial institutions. The refund to the customers was part of its effort to protect consumers of financial services in the country.

2.7 CBN limits Government stake in banks to 10%

The CBN in the revised code of corporate governance and whistle blowing guidelines for Deposit Money Banks and discount houses reiterated that effective October 1, 2014, governments holdings in banks should not be more than 10%. The CBN also directed banks to henceforth disclose the remuneration package of the board members in their annual reports. The CBN also prohibited investors from owning more than 5% stake in any bank without its prior approval.

2.8 Appointment of CBN governor

During the period under review a new Governor of the Central Bank of Nigeria, Mr. Godwin Emefiele was appointed. He officially assumed office on 2 June 2014, following the expiration of the tenure of the erstwhile Governor, Sanusi Lamido Sanusi.

2.9 Redeployment of Deputy Governor in CBN

The CBN had redeployed some of its Deputy Governors, with effect from June 23, 2014. Alhaji Suleiman Barau who was the Deputy Governor in charge of Corporate Services Directorate is now the Deputy Governor, Operations

Directorate. Dr. Kingsley Moghalu in charge of Operations Directorate is now the Deputy Governor Financial Systems Stability (FSS) Directorate while Mr. Adebayo Adelabu who was in charge of Financial Systems Stability (FSS) is now the Deputy Governor, Corporate Services. Dr. Sarah Alade retains her position as the Deputy Governor, Economic Policy Directorate.

2.10 Extension of Parallel Run of Pillar 1 of Basel II Implementation

The CBN had earlier released the guidelines on the implementation of Basel II/III for the Nigerian Banking Sector in December 2013, directing banks to commence the parallel run of Basel II/III Pillar 1 in January 2014, while full adoption was to start by June 2014. However, due to the challenges experienced, the CBN had directed banks in a circular BSD/GCA/BAS/CON/01/115 to continue for an additional three (3) months while the full adoption would commence on October 1, 2014.

2.11 CBN Review of Operations of the NIBSS Instant Payment (NIP) System and Other Electronic Payment Options

The CBN had issued a circular referenced BPS/DIR/GEN/CIR/01/011 reviewing the operations of NIBSS instant payment (NIP) system and other electronic payments options with similar features on the categorization of online funds transfer from low security to **highly secured transfer.** Banks are now expected to achieve "highly secured online funds transfer status within six (6) months, i.e. with a deadline of 31 December, 2014.

2.12 Revised Code of Corporate Governance for Banks and Discount Houses in Nigeria and Guidelines for Whistleblowing in the Nigerian Banking Industry

The CBN had in a circular referenced FPR/DIR/CIR/GEN/01/004 dated May 16, 2014 issued the Revised Code of Corporate Governance for Banks and Discount Houses in Nigeria and Guidelines for Whistle Blowing in the Nigerian Banking Industry for compliance. The revised Code of Corporate Governance was issued after taken into consideration the comments of various stakeholders. The code would eliminate perceived ambiguities and strengthen governance practices.

3.0 External Economy

The global economy continued to recover and prospects for acceleration in 2014 relative to 2013 was expected as a result of increased domestic demand in the advanced economies and the rebound of exports in emerging markets. The IMF had projected global growth to increase from 3.0% in 2013 to 3.7% in 2014 and then to 3.9% in 2015. In the US, growth is expected to be 2.8% in 2014, compared with 1.9% in 2013, driven by increased domestic demand as well as reduction in the fiscal drag due to the recent deal brokered on the Federal Budget.

Despite the euro area's continued adjustment to a high level of indebtedness and financial fragmentation, growth was expected to recover in the coming years and rise from 0.4% in 2013 to 1.0% in 2014 due to easier credit conditions, increased investor confidence, and expansion in exports.

The prevailing tight financial conditions as well as political uncertainty had impacted negatively on growth in most emerging markets and developing economies. Notwithstanding, overall growth in this group of countries was expected to increase from 4.7% in 2013 to 5.1% in 2014. While Global inflation was projected at 2.71% in 2014, representing an increase of about 40 basis points in relation to the estimates for 2013.

Consequently, the global economy continued to sustain favourable developments especially in the US and the Euro area in 2014 as growth in the emerging markets and developing economies was projected to rise from 4.7% in 2013 to 5.0% in 2014. The effects of tighter financial conditions in these economies are expected to be moderated by improved external demand from the advanced economies. The Committee noted that the rebound in global economic activity strengthened in the first half of 2014.

Global inflation was generally expected to remain subdued in 2014 with sustained sizable negative output gaps in the advanced economies, weaker domestic demand in several emerging economies, and falling commodity prices. The projected inflation rate at 1.5% in the Euro and the US was expected to remain below the long-term inflation expectations. The US is expected to commence tightening by the second half of 2015 as inflation hits the long run target and unemployment rate falls to the threshold level.

The monetary policy stance across the advanced economies could begin to diverge in 2014/15. In the United States, the Federal Open Market Committee (FOMC) rate was expected to increase, post-tapering, and in 2015. On the contrary, markets continue to expect a prolonged period of low interest rates and supportive monetary policy in the euro area and Japan.

3.1 Domestic Economy

The National Bureau of Statistics (NBS) had estimated real Gross Domestic Product (GDP) growth rate at 7.72% for the fourth quarter of 2013, which was higher than the 6.81%, recorded in Q3, 2013 and 6.99% in the corresponding period of 2012.

Non-oil sector continued to be the main driver of growth in Q4, 2013, recording 8.76 per cent. The growth drivers in the non-oil sector in Q4, 2013 remained wholesale and retail trade, agriculture and telecommunications which contributed 2.57, 2.27 and 1.97 percentage points, respectively. Based on the 2013 favourable performance, output growth had been projected at 7.7% for fiscal 2014.

However, Nigeria newly rebased its GDP from 1990 to 2010 at current market prices, resulted in an 89% increase in the estimated size of the economy. Due to the rebasing, Nigeria's estimated nominal GDP is USD 510 billion (compared to South Africa USD 352 billion), making the country Africa's largest economy.

The recently rebased GDP figures released by the National Bureau of Statistics (NBS) indicated that real GDP grew by 7.41% in 2013 compared with 5.09% and 6.66% recorded in 2011 and 2012, respectively. The new major sectors of the economy in 2013 in terms of their share in GDP were: Services (36.08%); Industry (21.73%); Agriculture (21.50%) and Trade (17.06%). The non-oil sector remained the main source of overall growth performance (7.77%), driven largely by: agriculture (0.43%), industry (1.28%) of which manufacturing was 1.26% and construction (0.62%); trade (1.54%) and services (3.89%).

In the first quarter of 2014, real GDP growth was 6.21 per cent, which was higher than the corresponding quarter of 2013. In line with the trend, non-oil sector was the main driver of growth in the first quarter of 2014, recording 8.21 per cent growth. The key growth drivers in the non-oil sector remained industry, agriculture, trade, and services which
Contributed 1.77, 1.26, 1.26 and 3.15 per cent, respectively. The oil sector continued to record improvements in performance with its growth rate improving from -9.36 and -11.40 per cent, respectively, in the fourth and first quarters of 2013, to -6.60 per cent in the first quarter of 2014.

3.2 Inflation

Inflation had remained in the target range. The downward trend in inflation, which commenced in December 2012, continued up to February 2014. The year-on-year headline inflation fell consistently from 9.5 per cent in February 2013 to 7.9% in November 2013, but rose marginally to 8.0% in December 2013 and January 2014. In February 2014, however, it moderated to 7.7%.

The deceleration was largely due to the moderation in food inflation, which moved from 9.3% in January 2014 to 9.2% in February 2014. Core inflation, on the other hand, exhibited a fair degree of volatility during the period;

having declined up to the first half of 2013. It commenced an upward trend in the latter half of the period but declined to 6.6% in January 2014, before inching up to 7.2% in February 2014. Similarly, Inflation had remained in the target range of 6.0% to 9.0% during the first and second quarters of 2014. The year-on-year headline inflation increased to 7.9% in April from 7.8% in March 2014 and 8.0% in May to 8.2% in June 2014. Food inflation, which was 9.3% in January, declined to 9.2% in February 2014 and later increased to 9.8% in June 2014. Core inflation which declined to 6.6% in January, increased to 7.2% in February, and rose further to 7.5% in April to 8.1% in June 2014. The inflation trend is illustrated in Table 1.

TABLE 2

DATE	HEADLINE INFLATION (%)	FOOD INFLATION (%)	CORE INFLATION (%)
Jun-2014	8.2	9.8	8.1
May-2014	8.0	9.7	7.7
Apr-2014	7.9	9.4	7.5
Mar-2014	7.8	9.3	6.8
Feb-2014	7.7	9.2	7.2
Jan-2014	8.0	9.3	6.6

Source: CBN

3.3 Money Supply

Broad money supply (M2) contracted by 2.24% in February 2014 over the level recorded at end-December 2013, which, on annualized basis, translated to a contraction of 13.42% as against a growth target of 15.52% for fiscal 2014.

Interest rates remained within the MPR corridor. The average interbank call rate for the period was 10.17% while the Open Buy- Back (OBB) rate was 11.01%. The weighted average inter-bank call and OBB rates which closed at 10.86 and 10.46% in December 2013, respectively, rose to 11.27 and 10.5% in February 2014, respectively.

Similarly, the (M2) increased by 1.94% in April 2014 and by 1.66% in June 2014 over the level recorded at end-December 2013. When annualized, M2 increased by 5.83% in April and 3.31% in June 2014. M2 was however, below the growth benchmark of 15.52% for 2014 in both months. The increase in money supply reflected the growth in the net domestic credit (NDC) of 1.62% in April and 1.77% in June 2014. Annualized, NDC grew by 4.85% over the end-December, 2013 level. It is, however, below the provisional benchmark of 28.5% for 2014. The expansion in aggregate domestic credit was mainly due to the increase in claims on the private sector which increased by 2.75 per cent in June 2014, which was however, moderated by the contraction in net credit to Government.

Money market interest rates remained within the MPR corridor of +/- 200 basis points; oscillating in tandem with the level of liquidity in the banking system. The monthly weighted average OBB rate was 10.38 per cent in May 2014 but it increased by 14 basis points to 10.52 per cent in June. The uncollaterized overnight rate was 10.50 per cent in June 2014, compared with 10.63 per cent in May 2014.

3.4 Capital Market

Activities in the capital market, however, were bearish as the All-Share Index (ASI) moderated from 41,329.19 at end-December 2013 to 39,269.4 on March 11, 2014 with market capitalization exhibiting similar trends.

The All-Share Index (ASI) increased from 38,748.01 in March 31, 2014 to 39,018.34 on May 16 to 42,482.48 at end-June 2014, indicating improvement in the economy. Similarly, Market Capitalization (MC) increased in the same direction.

3.5 The Naira Exchange Rate

The end-period exchange rate remained stable at the rDAS window but depreciated at the interbank appreciated at the BDC segment of the market. The exchange rate at the rDAS-SPT during the review period opened at

N157.61/US$ (including 1% commission) and closed at N157.26/US$, representing an appreciation of N0.35k or 0.22 per cent. At the Interbank foreign exchange market, the rate opened at N158.83/US$ and closed at N164.90/US$, averaging N161.89/US$, representing a depreciation of 3.68 per cent or N6 for the period. At the BDC segment of the foreign exchange market, the selling rate opened at N173.00/US$ and closed at N172.00/US$, representing an appreciation of 0.58 per cent or N1.00k. The BDC segment averaged N170.44/US$, representing an appreciation of 0.06 per cent.

However, the naira exchange rate remained stable at the rDAS window but depreciated at the interbank and the BDC segments of the market. The exchange rate at the rDAS-SPT during the review period, had remained at N157.29/US$ in May-June 2014 from N157.30/US$ in March 2014. At the Interbank foreign exchange market, the selling rate stood at N164.65/US$ in March 2014. During the period it opened at N162.20/US$ in May 2014 and closed at N162.95/US$ in June 2014, representing a depreciation of N0.75 or 0.46%.

3.6 External Sector Developments

Gross official reserves as at March 2014 stood at US$37.83 billion compared with US$42.85 billion at end-December 2013. The decrease in the reserves level was driven largely by the increased funding of the foreign exchange market in the face of intense pressure on the Naira and the need to maintain stability.

The project would enhance a robust infrastructure to handle faster processing of electronic payments related to banking and financial market services as well as the expansion of the functionality and effectiveness of government securities.

Similarly, gross official reserves stood at US$37.31 billion at end-June 2014 compared with US$38.30 billion as at May 2014 which appreciated from US$37.40 billion in March 2014.

3.7 Access Bank Appoints New Executive

The Board of Directors of Access Bank in January 2014, appointed Mrs. Titi Osuntoki as Executive Director in charge of Business Banking. Business Banking is a business division within the bank which is focused on Small and Medium (SMEs).

The appointment had been approved by the Central Bank of Nigeria. As such, Access Bank Board now comprises of sixteen (16) directors made up of seven (7) Executive Directors and nine (9) Non-Executive Directors, two (2) of whom are Independent directors.

3.8 Amangbo replaces Emefiele as Zenith Bank's GMD

Zenith Bank Plc had named Mr. Peter Amangbo as its new chief executive officer (CEO) with effect from June 1, 2014. Mr. Amangbo, was an Executive Director with the bank. He replaces Mr Emefiele who was appointed the Governor of CBN.

3.9 Mortgage Banks and Leasing

The CBN had directed all PMBs to maintain a minimum ratio of 50% of mortgage assets to total assets, 75% of which must be residential mortgages. Also, a minimum of 60% of PMBs' loan- able funds, defined as total deposits plus on-lending loans, should be devoted to the creation of mortgage assets. The PMBs are not to engage in leasing business or take proprietary position in real estate development.

3.10 Deadline on Data Security Standards

The CBN had extended the date for banks’ compliance with the Payment Card Industry Data Security Standard (PCI DSS) to November 30, 2014. The PCI DSS is a proprietary information security standard for organisations that handle cardholder information for the major debit, credit, prepaid, e-purse, Automated Teller Machines, and Point of Sale (PoS) cards. The standard was created to increase controls around cardholder data to reduce credit card fraud via its exposure. The need to extend the deadline followed requests by many banks seeking for more time to enable them complete the certification process.

FINANCIAL CONDITION AND PERFORMANCE OF INSURED BANKS IN THE FIRST AND SECOND QUARTERS OF 2014

BY

RESEARCH POLICY & INTERNATIONAL RELATIONS AND INSURANCE AND SURVELLANCE DEPARTMENTS

1.0 INTRODUCTION

In the first two quarters of 2014, the overall condition of Nigeria's banking industry has witnessed some improvements in both Assets and Liabilities.

The total assets of the banking sector increased by 2.52% from ₦23.283 trillion as at 31st March 2014 to ₦23.887 trillion as at 30th June 2014. This increment can be attributed to the increase in Cash and Due from other banks, Interbank Placements, Net Loans and Advances/Leases and Net Other Assets.

Net Loans and Advances/Leases increased to ₦9.955 trillion in June 2014 from ₦9.567 in March 2014, thereby resulting in an increase of 3.89%. Also, Net Other Assets decreased from ₦ 979.09 billion in March 2014 to ₦1.030 trillion in June 2014.

Asset quality remained relatively stable during the period under review as the ratio of Non-Performing Credits to Total Credits dropped from 3.6 percent in March 2014 to 3.51 percent in June 2014. There was an upward shift in profitability as Profit-Before-Tax stood at ₦288.806 billion as at June 2014 as against ₦138.978 billion in March 2014. The capital adequacy ratio reduced slightly as the Capital to Risk-Weighted Asset Ratio decreased by -6.29% points to 16.05% in June 2014 from 17.06% recorded in March 2014. However, the capital adequacy ratios in the two quarters were still above the prudential requirement of 10%. The average liquidity ratio declined to 42.66% as at June 2014 from 44.55% in March 2014.

On the liability side, all the major components decreased. Total deposits decreased from ₦70.90 trillion to ₦69.89 trillion as at 31st March 2014 and 30th June 2014 respectively. Other liabilities also decreased marginally from 10.06 trillion as at 31st march 2014 to 9.32 trillion as at 31st June 2014. And Reserves also decreased from ₦11.27 trillion as at 31st March 2014 to ₦11.06 as at 30th June 2014.

Apart from this introduction, the rest of this paper comprises of three sections. Section 2 presents the Structure of Assets and Liabilities; Section 3 assesses the financial condition of insured banks, while Section 4 concludes the paper.

2.0 STRUCTURE OF ASSETS AND LIABILITIES

During the period under review, the Total Assets of the industry increased by 2.53% from ₦23.283 trillion in March 2014 to ₦23.887 trillion in June 2014. The structure of the industry's total assets and liabilities as at 31st March and 30th June 2014 are presented in Table 1 and Charts 1A and 1B.

TABLE 1

Structure of Banks' Assets and Liabilities for the First and Second Quarters of 2014

Assets (%)	1st Quarter 2014	2nd Quarter 2014	Liabilities (%)	1st Quarter 2014	2nd Quarter 2014
Cash and Due from Other Banks	24.29	24.39	Deposits	70.90	69.89
Inter-bank Placements	1.83	1.92	Inter-bank Takings	0.54	0.95
Government Securities	16.08	15.07	CBN Overdraft	0.11	0.21
Other Short-term Funds	0.61	0.86	Due to Other Banks	0.90	1.24

Loans and Advances	41.05	41.68	Other Borrowed Funds	-	-
Investments	8.94	8.80	Other Liabilities	10.06	9.32
Other Assets	4.21	4.31	Long-term Loans	5.24	6.26
Fixed Assets	3.00	2.97	Shareholders' Funds (Unadjusted)	0.99	0.96
			Reserves	11.27	11.06
Total	**100.00**	**100.00**	**Total**	**100.00**	**100.00**

Source: Banks Returns

NOTE:

TOTAL ASSETS (N Trillion)

1st Quarter 2014 = ₦23.283

2nd Quarter 2014 = ₦23.887

OFF BALANCE SHEET ENGAGEMENTS (N Trillion)

1st Quarter 2014 = ₦ 7,757.40

2nd Quarter 204 = ₦ 7,483.23

CHART 1A: Structure of Bank's Assets for the 1st and 2nd Quarters of 2014

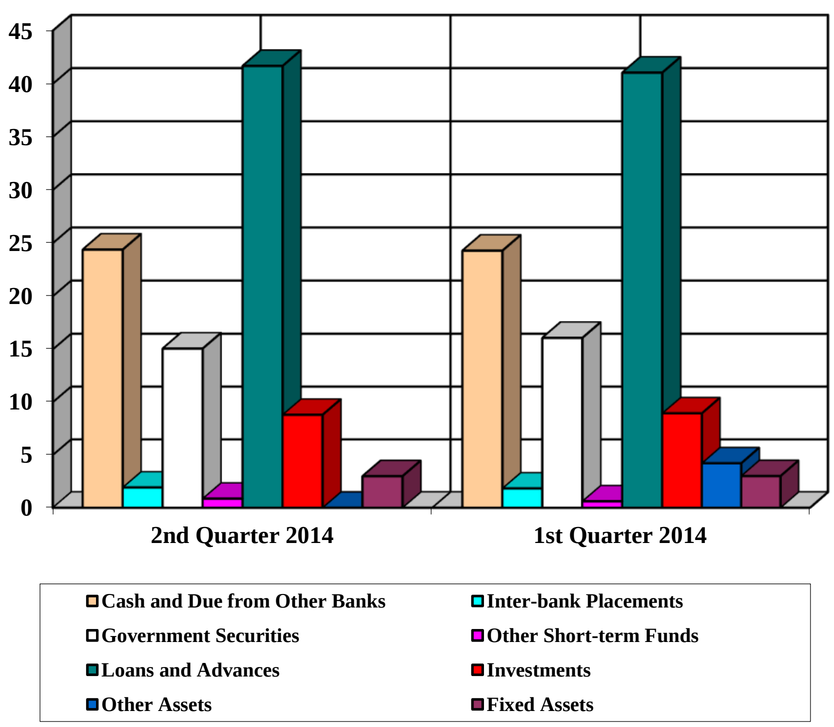
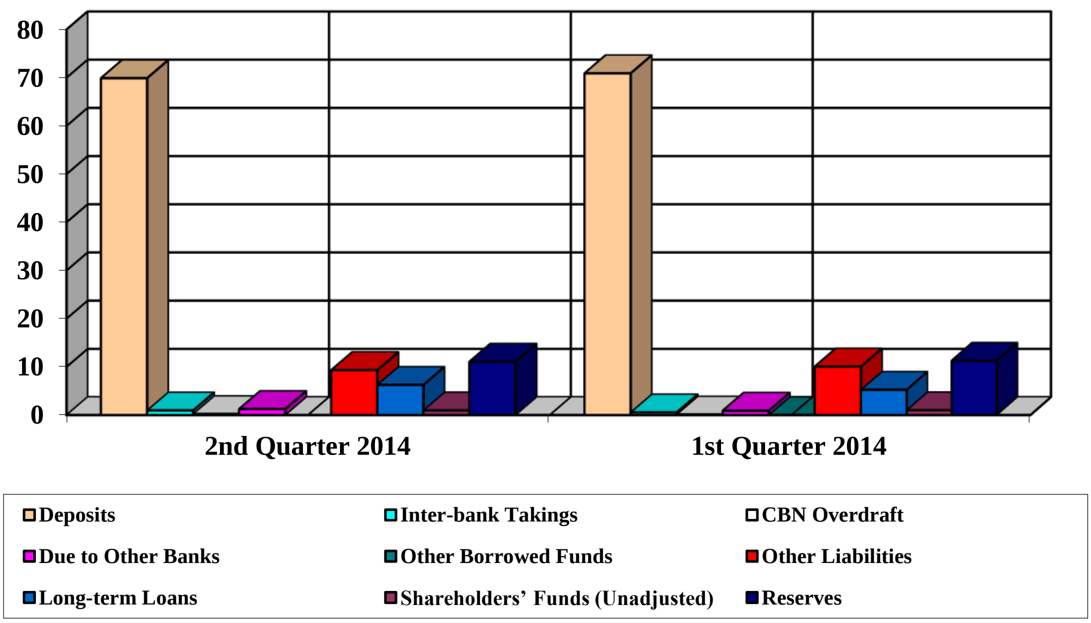


CHART 1B: Structure of Banks' Liabilities for the 1st and 2nd Quarters of 2014



The largest proportion of total assets during the two quarters was Loans and Advances which its components accounted for 41.05% and 41.68%in the first and second quarters respectively. Cash and Due from other banks followed as second with 24.29% and 24.39% during the same period. In the third position was Government Securities which decreased from 19.08% to 15.07%. For the other components of the industry's total assets; Interbank Placements increased to 1.92% from 1.83% during the period under review, Other Assets also increased from 4.21 % to 4.31%. There was a slight decline in fixed asset from 3.00% to 2.97% in the second quarter of 2014.

On the liabilities side of the balance sheet, Deposits remained the largest proportion accounting for 69.89% as at 30th June 2014 showing a slight decrease compared to the 70.90 recorded as at 31st March 2014.

Also, there was a decline in Reserves during the two periods from 11.27 % to 11.06%, corresponding to a marginal increase in Long Term Loans to 6.26% from 5.24% during the periods under review. Interbank Takings increased to 0.95% from 0.54% during the two quarters.

3.0 ASSESMENT OF THE FINANCIAL CONDITION OF INSURED BANKS

3.1 Asset Quality

The industry's Total Loans and Advances experienced an increase of 3.89% from ₦9.567 trillion as at 31st March 2014 to ₦ 9.955 trillion as at 30th June 2014. The quality of these assets continued to improve as the industry's ratio of Non-Performing Credits to Total Credits decreased to 3.51% from 3.6% during the 2 quarters. The Ratio of Non-Performing Credits to Shareholders' Fund increased by 0.74% from 13.25 in March 2014 to 13.35 in June 2014.The ratio of Provision for Non-Performing Loans to Total Non-Performing Loans also decreased by - 8.5 percentage points from 95.31 as at March 2014 to 87.8 as at June 2014.

Table 2 and Chart 2 present the indicators of insured banks Asset Quality for 1st and 2nd Quarters of 2014.

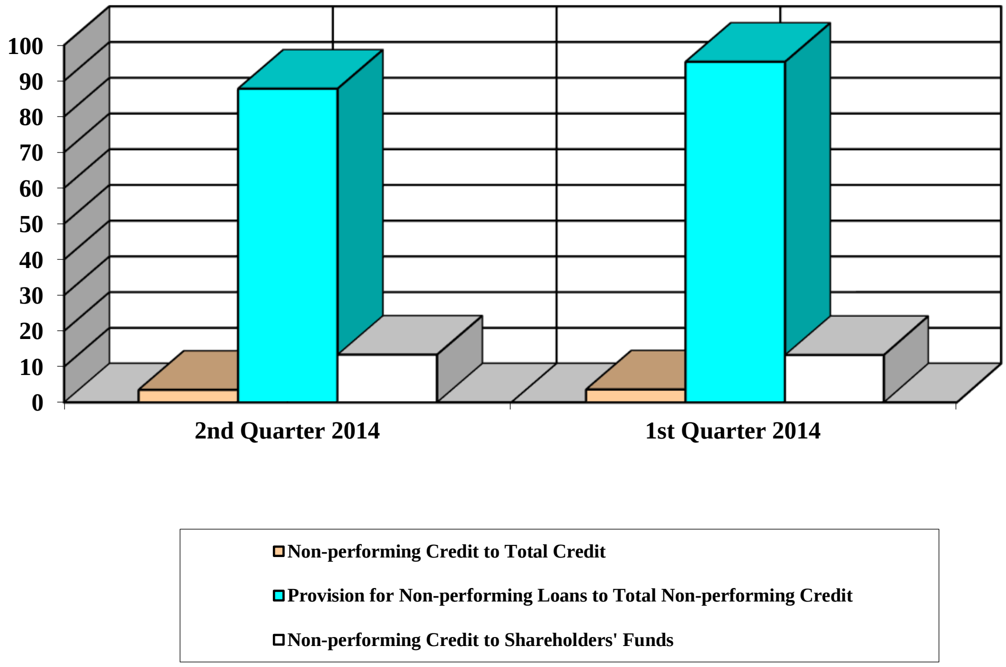
TABLE 2

Indicators of Insured Banks' Asset Quality for the 1st and 2nd quarters of 2014

Asset Quality Indicator (%)	Industry	
	2nd Quarter 2014	1st Quarter 2013
Non-performing Credit to Total Credit	3.51	3.6
Provision for Non-performing Loans to Total Non-performing Credit	87.8	95.31
Non-performing Credit to Shareholders' Funds	13.35	13.25

Source: Banks Returns

CHART 2: Indicators of Insured Banks' Asset Quality for the 1st and 2nd quarters of 2014



3.2 Earnings and Profitability

All the earnings and profitability indices showed that the total earnings of the banking industry increased in June 2014 compared to march 2014 except Return on Assets and Net Interest Margin.

The industry Non Interest Income increased to ₦323.24 billion as at 30th June 2014 from 174.18 billion as at 31st March 2014. Profit before tax increased to N288.806 billion as at 30th June 2014 compared to ₦138.97 billion as at 31st March 2014. Return on Assets decreased slightly to 0.59% from 0.6%, while Return on Equity increased slightly to 4.96% from 4.91%. These and other indices are depicted in Table 3 and chart 3 below.

Table 3

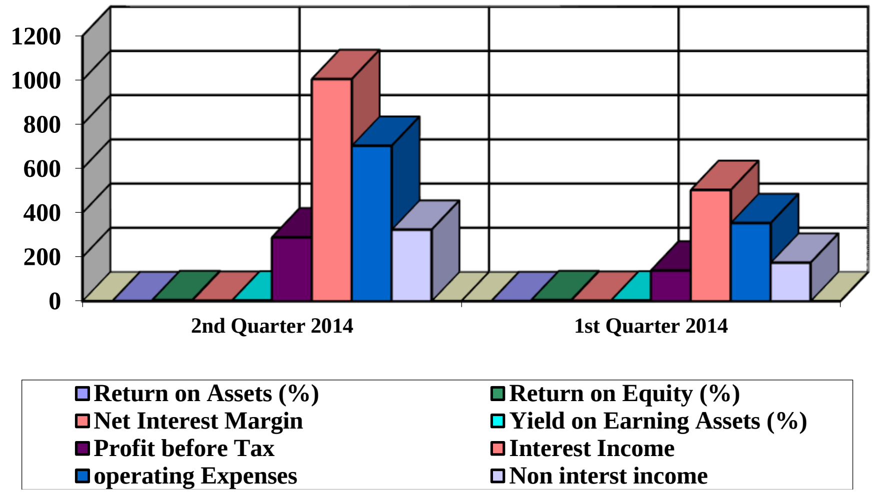
Insured Banks' Earnings And Profitability Indicators For The 1st Quarter
And 2nd Quarter 2014

Earnings/Profitability Indicator	Industry	
	2nd Quarter 2014	1st Quarter 2014
Return on Assets (%)	0.59	0.6
Return on Equity (%)	4.96	4.91
Net Interest Margin	1.93	1.95
Yield on Earning Assets (%)	3.09	3.13
Profit Before Tax (N' billion)	288.80	138.97
Interest Income (N' billion)	1,004.61	503.04
Operating Expenses (N' billion)	703.14	353.34
Non-Interest Income (N' billion)	323.24	174.18

Source: Banks Returns

As can be seen from Table 3, the positions of Return on Assets (ROA), decreased, and Yield on Earning Asset (YEA) also decreased; while Return on Equity (ROE) increased.

CHART 3: Insured Banks' Earnings and Profitability for the 1st Quarter and 2nd Quarter 2014



3.3 Liquidity Profile

The liquidity position of the banking industry experienced some slight changes during the period under review as depicted by the following relevant indices. Average Liquidity Ratio decreased to 42.66% from 44.55% during the period under review. However, despite the decline, the Average Liquidity Ratio remained above the 30% minimum requirement. On the other hand, Net Credit to Deposit Ratio increased to 62.79% from 60.97%, and Interbank Takings to Deposits Ratio also increase to 1.36% from 0.76% respectively. All banks in the system met the required Liquidity Ratio of 30% during the period under review. Table 4 and Chart 4 present the liquidity ratios of the banking industry as at March and June 2014.

TABLE 4

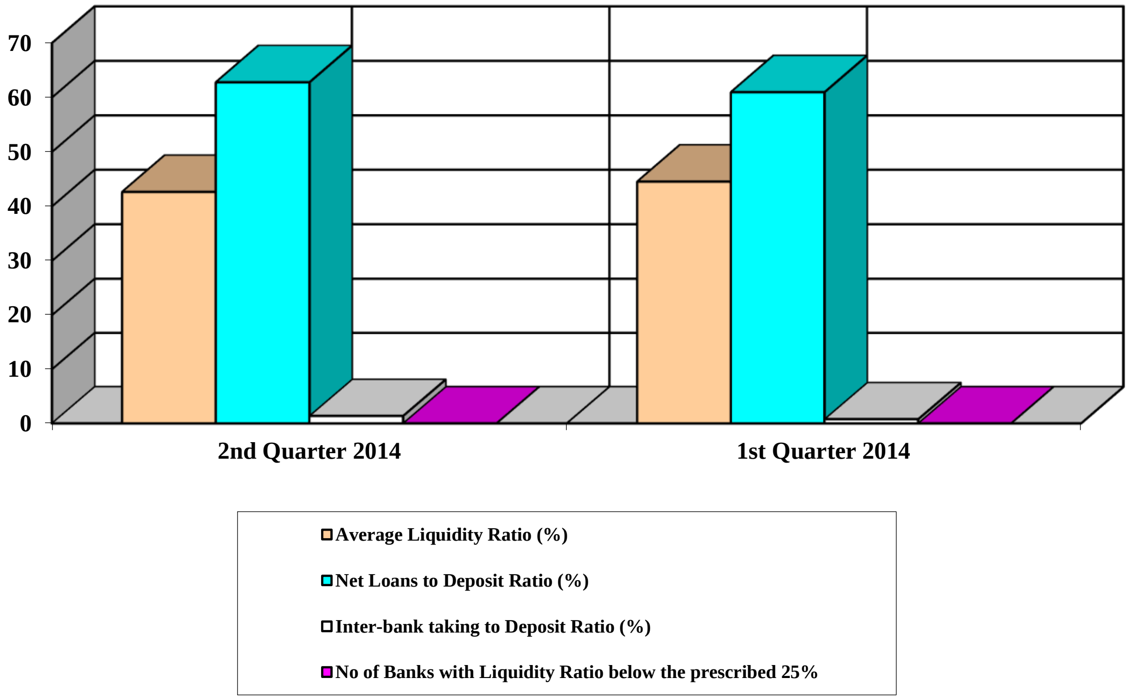
Indicators of Insured Banks' Liquidity Profile for the 1st and 2nd quarters of 2014

Liquidity	Period	
	2nd Quarter 2014	1st Quarter 2014
Average Liquidity Ratio (%)	42.66	44.55

Net Loans to Deposit Ratio (%)	62.79	60.97
Inter-bank taking to Deposit Ratio (%)	1.36	0.76
No of Banks with Liquidity Ratio below the prescribed minimum	0	0

Source: Banks Returns

CHART 4: Indicators of Insured Banks' Liquidity Profile for the 2nd and 1st Quarters of 2014



3.4 Capital Adequacy

During the periods under review, the capital adequacy ratios of the industry stood at 17.06% and 16.05% as at March and June 2014 respectively. This is an indication that the banking industry is well capitalized since the minimum of 10% has been exceeded. However, only two banks remained undercapitalized as at the end of the third quarter while three Banks remained under capitalized as at the end of June 2014.

Table 5 depicts the capital adequacy position of the industry for the period under consideration

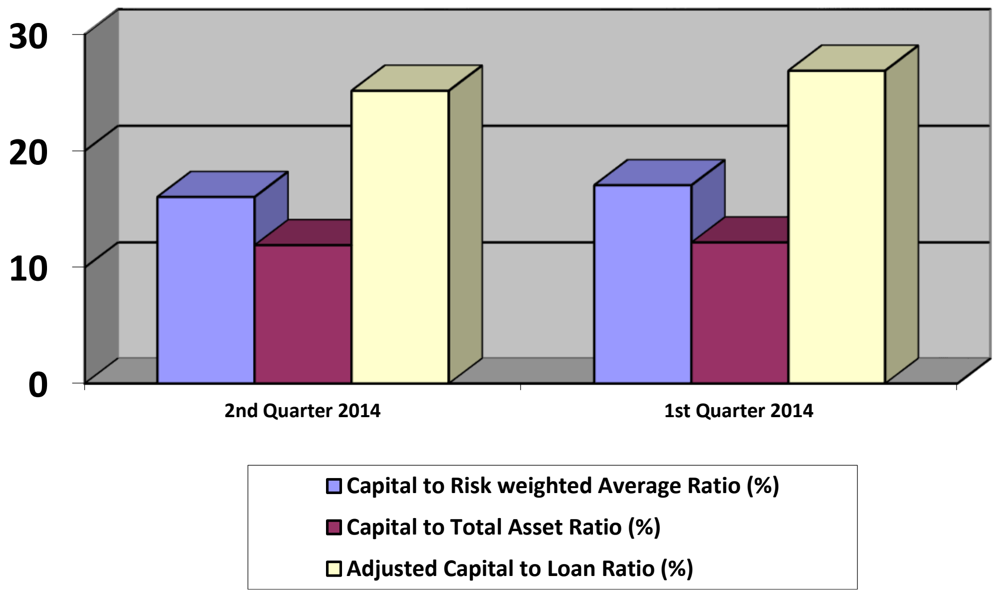
TABLE 5

Indicators of Insured Banks' Capital Adequacy Position for the 1st and 2nd quarters of 2014

Capital Adequacy Indicator	**Period**	
	2nd Quarter 2014	**1st Quarter 2014**
Capital to Risk weighted Average Ratio (%)	16.05	17.06
Capital to Total Asset Ratio (%)	11.92	12.15
Adjusted Capital to Loan Ratio (%)	25.16	26.88

Source: Banks Returns

CHART 5: Indicators of Insured Banks' Capital adequacy position for the 1st and 2nd Quarters of 2014



4.0 CONCLUSION

The indices in the various sections above depicted a very strong and stable condition of the banking industry within the period reviewed. The industry recorded strong liquidity and capital positions, as well as positive changes in asset quality and profitability, all going to show that the banking industry remained on track in terms of performance during the period under review.

STUDY REPORT ON EARLY WARNING SIGNALS FOR BANKS IN NIGEIRA

2013

1.0 INTRODUCTION

Over the years, bank supervisors worldwide have developed a number of tools which they employ in monitoring the health of individuals banks as well as that of the banking industry as a whole. The most useful tool for identifying problem institutions is on-site examination, in which examiners travel to a bank and review all aspects of its safety and soundness. However, on-site examination is costly to bank supervisors and burdensome to bankers because of the intrusion into day-to-day operations of banks. As a result, supervisors also monitor bank condition off-site. In off-site surveillance, supervisors rely primarily on analysis of regulatory returns submitted by banks to give forewarning of safety and soundness problems. One basic result from such analysis is the so-called CAMEL Ratings which is a combination of financial ratios derived from bank balance sheets and income statements to diagnose the condition of a financial institution. In most jurisdictions, bank supervisors regard CAMEL rating as the best single indicator of banks' condition. Supervisors draw on their experience to weigh the information content of these rations. Results from the analysis of these ratios act as early warning signals for supervisors in their efforts at effectively controlling the operating risk of the whole body of financial institutions and prevent financial crisis from occurring. In more economically advanced economies, an additional tool is econometric/statistical models. These models, however, rely on a computer rather than judgement to combine ratios, boiling the information about bank condition in the financial statements down to one number. Both CAMEL Ratings and econometric/statistical models are used as early warning signals to gauge the financial condition of banks.

A financial early warning system is a system that performs two important functions of financial supervision and diagnosing operating conditions of financial institutions. The importance of establishing an early warning system is numerous. One, it is able to provide the financial supervisory authorities with information as to the priority order, scope and frequency of on-site examination, in order to effectively match the available personnel. Second, through its functioning, the early warning system could objectively and quickly discovers problem financial institutions. This could urge the authorities to strengthen their supervision and, management of such institutions as a precautionary measure. Third, an early warning system is able to predict early, the likely deteriorating trend of problem financial institutions. Fourth, it is able to gather on a regular basis the financial information that is reported by the financial institutions, and to tidy up, compile and analyse such data to obtain and accurate picture of these financial institutions 'operating conditions. Fifth, the rating results derived from the early warning system can serve as important reference material for handling problem financial institutions and as a basis for improving the operating conditions of financial conditions. Finally, if the deposit insurer incorporates different risk premiums based on different levels of risk, the financial early warning system can provide different risk evaluation rankings, which will serve as basis for determining the risk-based deposit insurance premiums.

In Nigeria, banking supervisors that is CBN/NDIC, use financial ratios to gauge the financial condition and performance of banks. Although useful as an element within an early warning system, financial performance indicators have a number of shortcomings if used as the sole indicator in an early warning system. For instance, they can be characterized as after-the-fact or lagging indicators of risk, problems and failure-given that they measure business that has already been conducted and, more impotently, problems that have already occurred (Walker 2002). Second, they do not provide any obligation of whether the financial results were obtained based on sound management practices and whether the indicators used are based on quality, reliable and timely data. Above all, it is generally recognized that financial ratios are not sufficient on its own to identify the complex nature of risks undertaken by banks, particularly large banks and specialised banking institutions (Sahajwala & Bergh 2000). In addition weights assigned to each of the ratios are usually determined on the basis examiner experience and once assigned they remain fixed and may fail to adjust for temporal shifts rendering the assessment insufficient. For these reasons among others, supervisors in many jurisdictions developed a more comprehensive risk assessment for the early warning of financial institutions' problems. In addition to financial performance and condition indicators, market information and other economic and emerging information are usually part of the major components of the model currently in place in many countries.

The main objective of this study, therefore, is to design an early warning system for insured banks that takes into consideration the present tool in use, that is, CAMEL rating system as well as econometric/ statistical models which incorporates market information in addition to financial ratios which are primarily used to rate banks under the former approach. The combination of the two approaches has been seen to produce a better result than the CAMEL rating alone using supervisory experience ((Sahajwala & Bergh 2000). In fact, in many jurisdictions, the econometric model approach has been adjudged to be better than the supervisory experience based on financial ratios even though the supervisory screen continues to enjoy considerable popularity in the surveillance community (Gilbert, Meyer & Vaughan 1999). It is our opinion that an appropriate combination of these approaches could best decimate between a problem a bank and non-problem bank. To achieve this objective, this paper is divided to five sections. Apart from this introduction, Section Two review the literature and in Section Three, we discuss the early warning system presently in use by the Corporation. In Section Four, we construct econometric/statistical models for early warning system. In Section Five, we provide the result of the combinations of the supervisory screen that is, CAMEL Rating and the econometric model/statistical models as early warning signals for insured banks in Nigeria. Section Six concludes the study.

2.0 REVIEW OF LITERATURE

Over the past 30 years, a great deal of research has investigated the potential usefulness of a variety of early warning models (EWM) as off-site supervisory tools on the performance of the banking industry. Accurate off-site models give bank supervisors the capability to identify high-risk banks in a timely manner before their financial conditions markedly deteriorate, in between expensive, time-consuming on-site examinations. This capability allows scarce examination resources to be used more efficiently and permits supervisory constraints to be imposed or rehabilitative strategies put in place expeditiously, reducing the risk of costly failures.

Cornyn and Gunther (1992), appraised the *'Financial Institutions Monitoring System'* (FIMS) for banking systems. The FIMS was created by the Federal Reserve System of United States of America (USA) to make up for the limitations in the CAMEL/CAEL ratings and other previously used off-site bank monitoring systems in the estimates of financial conditions of federally insured institutions in-between on-site examinations. FIMS used specialized 'Limited dependent variable' estimation technique, as others were found not to produce accurate results. The Ordinary-level logistic regression methodology was used to produce the FIMS rating, whereas the Binary logistic regression methodology was used to produce the FIMS risk rank. The study found out that The FIMS model was considered fairly reliable as it was adequate in the correct classification of CAMEL ratings of individual banks. However in a test against a previous model, the FIMS model recorded 17.1% type 1 error and 4.4% type 2 error. This therefore points out that the model cannot be considered as perfect.

Hexeberg (1995), computed early warning indicators based on banks' interim reports. The purpose of these indicators was to identify potential problem banks and to obtain a general picture of the health of the banking industry, based on the experiences of the Norwegian banking crises between 1988-1992. The paper evaluated a set of indicators for the identification of potential problem banks both as independent indicators and as part of a simultaneous indicator system. The indicators used described different aspects of the banks' conditions and was based on the CAMEL system of banking supervision. The analysis was based on observations of the 25 banks that were hard hit by the banking crises some time prior to their appearance as problem banks, compared to observations of banks that never became. The study employed multiple discriminant analysis, which is a classification technique that seeks to determine which other bank characteristics go most frequently with bank failure. A joint probability distribution of indicators and failure was assumed, with no theory of causation implied. The model assumed that the conditional distribution for the event that a bank seeks financial assistance is logistic, implying what is known as a logit model. The study found that the capital adequacy and the asset quality indicators selected were relevant as found in previous studies. Management competence indicators were found to be non-standard, while dependence on interest sensitive funding was relevant when classified as an earnings indicator.

Forbush et. al. (2002), studied the functioning and performance of the '*Statistical CAMELS Off-Site Rating' (SCOR)* System which was developed by the Federal Deposit Insurance Corporation as an off-site system basically to supplement on-site examinations. The SCOR model used examination ratings which it compares with the financial ratios of the previous year. The model identified which financial ratios were most closely related to examination ratings and uses that relationship to forecast future ratings. The system of weights was also used in this model to produce both a composite rating as well as ratings for the components. The results showed that the SCOR model was not considered extremely accurate due to its high level of dependence on financial reporting; it was, however, very informative. It also has the advantage that it was easier to analyze than the CAMEL ratings.

Soyibo and Alashi (2004) used descriptive analysis and logit modelling techniques to examine the extent to which the determinants of bank conditions in Nigeria conform to those established in the literature. A priori expectation was that government owned banks, small-sized banks, new generation banks and banks not quoted on the stock exchange to be more prone to distress. The paper also postulated that the probability of failure of banks is a function of number of factors, including earnings/profitability, operational efficiency, capital adequacy, risk/diversification and deposit composition among others. EWS models using sub-samples of the data set was also constructed. The effectiveness of these models was evaluated using the proportion of their types 1 and 11 errors. Additionally another CAMEL-based EWS was constructed and its predictive power was evaluated due to critique of the present EWS. Weights attached to the different CAMEL factors were modified, while data was collected in two stages from the returns of banks to NDIC. The variables used for the study were: interest expense/total liabilities, equity capital/total assets, total loans/total assets, bank type, real estate loans/total loans, agric loans/total loans and ownership. The study found out that banks that are profitable and highly capitalized tended not to be distressed; also, banks not quoted on the stock exchange failed more and a high proportion of new generation banks failed more than the old ones.

Whalen (2005) attempted to verify if the accuracy of conventional EWMs estimated in more stable time periods decline markedly when economic conditions change significantly and if it is necessary to re-specify or re-estimate EWMs to obtain sufficiently accurate risk forecasts. To answer these questions, a set of Cox Proportional Hazard Composite Downgrade model was used to estimate a sample of low-risk community banks at five different year-end dates ranging from 1997 through 2002 with the exception of year 2008.

For simplicity and to permit a reasonable test of out-of-sample forecast accuracy, models were estimated using only year-end annual data for the explanatory variables. The survivor functions of the models were used to predict the probability that a low-risk community bank (composite CAMELS of 1 or 2) will not be downgraded to high-risk status (composite CAMELS of 3, 4, or 5) over an eight-quarter time horizon beginning with the second quarter after the year-end estimation date. The specifications of the models were allowed to differ across the estimation periods, but the set of explanatory variables used in each model was intentionally limited to a small number of statistically significant risk indicators employed in previous empirical work. The intent of this constraint was to investigate the accuracy of simple, low-cost EWMs over time. When the analysis focused on the 500 riskiest banks identified by the models, the conventional Type I and Type II error rates of all of the models were almost always in the low- to mid-30 percent range in all forecast years, including the most recent one where the models are used to predict downgrades through the first quarter of 2010. This means that the forecast accuracy does not consistently or sharply decline with model age. This pattern indicates that this type of EWM can be a valuable supervisory tool, even if it is not re-specified or re-estimated frequently. In addition, a supplemental analysis of forecast accuracy indicates that a considerable number of banks categorized as Type II errors by the models in each forecast period appear to be high risk ex post. The implication is that the "true" Type II error rates of the models were lower than the conventional figures reported in the tables.

Lewis (2006), attempted to apply a semi parametric technique to estimate the probability of banking crises conditional on bank specific characteristics as well as the impact of exogenous macroeconomic variables and changing financial market conditions on transition possibilities. The '*General Maximum Entropy*' (GME) was the model used alongside the 'Markov Process' for characterisation. Eventually, estimates from the CGE-IV estimation approach was found to capture significant nuances in the likelihood of banks transitioning from one state to another that would be omitted in the state which uses only proportional state information.

Anderson (2008) identified the set of indicators that best discriminates between problem and non-problem banks in the Norwegian banking sector. Logit analysis was employed in the study. Logit models were employed to find the explanatory factors behind a certain event taking place, in this case a bank failure. For the purpose of the study, a bank was defined as having failed if it underwent any one of the following events due to illiquidity or insolvency: liquidation, takeover or merger and/or capital adequacy ratio below 8 per cent. In the study, the date of failure of the problem banks, as selected given the above definition of bank failure, was set equal to the date when the first sign of insolvency and/or illiquidity is documented in the internal reports of the Financial Supervisory Authority of Norway. The results of the analysis showed that the risk index consisting of the capital adequacy ratio (Capital adequacy), the ratio of Residential mortgages to Gross lending (Asset quality), the expected loss measure (Asset quality), the concentration risk measure (Asset quality), the return on assets (Earnings) and the Norges Bank's liquidity indicator (Liquidity) were sufficient to predict failures and provide valuable information about troubled banks with sufficient lead time to allow preventive or remedial actions at problem banks to be taken. The risk index should, however, be used in conjunction with market indicators, macroeconomic indicators and qualitative information to assess and understand what vulnerabilities and potential shocks are most threatening at any time.

Tatom (2011), attempted to find the effectiveness of binary models in forecasting failure for the entire commercial banking industry. Data was collected from individual quarterly commercial bank call reports and government data. The variables used were the CAMELS parameters with stated proxies used in determining each parameter. The study found out that probit and logit models were effective in predicting failure and also that capital adequacy, asset quality, and earnings variables were by far the most significant predictors of failure in the model with two years, one year, or one quarter of data for measures of the independent variables.

3.0 CURRENT EARLY WARNING SYSTEM

The EWS in use by the CBN/NDIC is based on the CAMEL parameters. For this purpose, thresholds based on international and local conditions are used to assess a bank's financial condition. A composite measure that is a weighted average of the scores on the various components of the CAMEL system is assigned to each bank. These weights are not scientifically determined, however, but based on subjective judgement.

The combination of the ratios and the attached weights result in composite score and the rating system used by the supervisory and regulatory authorities in Nigeria. The five ratings and their different composite scores are shown in Table3.1. As shown in Table 3.1, banks rated "A" are regarded as very sound, while those rated "B" are called sound. In both cases, financial institutions under these two categories exhibit the strongest performance and risk management practices relative to the institution's size, complexity and risk profile and give no cause for supervisory concern.. A bank with a rating "C" is one whose financial condition is fundamentally sound and stable and which should be able to withstand business fluctuations; its adverse findings are minor in nature, with supervisory concern limited to the extent that findings are corrected.

The next two classes of banks give regulators cause to worry. An institution rated "D" and classified as "marginal" is likely to have some serious financial weaknesses, with unsafe and unsound conditions existing but not being satisfactorily addressed. For such an institution, close supervision and definite plans for correcting deficiencies must be evolved to prevent further deterioration of a situation that is likely to impair further viability and lead to high risk failure.

Table 3.1: Bank classification based on the composite rating scheme

Class	Composite Score (%)	Rating
A	86-100	Very sound
B	71-85	Sound
C	56-70	Satisfactory
D	41-55	Marginal
E	0-40	Unsound

Finally, banks rated "E" and classified as unsound have immediate probability of failure. Weaknesses are severe and critical, requiring urgent assistance from owners or other financial sources.

The use of off-site computerized surveillance screens allowed supervisors to analyse systematically, every quarter, various data reported by banks in the call reports. Over the years the analysis of these financial ratios have evolved from being a simple off-site calculation to a formal risk assessment tool that is often used as an early warning tool in Nigeria. In spite of its usefulness in that regard, the use of off-site surveillance screen as a single tool of early warning system has inherent weaknesses. Soyibo, Alashi & Ahmad (2004) discussed these extensively. First, financial ratios analysis is extensively and almost exclusively based on the data reported under regulatory reporting and annual data. The integrity, timeliness and process of data as well as sound accounting practices are a precondition for the analysis to be effective. Though the CBN/NDIC had made strenuous effort to improve the standard of reporting by insured banks, there are still questions about the integrity of data submitted by these banks upon which the quarterly analysis is based.

The second observed weakness relates to the thresholds upon which the analysis is based. Many of the thresholds are selected more or less on rule of the thumb. For instance, the adjusted capital ratio is difficult to justify as the basis for arriving at the benchmark cannot be easily understood. Though it is used to measure under-trading or overtrading, a superior measure of that would been loan to deposit ratio. The relevance of capital growth ratio is not essentially clear. At best, it is complementary to risk-weighted assets ratio. The determination of the maximum of non-performing risk assets to total risk assets does not seem to be based on any scientific consideration. The ratio of reserves for losses to non-performing risk assets also appears redundant and at best complementary as it will give the same ratio as non-performing assets total assets in as situation where the classified other assets and off-balance sheet engagements are not significant. The ratio of non-performing risk assets to capital and reserves relates more to capital adequacy than to asset quality. It therefore appears superfluous.

The quality of management makes the difference between a sound bank and an unsound one. A study of the CAMEL Rating system shows that the measure as well as the weight given to this indicator may be inadequate. For instance, there is no measure to capture fraud and this is a serious lapse of management that portrays the internal control as defective and porous. Another indicator of management problem that could be captured is excessive growth in insiders' loans. Overall, is not clear whether the measures used to capture Management reflect what is intended to be achieved. In some jurisdictions, because of the difficulty involved in measuring this indicator off-site, the rating system using off-site surveillance screen is limited to only CAEL instead of CAMEL.

Another concern with the current approach is the reliance solely on accounting-based information to the neglect of market-based data. It has been argued that a combination of both types of data would have mitigated the problem integrity associated with accounting-based data.

Finally, the present method is static as only "point –in-time" information is analysed. Ín addition, neither are the ratings forward looking nor specifically designed to distinguish banks likely to fail from banks likely to survive in the future.

4.0 CONSTRUCTING MODELS FOR EARLY WARNING SYSTEM

The aim of this section is to identify the models that best discriminate between problem and non-problem banks in the Nigerian banking sector. The output of the models is the probabilities of failure that can be used as early warnings and as signals that banks with high and increasing failure probabilities should be analysed in more detail and, if necessary, that remedial policy or pre-emptive action should be taken. The predicted status of the banks by our models that are designated "Distressed" correspond to the CAMEL rating of "UNSOUND" or "MARGINAL". Similarly, our models prediction for banks classified as "Comfortable" are equivalent to the CAMEL rating of "SATISFACTORY" or "SOUND".

4.1 Methodology

There is a great variety of statistical, econometric and artificial intelligence-based early warning models used to produce estimates of banking failure. These models are data-driven and use advanced quantitative techniques that attempt to translate various indicators of bank strength and performance into estimates of risk. In their review of bankruptcy prediction models from 1930 to 2007, Bellovary et al (2007) categorised bankruptcy prediction models into discriminant analysis, logit and probit analysis, neural networks (artificial intelligence) and others. Discriminant analysis, logit and probit analysis can be grouped under econometric models, decision trees algorithms are classified as artificial intelligence techniques while credit risk models are considered to be statistical techniques.

A further classification is provided by Chan-Lau (2006). He reviewed a number of different techniques for estimating default probabilities and classified them into market-based techniques which rely on security prices and ratings and fundamental-based techniques, which rely on financial statement data and/or systematic market and economic factors. Discriminant analysis, logit and probit analysis, decision trees and credit risk models will be employed in this study.In this paper, credit risk model is categorised as a market-based technique, while the econometric and artificial intelligence algorithms are regarded as fundamental-based methods.

In the following sections, we present a brief description of the selected models, rationale for their selection; variables used as inputs into the models and conclude with data selection.

4.1.1 Econometric Models

The most prominent and early examples of early warning models are found at US Federal Reserve and FDIC. These two regulators are currently using early warning models that estimate individual bank's distress status based on quarterly call report data. The US Federal Reserve developed two variants of its System for Estimating Examination Ratings (SEER) model in 1993, previously called Financial Institutions Monitoring System (FIMS) model. The first variant called the SEER rating model employs a multinomial logistic regression to estimate a bank's probable CAMELS composite rating on the basis of the most recent call report data. The FDIC developed the Statistical CAMELS Off-site Rating (SCOR) model in 1995 to replace theCAEL off-site rating system. SCOR is run every quarter on the basis of call report data, and uses anordered logit model of CAMELS ratings to estimate likely downgrades of banks with a current composite CAMELS examination rating of 1 and 2. Please refer to Sahajwala et al (2000) for a detailed discussion of these models.

(a) Logit

Logit (logistic regression) is a multivariate econometric method that is used to predict bank failures. In logit models, the dependent variable is constructed as a binary variable, such that it can take the value 0 if the bank is distressed and the value 1 if the bank is not distressed. The modelled probabilities constitute a non-linear S-shaped function within the interval (0, 1), that is dichotomous.

For logit models, the cumulative distribution function (CDF) of a random variableis used to model regressions where the response variable is dichotomous. The CDFs most commonly chosen to represent the 0–1 response models are the logistic (logit model) and the normal that gives rise to the probit (or normit) model. Although the probabilities lie between 0 and 1, the logits are not so bounded. Logit therefore does not require that the explanatory variables be distributed normally as obtained in discriminant analysis.

(b) Probit

The probit model uses the normal CDF. The estimating model that emerges from the normal is popularly known as the probit model, although sometimes it is also known as the normit model.

The only difference between logit and probit models is that the CDF of probit is standardized and the cumulative standard normal distribution function of the random variable is calculated in order to obtain the probabilities. Logit model on the other hand requires the CDF of the random variable to be logistic distribution.

Very popular probit models for default prediction are Financial Institutions Monitoring System (FIMS) and System for Estimating Exam Ratings (SEER)models of US Federal Reserve Bank. The SEER model uses 11 ratios to predict distress of banks.

(C) Discriminant Analysis

Multiple discriminant analysis (MDA) is a statistical technique used to classify an observation into one of several a *priori* groupings dependent upon the observation's individual characteristics. Its main purpose is to classify and/or make predictions in problems where the dependent variable appears in qualitative form, for example, bankrupt or non-bankrupt based on a number of characteristics.

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The first step in using MDA technique is to establish explicit group classifications. The number of original groups can be two or more. After the groups are established, data are collected for the objects in the groups. The simplest MDA technique attempts to derive a linear combination of these characteristics which "best" discriminates between the groups. The MDA determines a set of discriminant coefficients for all the banks in the analysis using their individual characteristics (the financial ratios). When these coefficients are applied to the actual ratios, the analyst then decides whether the bank is bankrupt or not.

A major drawback to the use of discriminant analysis is that, although it permits model assessment based on classification, it does not readily allow for testing the relative importance (statistical or economic) of different independent variables (King et. al., 2005).

4.1.2 Statistical Models

Existing statistics-based credit risk models can be grouped into two classes: structural or firm-value and reduced-form models. Structural models originated from Black and Scholes (1973), Merton (1974), and Black and Cox (1976). Important contributions to the literature on reduced-form models are Jarrow and Turnbull (1995), Landor (1998), Duffie and Singleton (1999), and Blanchet-Scalliet and Jeanblanc (2004), among others. In this section, we are interested in the Merton (1974) structural model for failure prediction of Nigerian banks.

(a) Merton (1974) model

The most well-known app*roa*ch of calculating default probabilities using stock market information is the Merton (1974) model. The Merton model solves for risk-neutral probabilities of default (EDFs) that represent the probability that the asset value of a firm will fall below the value of debt, assuming that the underlying asset return (change in asset value) process has a mean return equal to the risk-free rate. This model views a firm's liabilities (equity and debt) as contingent claims issued against the firm's underlying assets. By backing out asset values and volatilities from quoted stock prices and balance sheet information, the Merton model produces instantaneous updates of a firm's default probability. The default probability in the model is a nonlinear function (where the default probability has to be solved for iteratively) of the firm's stock price, stock price volatility, and leverage ratio.

Distance to default (DD), a measure calculated from Merton's (1974) model has been used to monitor risks of financial institutions by international organizations and financial authorities. For example, European Central Bank (2005) treats the DD as an important forward-looking indicator that can provide early signs of financial fragility.

The famous rating agency, Moody's, has developed a procedure for estimating the default probability of a firm that is based conceptually on Merton's 1974 option-theoretic, zero-coupon, corporate bond valuation approach.

4.1.3 Artificial intelligence techniques

Artificial intelligence (AI) based models are computer programs designed to emulate the human behaviour. AI models are designed to be sophisticated techniques that are capable of learning and refining processes and steps so as to segregate data into bankrupt and non-bankrupt, for instance. In the AI area, these processes have manifested themselves in a number of well-recognized and maturing areas including Decision Trees (DT), Neural Networks, Expert Systems, Genetic Algorithms, Intelligent Agents, Robotics and Fuzzy Logic. Decision Trees are considered to be one of the most popular approaches for representing classifiers (Rokach and Maimon, 2007).

(a) Decision Trees

The DT methodology generates a number of sub-samples from the data set. These sub-samples are randomly generated, sampling with replacement from the list of banks in the data set. A decision tree is grown for each replica. In DT technique, each decision tree is a trained classifier on its own, and could be used in isolation to classify new banks. It should be noted that the predictions of two trees grown from two different bootstrap replicas may be different. If the majority of the trees predict one particular class for a new bank, it is reasonable to consider that prediction to be more robust than the prediction of any single tree alone. Moreover, if a different class is predicted by a smaller set of trees, that information is useful, too. In fact, the proportion of trees that predict different classes is the basis for the classification scores that are reported by the ensemble when classifying new data.

The first step of using decision trees is to train a classifier, and then use it to assign a distress prediction to a bank based on new ratios. The last step is to profile or evaluate the quality or accuracy of the classifier. This process is also known as validation or back-testing. The existing historical data (or the *In-sample*) is used as the starting point to train the decision tree that will automate the distress prediction. The training process falls can be referred to as supervised learning. The classifier is then used to assign ratings to new banks.

The advantages of decision trees include its simplicity to understand and interpret. The technique also requires little data preparation. Other techniques often require data normalisation, dummy variables need to be created and blank values to be removed.

4.2 Variable Selection and Data

4.2.1 Variable Selection

In distress prediction, an issue that requires great attention is not only the model to use, but also the data and factors that are employed to develop the model. For example, Boritz and Kennedy's (1995) model is a 14-factor neural network while Altman's (1968) model is a five-factor multivariate discriminant analysis model. According to Bellovary et al (2007), the number of factors considered in their study of bankruptancy prediction[1] ranges from 1 (one) to 57 factors. Therefore, the number of factors to use in banking distress prediction is based on available data, model type and coverage of vulnerability indicators.

In line with Andersen (2008), Sinkey (1975), Martin (1977) and King et. al. (2005), we use ratios that emerged as important predictors of banking problems: profitability, capital, asset quality, and liquidity. Coincidentally, these ratios ensure coverage of the most important aspects of bank vulnerability as recognised by the CAMEL system.

The factors/variables used in this paper are as follows:

Capital adequacy: Capital serves as a buffer for unexpected losses. The higher the capital ratio, the less likely it is that losses will make the bank fail. Bank capital can absorb unexpected losses and also preserve confidence of banks. The risk of a distress should be lower for banks with higher capital ratios, so the coefficients on capital adequacy in the estimated equations should be negative if you are predicting distress.We used one variable (ratio) in our models as capital adequacy.

[1]from 1930 to 2007 models

Liquidity: Several studies indicate that the probability of bank distress is a negative function of liquidity. Indicators assessing Liquidity capture the ability of a bank to meet deposit outflows and credit line withdrawals by selling assets or by acquiring additional liabilities. Liquidity ratio is included as a variable in our models.

Credit Risk (Asset quality): The next four explanatory variables in our models are indicators of credit risk. The first of these ratios is gross credits to deposit ratio. The second is ratio of non-performing credits to total credits. The third is *Bank Pro*vision to non-performing credits. The final ratio concerned with credit risk and loan quality is ratio of performing credit to shareholders funds. Because banks with more credit risk are more likely to be distressed, the estimated coefficient on all of these variables should be negative if predicting bank failure.

Earnings

Return on assets (*ROA*) and Return on Equity (*ROE*) are ratios that have been used in distress prediction models so that the econometric/statistical procedures considered can classify the banks into problem and nonproblem categories. These ratios capture both the income that a bank earns and the efficiency of bank operations. Both *ROA* and *ROE* are the two measures of Earnings (CAMEL ratings) in our models.

Total Assets

We also construct a proxy variable for bank size defined as the natural logarithm of total assets[2]. We expect that small banks are more vulnerable to failure, thus the probability of failure will be negatively associated with bank size.

The variables, proxy of CAMEL ratings (in italics and bold) and abbreviations are presented in Table 4.1.

[2] The logarithm is used to reduce outlier possibilities and to adhere to statistical assumptions

Table4. 1: Variables and their CAMEL proxies

Capital Adequacy	
Capital Adequacy	(***Cap_Adeq***)
Liquidity	
Liquidity Ratio	(***Liq_Rat***)
Asset Quality	
Gross Credits To Deposit Ratio	(***Gross_Cre***)
Non-Performing Credits To Total Credits	(***Num_Perf***)
*Bank Pro*vision To Non-Performing Credits	(***Bank Pro***)
Non-Performing Credit To Shareholders' Funds %	(***No PerfSh***)
Change in Net Credit	(***Ch Net Ass***)
Earnings	
Return To Average Assets	(***RoA***)
Return On Equity %	(***RoE***)
Log Of Total Assets	(***TotAss***)

All the above variables are used in econometric and decision tree models. Credit risk models use market data as input.

Market Data

Variables used for credit risk models are collectively regarded as market data. Market data used for bank failure prediction of publicly traded insured banks is of three kinds: equity information (prices and trading volumes), debt information (debt ratings and sub-ordinated debt prices), and analysts' reports.

Just as five variables are used in the classic Black-Scholes-Merton (BSM) model of put option valuation for stocks, the credit risk option valuation model will also depend on the value of five similar variables. They are asset value and equity, debt, risk-free interest rate and time to maturity. Further details of analysis using credit risk models and market data are presented in the following sections.

4.2.2 Frequency of Update

According to Sahajwalaet. al. (2000), the SEER bank distress prediction model of the US Federal Reserve System is run every 3 months with new Quarterly call report data. Similarly, the SCOR model of FDIC is run every quarter on the basis of call report data.

All the models used in this paper should therefore be run every quarter based on new Call Report as well as market data.

4.2.3 Sample

Our data (for econometric and artificial intelligence models) are taken from the quarterly Call Reports filed by all NDIC-insured deposit money banks through the EFASS, which collects this information on behalf of the two primary banking regulators-the Nigeria Deposit Insurance Corporation ("NDIC") and central Bank of Nigeria (CBN). The data are taken from September 2006 to June 2012. The sample of banks does not include the AMCON recapitalized banks because the sample was collected from 2006. However, the former banks (AFRI, Platinum Habib and Spring) that were recapitalised are included. Our sample also includes Oceanic and Intercontinental that have already been merged with other banks.

Our sample includes a total of 2622 observations.Table4.2 presents summary statistics for all the different variables used in the four econometric and artificial intelligence models.

Table 4.2: Summary Statistics

Capital Adequacy

Liquidity

Year	No	Mean	Median	STD	Minimum	Maximum
2006	125	55.61	45.5	51.41	0	331.34
2007	297	59.29	48.9	32.25	16.23	314.18
2008	288	47.45	44.55	22.12	-33.1	130.38
2009	288	39.28	38.11	21.81	-54.9	112.13
2010	288	46.65	44.34	22.02	0	121.07
2011	288	58.52	53.76	24.03	5.99	191.62
2012	126	63.04	59.02	21.71	0	102.15

Gross Credits To Deposit Ratio %

Year	No	Mean	Median	STD	Minimum	Maximum
2006	125	0.922	0.85	0.638	0	4.86
2007	297	1.087	0.94	0.568	0.41	5.71
2008	288	1.085	0.99	0.441	0.23	2.88
2009	288	1.128	1.085	0.327	0.42	2.19
2010	288	0.967	0.95	0.280	0	1.82
2011	288	0.741	0.705	0.341	0.08	1.59
2012	126	0.648	0.64	0.325	0	1.4

Non-Performing Credits to Total Credits

Year	No	Mean	Median	STD	Minimum	Maximum
2006	125	5.678	2.49	7.869	0	40.32
2007	297	39.49	4.51	378.1	0	4666
2008	288	10.35	3.56	15.35	0	89.24
2009	288	15.39	6.87	20.14	0	87.82
2010	288	33.95	18.33	30.58	0	113.51
2011	288	21.64	9.09	37.27	0.03	523.66
2012	126	8.058	4.215	18.58	0	152.1

*Bank Pro*vision to Non-Performing Credits

Year	No	Mean	Median	STD	Minimum	Maximum
2006	125	6006	87.98	28938.97	-1632.87	237980
2007	297	2675	102.27	17240.42	0	143639.7
2008	288	117	103.52	74.02233	0	538.05
2009	288	143	108.13	161.3337	0	1575.48
2010	288	95.39	87.91	36.613052	0	249.36
2011	288	120.35	91.47	271.18	6.08	4523.53
2012	126	378.6	112.74	1129.74	0	9702.67

Non-Performing Credits to Total Credits

Year	No	Mean	Median	STD	Minimum	Maximum
2006	125	14.29	5.19	19.17	0	85.7
2007	297	110.34	17.46	1058.09	-284.07	15054.39
2008	288	18.02	7.67	89.66	-866.35	266.76
2009	288	36.18	16.62	154.19	-1467.37	872.28
2010	288	30.01	17.69	606.92	-902.26	6719.39

2011	288	19.52	19.35	69.69	-151.23	508.73
2012	126	21.43	12.78	43.38	0	336.44

Return to Average Assets %

Year	No	Mean	Median	STD	Minimum	Maximum
2006	125	0.38	0.25	1.36556	-998	8.5
2007	297	-1.59	0.46	37.09	-637.77	7.25
2008	288	0.37	0.36	0.70	-7.27	4.44
2009	288	-0.81	0.09	3.92	-28.64	8.23
2010	288	0.33	0.14	1.39	-3.37	11.9
2011	288	-0.08	0.12	3.91	-46.68	41.57
2012	126	0.20	0.2	0.24	-0.38	1.4

Return on Equity %

Year	No	Mean	Median	STD	Minimum	Maximum
2006	125	2.19	1.75	3.78	-15.59	14.8
2007	297	-147.07	2.82	2506.50	-43156.9	33.01
2008	288	2.63	1.87	4.81	-29.04	35.12
2009	288	-4.80	0.82	25.38	-207.68	93.09
2010	288	-0.67	0.38	24.65	-385.29	89.57
2011	288	8.46	0.465	154.16	-89.22	2610.97
2012	126	1.79	1.65	3.42	-5.81	22.71

% change in net credit

Year	No	Mean	Median	STD	Minimum	Maximum
2006	125	20817.43	3.72	42019.66	-100	122882.9

2007	297	1802.99	4.86	13774.4	-99.62	115132.2
2008	288	5.36	3.77	19.98	-70.50	232.43
2009	288	-0.56	0.71	11.81	-54.14	56.14
2010	288	0.10	1.27	10.91	-79.17	36.08
2011	288	-0.39	1.42	22.42	-100	252.87
2012	126	-14.14	1.09	39.63	-100	57.75

Market data used in credit risk models are obtained from Reuters and consists of stock price history from October 2007 to September 2012.

4.2.4 Correlation analysis

A downward bias in the t-values of estimated coefficients is possible in econometric models due to multicollinearity that is introduced as a result of high correlation between independent variables.

For the econometric models, we therefore carry out correlation analysis to ensure that there is low correlation between variables that measure any of the CAMEL parameters.

The correlation coefficient between *RoA* and *RoE* is 0.554 and the t-values show that *RoE* is insignificant; we therefore use only *RoA* to represent *Earnings*.

Measures of *Asset Quality* in our model are gross credits to deposit ratio, number of performance credits to total credit and *Bank Pro*vision to Non-Performing credits. Others are number of performance credit to s/holders funds and % change in net credit. The correlation analysis of these variables is presented in Table 4.3.

Table 4.3 Correlation Analysis

	Gross_Cre	*Num_Perf*	*Bank Pro*	*No PerfSh*	*Ch Net Ass*
Gross_Cre	1.0000	-0.0083	-0.0186	-0.025	-0.0175
Num_Perf	-0.0083	1.0000	-0.0126	0.9551	-0.0115
Bank Pro	-0.0186	-0.0126	1.0000	-0.0053	-0.0136
No PerfSh	-0.0250	0.9551	-0.0053	1.0000	-0.0026
Ch Net Ass	-0.0175	-0.0115	-0.0136	-0.0026	1.0000

Two of the indicators assessing Asset quality (Table 3) correlate strongly. The N/Performance Credits To Total Credits (*Num_Perf*) correlates positively with N/Performance Credit To S/Holders Funds *No Perf Sh*. It is problematic to include both these indicators in the model, we will therefore include only *Num_Perf*. All others exhibit low correlation.

4.3 Estimation and analysis

We estimate model parameters based on econometric models (logit, probit and discriminant analysis) and decision trees algorithm using data reported in Table 1. Our analysis is based on three groups or categorization as follows:

a) Whole sample (2006 to 2012)
b) *One-year* based prediction models.
c) Two-year based prediction models.

All the above data is divided into *In-sample* for estimation and *Out-sample* for forecasting. We also use market data as input into the option valuation Marton 1974 model in order to additionally and more accurately forecast bank distress.

4.3.1 Whole sample

In the bank distress analysis using the full sample, we first perform the *In-sample* estimations for both the econometric models (logit, probit and discriminant analysis) and decision trees algorithm; we then compare the out-of-sample forecast accuracy of the models.

For the Logit and Probit models, we initially estimated the models' parameters where all the 10 indicators presented in Table 4.1 are included. Details on this estimation procedures are reported in Tables 1 (probit) and 2 (logit) in the appendix. The required level of statistical significance is set at 5 %. We then sequentially excluded the least significant variables and ended up with a model that includes only statistically significant indicators (*Cap_Adeq*, *Liq_Rat*,*Num_Perf*, *RoA* and *TotAss*) as presented in Table 4.4(a)

In the case of discriminant analysis-based models, we also estimated the coefficients for the 10 indicators presented in Table 4.1 and then through an iterative process reduced the number of indicators to six (6). In order to arrive at the reduced number of variables, we considered the correlation between the variables, statistical significance of the variables and the judgement of the modeller. This is in line with Altman (1968). The estimated coefficients and resulting equations are presented in Table 4.4b.

In-sample estimation

Table 4.4(a) presents the *In-sample* estimation results for logit and probit models using 5 indicators. The unequal frequency of banks with low CAMEL rating in our sample suggests the use of logit rather than probit estimation because logit is not sensitive to the uneven sampling frequency problem (Thompson, 1991). But since the two techniques are very similar, we compare the accuracy of the models based on their predictive ability and significance of estimated coefficients.

Table 4.4(a): Logit and Probit Models				
	Logit		Probit	
Variable	*Coefficient*	*Probability*	*Coefficient*	*Probability*
Const	-18.66926	0.000037	-10.312120	0.000012
Cap_Adeq	0.063420	0.000000	0.026197	0.000000
Liq_Rat	0.038186	0.000000	0.020356	0.000000
Num_Perf	-0.066335	0.000000	-0.031107	0.000000
RoA	0.361565	0.000505	0.268103	0.000001
Tot Ass	0.653015	0.000075	0.366715	0.000020

We observe from Table 4.4 (a) that *Constant/intercept* and *Num_Perf* have negative effect on the health status of the bank in both logit and probit models. Other variables have positive effect. Statistically, all the variables are significant. Together all the regressors(variables) have a significant impact on the final predicted status of the bank, as LR-ratio has a p value of 0.00, which is very small.

We also compare the performance of the models with both 5 and 10 factors (variables). The 10-variable probit model has a McFadden R-squared of 0.5185 against 0.5139 produced by the 5 variable model. Both models (with 5 and 10 variables) produced the same p-value. Therefore, we can say that there is no significant improvement of the model when the insignificant factors are removed from the 10 variable model. Similar results and performance are obtained in the case of logit 10-variable and 5-variable models. The weights of the variables obtained using the multivariate discriminant analysis based on the In-sample is presented in Table 4.4b.

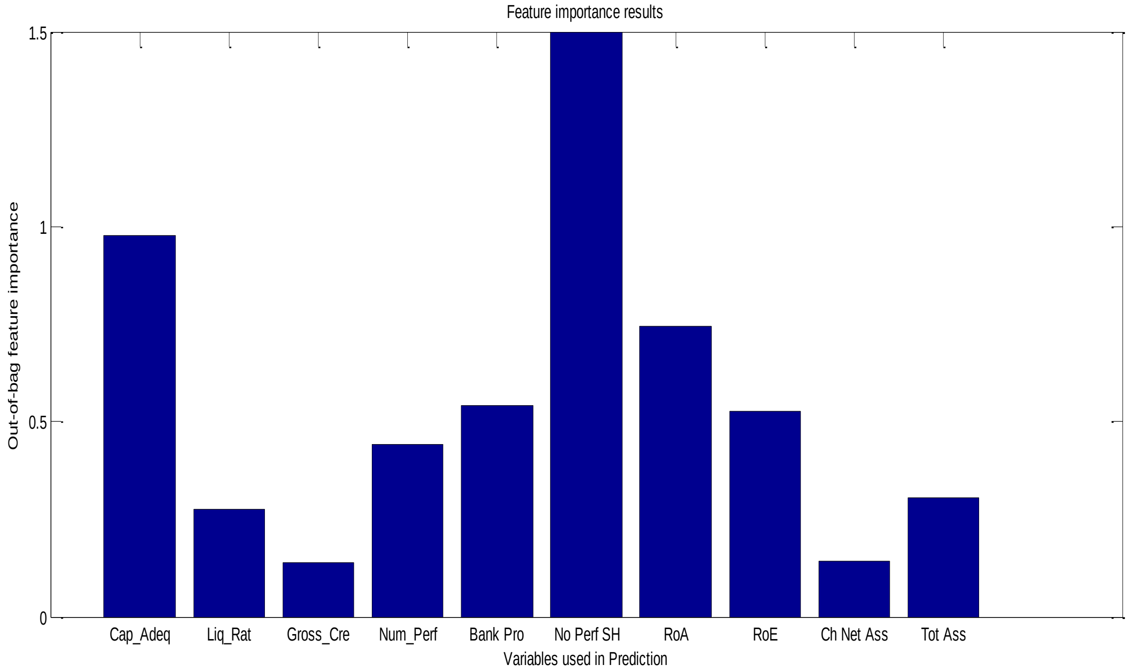
Table 4.4b: Multivariate Discriminant Analysis (MDA) variables and their weights

Variables	**Weight**
capAdeq	0.0060
liqRat	0.0320
groCred	0.0345
numPerf	-0.0544
bnkProv	0.0004
noPerfSh	-0.0001
RetAsset	0.1163
RoE	0.0015
ChNetCR	0.0019
TotAss	0.2249

Similar to logit and probit models, *Cap_Adeq, Liq_Rat,Num_Perf, RoA* and *Tot Ass* are all reported by MDA as very significant to predicting bank distress. However, *groCred* is more significant than capAdeq according to this technique in predicting bank failure. It should be noted that *groCred* is insignificant according to logit and probit for predicting bank distress.

Similarly, we used the 10 indicators (the predictors) and the eFASS rating (the response) to fit a particular type of artificial algorithm technique called a decision tree (DT). This is used to classify the banks in the In-sample as distressed or healthy based on the variables. As analysed in econometric models, we are interested in finding out whether all the variables are important for the accuracy of our DT algorithm. This is illustrated in Figure 1 where we plot the results to visually find the most important features.

Figure 1: Decision Trees Full Sample factor importance for distress prediction



Capital adequacy (*Cap_Adeq*), Non-performing Credit To S/Holders Funds %(*NoPerfSh*) and Return on Assets (*RoA*) stand out from the rest. *No PerfSh*, factor 6, is the most important predictor for this data set. Gross Credits To Deposit Ratio (*Gross_Cre*), Change In Net Credit (*Ch Net Ass*) and Liquidity Ratio (*Liq_Rat*) are the least important in predicting bank distress using the In-sample based on DT.

It should be noted that the variable importance measure used in the DT algorithm is a ranking mechanism that estimates the relative impact of a feature by measuring how much the predictive accuracy of the classifier (factor) deteriorates when this feature's values are randomly permuted. Second if two highly correlated variables are important, they will both rank high in this analysis. In this case, keeping one of these factors should suffice for accurate classifications, but one would not know that from the ranking results alone. The correlation analysis carried out in the previous section can be used here or an expert's judgement.

All the econometric models (logit, probit and discriminant analysis) reveal the same variables (factors) as most significant indicators of bank distress. The factors are *Cap_Adeq, Liq_Rat,Num_Perf, RoA and Tot Ass.* Artificial intelligence-based DT also reported the same factors as important but to a far greater different degree. *Gross_Cre* and Ch_Net_Ass are insignificant for predicting distress according to DT, but the technique also reported that *Liq_Rat* and Tot_Ass are less important than Bank_Pro and *Num_Perf*. DT also reported *RoE* is more important than *RoA* in predicting distress.

4.3.3 One-year and Two-year based prediction models

In this section, we estimate parameters for *One-year* and *Two-year* models using 298 and 576 sample sizes, respectively, as the In-sample. Table 5 reports the estimates of the models and their probabilities.

Table 4.5a: Logit and Probit Models				
In-Sample				
Variable	***Logit: One-year Model***		***Probit: One-year Model***	
	Coeff	*Prob*	*Coeff*	*Prob*
const	7.112701	0.415586	4.430534	0.360336
Cap_Adeq	0.057300	0.001418	0.031652	0.001436
Liq_Rat	0.001786	0.893738	0.000842	0.911371
Gross_Cre	-1.274507	0.054271	-0.677728	0.069097
Num_Perf	-0.133671	0.000002	-0.074689	0.000000
	-0.000774	0.564398	-0.000448	0.538622

Bank Pro	
NoPerf SH	
RoA	
RoE	
ChNetAss	0.46230.4591
Tot Ass	
	-106.0671 -106.7012
McFadden R-Squared	
Log-Likelihood	

Table 4.5b: Logit and Probit Models				
In-Sample				
Variable	***Logit: Two-Year Mode***		***lProbit: Two-Year Model***	
	Coeff	*Prob*	*Coeff*	*Prob*
const	-9.158415	0.110334	-6.747853	0.029758
Cap_Adeq	0.036649	0.002036	0.010854	0.018204
Liq_Rat	0.020926	0.011895	0.015440	0.000567
Gross_Cre	-0.094805	0.856275	0.223543	0.422994
Num_Perf	-0.094041	0.000000	-0.048098	0.000000
Bank Pro	-0.000532	0.589257	-0.000424	0.454508
NoPerf SH	-0.002399	0.223157	-0.001007	0.163974
RoA	0.346227	0.006107	0.211625	0.000853
RoE				
ChNetAss				
Tot Ass				
	0.4805		0.4674	
McFadden R-				

Squared Log-Likelihood	-207.2573	-212.4972

From Tables 4.5a and 4.5b, the Two-year models, as expected[3], have higher R-Squared than the *One-year* models. Thus, the Two-year models have higher explanatory power than *One-year* models in terms of Pseudo R-Squared. We will therefore expect the Two-year models to outperform the *One-year* models in predicting bank distress. Among the Two-year models, the logit model has higher R-Squared than the probit model. However, a drawback to McFadden (Pseudo) R-Squared is that this measure does not impose any penalty on the number of independent variables added to the model (Andersen, 2008). An alternative measure of explanatory power is the Akaike Information Criterion (AIC) which is defined as follows:

AIC = -2 *loglikelihood*+ 2*n*, where *n* is the number of parameters estimated.

A low AIC is an indication that the explanatory power of the model is high. The AIC simply penalizes over-parameterized models severely. The logit Two-year model has AIC of 436.5146, 446.9944 is the AIC value of the probit Two-year model.

Our preliminary conclusion is that the logit Two-year model should be preferred over the probit Two-year model. The *In-sample* and *Out-sample* predictions will be evaluated to reveal further insights.

In terms of significance of variables, the Logit and probit *One-year* and Two-Year models reveal that *groCred, BankPro, RoE, ChNetCR* and *TotAss* are insignificant in predicting distress. *LiqRat* is also reported as insignificant by the Logit*One-year* and Two-Year models as well as probit *One-year* models.

[3] Because the Two-year model use more data for estimation

Similarly, *noPerfSh* is found to be significant by logit Two-year model only, all the other three models find this variable to be insignificant.

We also analysed the performance of the *One-year* and Two-year models using multivariate discriminant analysis (MDA) and reported the weights assigned to the factors (variables) in Table 4.5c.

Table 4.5c: Multivariate Discriminant Analysis (MDA) variables and their weights

One-year Model		**Two-Year Model**	
Variables	***Weight***	***Variables***	***Weight***
capAdeq	0.0636	capAdeq	0.0308
liqRat	0.0420	liqRat	0.0348
groCred	-0.5335	groCred	-0.3955
numPerf	-0.0964	numPerf	-0.0769
bnkProv	0.0006	bnkProv	0.0019
noPerfSh	-0.0024	noPerfSh	-0.0001
RetAsset	0.1946	RetAsset	0.1222
RoE	0.0261	*RoE*	0.0125
ChNetCR	0.0246	ChNetCR	0.0241
TotAss	0.6032	*TotAss*	0.7431

The factors with the least weight for predicting bank distress using the *One-year* model based on MDA are *bnkProv, noPerfSh, RoE and ChNetCR*. The Two-year model revealed similar result as the On-year sample. However, the logit/probit models found *groCred* and *TotAss* to be insignificant in bank failure prediction using *One-year* and Two-year samples as opposed to the corresponding MDA technique.

Decision trees algorithm is also used to predict bank survival or failure using *One-year* and Two-year samples. Figures 2 and 3 shows the most important variables for predicting bank distress using *One-year* and Two-year samples.

Figure 2: Decision Trees *One-year* Sample variable importance for distress prediction

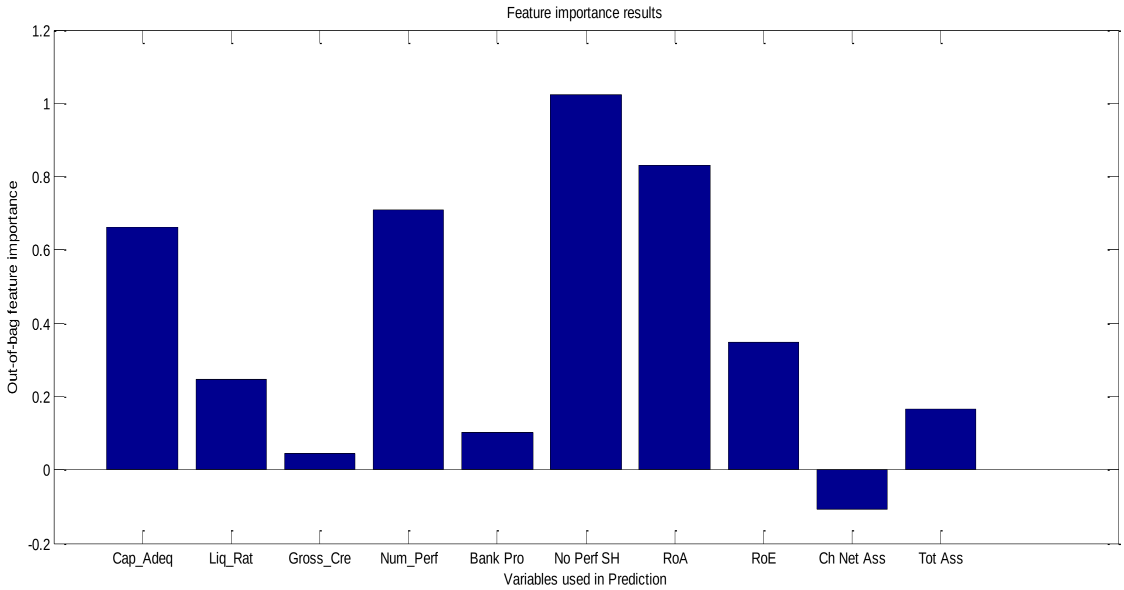
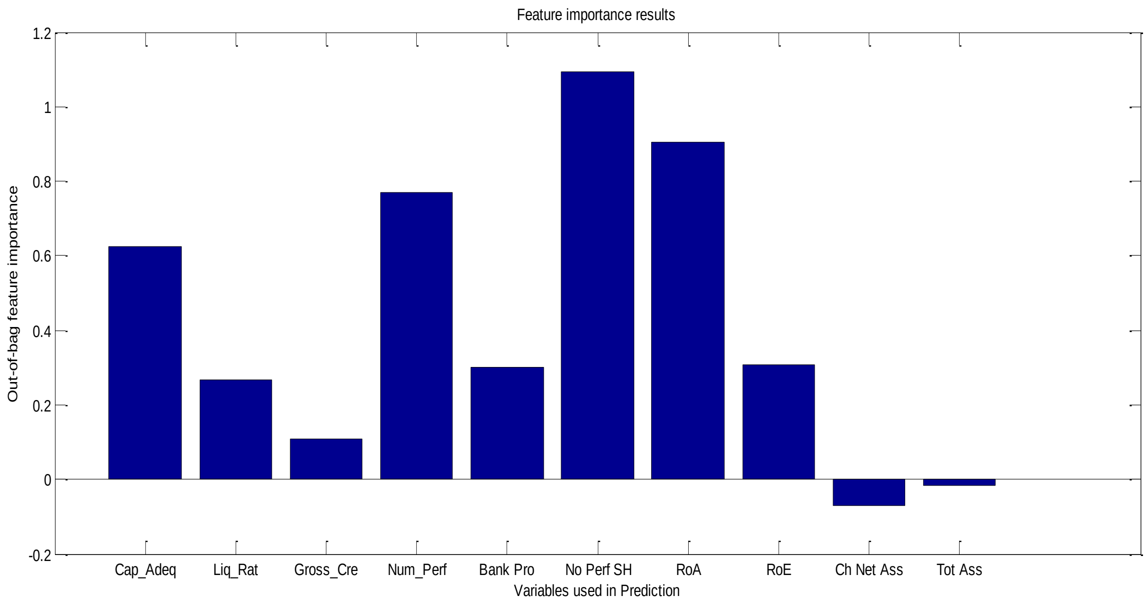


Figure 3: Decision Trees Two-year Sample variable importance for distress prediction



From figures 2 and 3, Capital adequacy (*Cap_Adeq*), non-performing Credits To Total Credits (*No PerfSh*), N/Performance Credit To S/Holders Funds %(*No*

PerfSh) and Return on Assets (*RoA*) stand out from the rest of factors as the best predictors of bank distress. *No PerfSh*, factor 6, is the most important predictor for the full sample, *One-year* and Two-year models. The least important factors according to *One-year* sample are: Gross Credits To Deposit Ratio (*Gross_Cre*), *Bank Pro*, Change In Net Credit (*Ch Net Ass*) and log of total assets (*Tot Ass*). *Gross_Cre*, Change In Net Credit (*Ch Net Ass*) and log of total assets (*Tot Ass*). Liquidity Ratio (*Liq_Rat*) are the least important factors useful for predicting bank distress based on the Two-year sample.

4.3.4 Out-Sample Forecasting and Accuracy of Models

The *One-year* model consists of records from December 2008 to December 2009 as the *In-sample*. The *Two-year* model's *In-sample* size has banks' information from Janaury 2009 to December 2010. We also assessed the accuracy, flexibility and forecasting ability of the *One-year* model using an out-of-sample period of the four quarters of 2010 (that is January-December 2010). The *Two-year* model has banking information of two consecutive years. We are therefore interested in the forecasting ability of this model with six (6) months, one year and one year-six (18 months) of data into the future.

The criterion for judging bank distress models is the classification accuracy of the model. That is, how precise is the model in discriminating between distressed and nondistressed banks within the sample, and how effective is it in discriminating between distressed and non-distressed banks outside the sample? We therefore examined the predictive properties of the four models (logit, probit, DT and MDA) based on percentage accuracy, Type I and Type II errors. According to Andersen (2008), because most supervisors prefer investigating too many banks instead of too few, Type I errors (the failure to predict an actual failure) are normally perceived as more serious than Type II errors(a false prediction of failure). Table 4.6 shows the *In-sample* and out-sample prediction accuracy of the models based on the ratios (factors) with associated Type I and Type II errors.

From Tables 4.6a and 4.6b, the decision trees model has the highest percentage accuracy and reported the least Type I error based on the *In-sample*. The least accurate model based on the *In-sample* is MDA with the highest Type I error and least predictive ability. In addition, the *One-year* model of Table 4.6a reports high accuracy ratio for half the size of Type I errors. The high rate of Type I errors (80%) over Type II is a source of concern. The best model based on the In-sample is therefore decision trees followed by the logit model. The accuracy of the models is comparable to what is found by other researchers.

Table 4.6a: In-Sample: *One-year* Model						
Model	**Total Errors**	**% Accuracy**	**Type 1**	**Type II**	**% Type I/Total Errors**	**% Type II/Total Errors**
LOGIT	42	85.91%	34	8	80.95	19.05
DT	0	100.00%	0	0	0	0
PROBIT	41	86.24%	34	7	82.93	17.07
DA	46	84.56%	43	3	93.48	6.52
Table 4.66b: In-Sample: Two-year Model						
Model	**Total Errors**	**% Accuracy**	**Type 1**	**Type II**	**% Type I/Total Errors**	**% Type II/Total Errors**
LOGIT	70	87.85%	60	10	85.71	14.29
DT	5	99.13%	2	3	40.00	60.00
PROBIT	73	87.33%	64	9	87.67	12.33
DA	94	83.68%	88	6	93.62	6.38

The performance of the *Out-sample* models is presented in Tables 4.6c-4.6h. Similar to Thompson (1991), the out-of-sample classification accuracy of the Two-year model increases as we move further from the call date of the In-sample experiment. Except for DT, all other models report higher and improved accuracy in the *Out-sample* than in the *In-sample*.Logit model is the most accurate in predicting distress when using large sample (2 years) to forecast longer horizons (from 6 months to 18 months). Using the full sample to predict bank distress produces the least accurate output than using sub-samples (1 or 2 year data).

Table 4.6c: OUT SAMPLE (Full Sample: All Variables)						
Model	**Total Errors**	**% Accuracy**	**Type 1**	**Type II**	**% Type I/Total Errors**	**% Type II/Total Errors**
LOGIT	210	70.00%	113	97	53.81	46.19
DT	197	71.86%	146	51	74.11	25.89
PROBIT	200	71.43%	114	86	57.00	43.00
DA	242	65.43%	131	111	54.13	45.87
Table 4.6d: OUT SAMPLE (Full Sample; 6 Variables)						
Model	**Total Errors**	**% Accuracy**	**Type 1**	**Type II**	**% Type I/Total Errors**	**% Type II/Total Errors**
LOGIT	221	68.43%	106	115	47.96	52.04
DT	197	71.86%	197	0	100.00	0.00
PROBIT	211	69.86%	106	105	50.24	49.76
DA	537	23.29%	10	527	1.86	98.14
Table 4.6e: OUT SAMPLE 2 YEARS (6MNTHS)						
Model	**Total Errors**	**% Accuracy**	**Type 1**	**Type II**	**% Type I/Total Errors**	**% Type II/Total Errors**
LOGIT	12	91.04%	1	11	8.33	91.67
DT	25	81.34%	0	25	0.00	100.00
PROBIT	14	89.55%	2	12	14.29	85.71
DA	13	90.30%	10	3	76.92	23.08
Table 4.6f: Out-Sample: 1 YEAR						
Model	**Total Errors**	**% Accuracy**	**Type 1**	**Type II**	**% Type I/Total Errors**	**% Type II/Total Errors**
LOGIT	33	88.54%	23	10	69.70	30.30
DT	28	90.28%	23	5	82.14	17.86

PROBIT	32	88.89%	23	9	71.88	28.13
DA	56	80.56%	53	3	94.64	5.36

Table 4.6g: Out-Sample: 2 YEAR (12MNTHS)

Model	**Total Errors**	**% Accuracy**	**Type 1**	**Type II**	**% Type I/Total Errors**	**% Type II/Total Errors**
LOGIT	24	92.05%	7	17	29.17	70.83
DT	44	85.43%	5	39	11.36	88.64
PROBIT	27	91.06%	9	18	33.33	66.67
DA	39	87.09%	36	3	92.31	7.69

Table 4.6h: Out-Sample: 2 YEAR (18MNTHS)

Model	**Total Errors**	**% Accuracy**	**Type 1**	**Type II**	**% Type I/Total Errors**	**% Type II/Total Errors**
LOGIT	26	92.57%	9	17	34.62	65.38
DT	44	87.43%	5	39	11.36	88.64
PROBIT	30	91.43%	11	19	36.67	63.33
DA	47	86.57%	44	3	93.62	6.38

We conclude this section by asking, what are the models and sample to use for predicting distress of Nigerian deposit money banks?

We found that:

- logit model is the most accurate in predicting distress when using large sample (2 years) to forecast longer horizons (from 6 months to 18 months) based on econometric and artificial intelligence techniques.
- Using longer sample to forecast from 1 year and further into the future produces more Type II than Type I errors.
- The accuracy of the four models when used for predicting bank failure is in line with percentage accuracy reported by Andersen (2008), Bellovary et al (2007) and Thompson (1991). The accuracy of the four models is very high for predicting bank distress in Nigeria.

4.4 Predicting Survivals & Failures and Sign of Variables

In this section, we compare the performance of the models when predicting survival, failure and the combination of the two. The result of this analysis is is presented in Table 4.7a. We observe that the best model for individual *In-sample* prediction of failure and success is decision trees. The best performing model in this case is discriminant analysis for *In-sample* prediction of combined failure and survival in one model.

Table 4.7a: In-Sample: 2 Years			
	Percentage of Correct Predictions using In-Sample		
Model	**Survivals**	**Failures**	**Combined**
LOGIT	93.42	87.56	85.71
DT	99.00	99.00	86.57
PROBIT	93.14	87.56	87.67
DA	93.42	87.27	93.62

We also present the variables, their sign and level of significance in Tables 4.7b and 7c.Based on whether the goal is to predict failure (survival), the standard practice is to assume positive (negative) values of the index variable are associated with failure (survival), while negativevalues are associated with survival (failure). Table 4.7b and 4.7c show that the sign of the variables changes based on whether we are predicting failure, survival or their combination. We also observe that the sign of variables use for predicting failure is closer to the sign used for predicting both failure and survival in one model based on logit and probit techniques.

Table 4.7b: **Logit**

	Failure		**Survivals**		**Combined**	
	Coeff	**Prob**	**Coeff**	**Prob**	**Coeff**	**Prob**
const	*-29.1146*	0.001833	*-32.5968*	0.028119	*-9.15842*	0.110334
Cap_Adeq	0.005172	0.693094	0.008832	0.594359	0.036649	0.002036
Liq_Rat	0.04262	0.00241	0.044658	0.026749	0.020926	0.011895
Gross_Cre	0.071116	0.936611	2.701862	0.058515	*-0.09481*	0.856275
Num_Perf	*-0.07543*	0.000781	*-0.081*	0.000212	*-0.09404*	0.000000
Bank Pro	*-0.00797*	0.08063	0.027492	0.012129	*-0.00053*	0.589257
No Perf SH	*-0.00273*	0.231475	0.002036	0.524095	*-0.0024*	0.223157
RoA	0.489997	0.013177	0.118212	0.585626	0.346227	0.006107
RoE	0.015896	0.178251	0.012979	0.697571	0.004294	0.572848
Ch Net Ass	0.058318	0.066524	-0.00358	0.90555	0.006149	0.694663
Tot Ass	1.017421	0.001448	1.057572	0.035428	0.351496	0.079497

Table 4.7c: Probit						
	Failure		**Survivals**		**Combined**	
	Coeff	**Prob**	**Coeff**	**Prob**	**Coeff**	**Prob**
const	-17.1498	0.001118	-16.3913	0.023811	-6.74785	0.029758
Cap_Adeq	0.002214	0.740089	0.002482	0.68462	0.010854	0.018204
Liq_Rat	0.025372	0.001295	0.019596	0.029602	0.01544	0.000567
Gross_Cre	*-0.00286*	0.995567	1.424632	0.042018	0.223543	0.422994
Num_Perf	*-0.04394*	0.000493	-0.04458	0.000064	*-0.04810*	0.000000
Bank Pro	*-0.00466*	0.075961	0.012247	0.018582	*-0.00042*	0.454508
No Perf SH	*-0.00168*	0.185658	0.001411	0.409601	*-0.00101*	0.163974
RoA	0.280202	0.010832	0.067742	0.466528	0.211625	0.000853
RoE	0.009891	0.146813	0.004834	0.723007	0.004198	0.284156

Ch Net Ass	0.033809	0.071725	0.00481	0.745037	0.006013	0.483358
Tot Ass	0.600494	0.000946	0.546699	0.026864	0.246835	0.023549

Similarly, Table 4.7d show that the sign of the variables changes based on whether we are predicting failure, survival or their combination using discriminant analysis. We also observe that the sign of variables use for predicting failure is closer to the sign used for predicting both failure and survival in MDA, logit and probit techniques.

Table 4.7d: Weights obtained using MDA

	survivals	**Failures**	**Combined**
Cap_Adeq	0.0624	0.0155	0.0308
Liq_Rat	0.0253	0.0415	0.0348
Gross_Cre	0.8163	*-1.3268*	*-0.3955*
Num_Perf	*-0.2174*	*-0.0425*	*-0.0769*
Bank Pro	0.0065	*-0.0003*	0.0019
NoPerf SH	0.0174	*-0.0001*	*-0.0001*
RoA	*-0.229*	0.0939	0.1222
RoE	0.0218	0.0066	0.0125
ChNetAss	0.0525	0.0253	0.0241
Tot Ass	0.8158	1.1733	0.7431

Figures 4-6 present the importance of variables used in predicting bank survival, failure and combination of both failure and survival, respectively, using decision trees. The variation of the relative importance of the variables in the figures is immediately apparent.

Figure 4: Decision Trees Model using Two-year Sample showing variable importance for Bank SURVIVAL Prediction

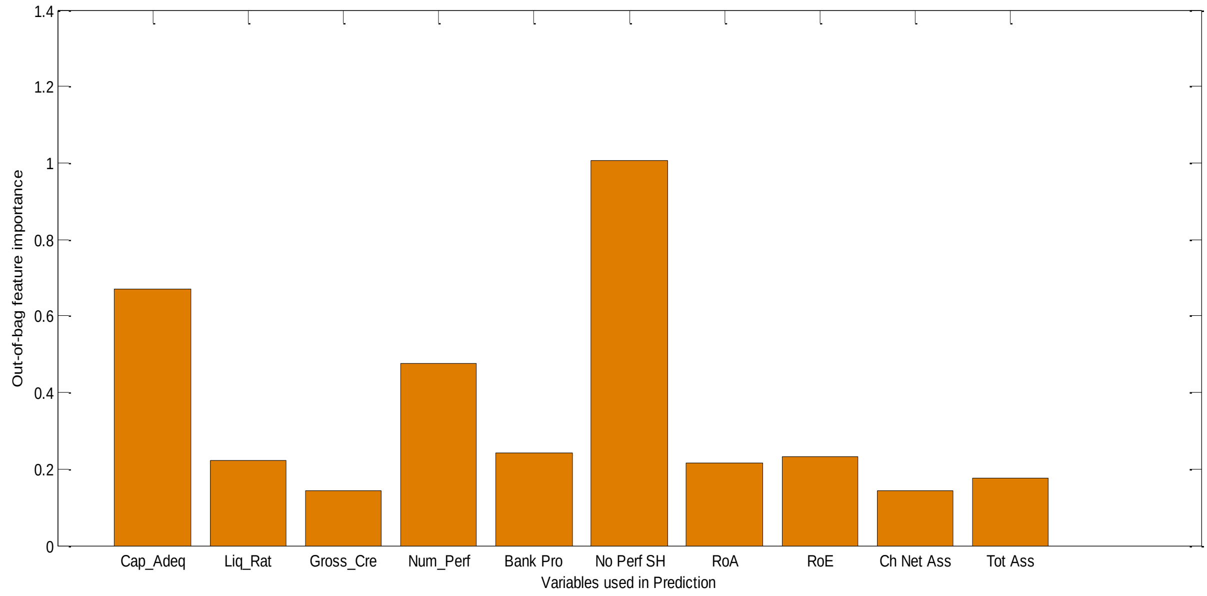


Figure 5: Decision Trees Model using Two-year Sample showing variable importance for bank FAILURE prediction

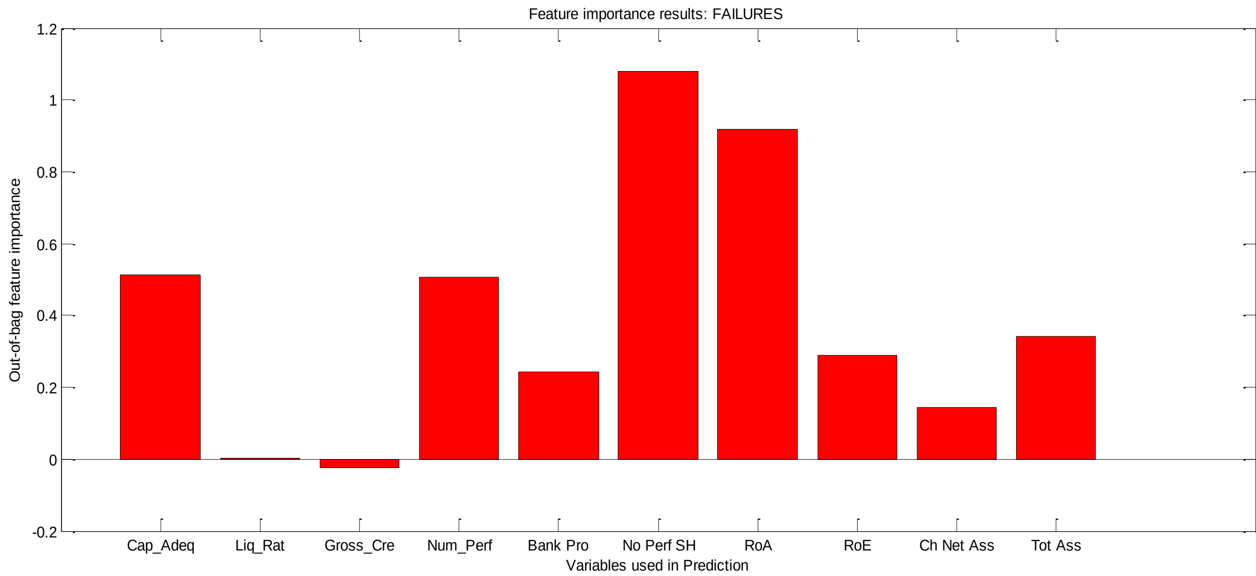
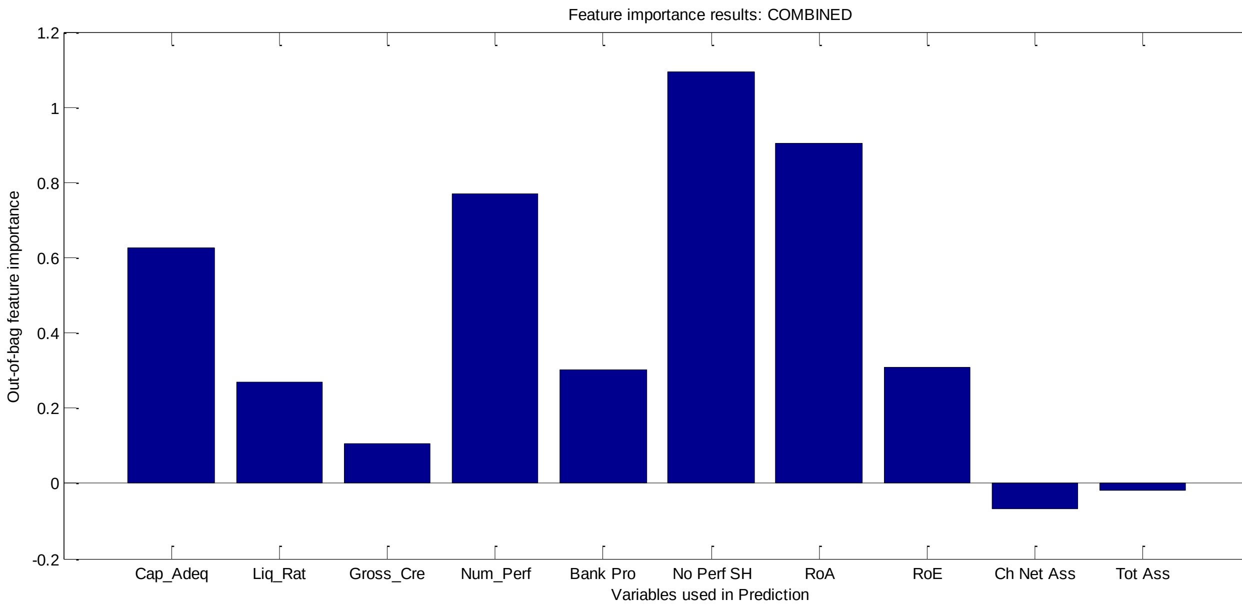


Figure 6: Decision Trees Model using Two-year Sample showing variable importance for bank FAILURE & SURVIVAL prediction



We conclude this section with the observation that the sign of the variables and the significance (weight) of the variables changes based on whether failure, survival or their combination is being predicted using the four models.

4.5 Credit Risk Models and Market Data

In this section, we applied Merton 1974 model to the Nigerian deposit money banks whose equity prices are traded on the Nigerian Stock Exchange. We derive the probability of default based on Merton (1974) model. The probability of default (*PoD)* in this case is a function of the bank's capital structure, the volatility of the asset returns and the current asset value. The *PoD* is bank specific and can be mapped into any rating system to derive the equivalent rating of the obligor (Crouhy et. al., 2000).

It should be noted that the credit risk of the banks is essentially driven by the dynamics of the asset value of the bank. This is based on the current capital structure of the bank (that is the composition of its liabilities: equity, short-term and long-term debt).

4.5.1 Probability of default

The derivation of the probabilities of default under Merton (1974) model is in 3 steps as follows: estimation of the market value and volatility of the bank's assets; calculation of the probability of default; and scaling of the probability of default to actual probabilities of default using a default database. After carrying out the above steps, the estimated equity volatility of each bank (column 2), estimated probability of default and equivalent Moody's RiskCalc equivalent 1 year rating (column 3) are all presented in Table 8. Columns 3-6 of Table 8 show previous ratings of the banks by leading credit rating agencies.

Table 4.8: Estimated Volatility and ratings of banks

	Estimated Equity Volatility	**FITCH (rating & date)**	**AG.& Co. (rating & date)**	**S&P (rating & date)**	**Previous**

UBA	47.47 %	B+(30TH June 2012)	A+	B+	A+(2009)
Skye	41.04 %			BBB (April2012)	
GTB	31.09 %	B+	"Aa" (expires 2014)	BB- 7th November 2012	"Aa"
First	44.74 %	B+ (2012)		BB(2012)	
Zenith	33.50 %	B+		B+ (July6, 2012)	AA- (2009)
Ecobank	47.80 %	B-			BBB- (2009)
FCMB	42.86 %			A+(GCR) - Jan2013	
Fidelity	42.98 %			BBB+/- (July2012)	
Diamond	47.16 %	B			A-(2009)
IBTC	36.52	AAA			AAA(2009

	%				)
Unity	47.20 %	"Bbb" (2012)			Bb
Access	57.22 %	B	"A-"30th -June 2013	B 30th may 2012	"Bbb"
Wema	49.95 %		N/A		
Sterling	52.43 %			BBB (Aug2012)	
Union	64.33 %	B+			A+

4.5.2 Distance to Default (DD)

The DD is based on a structural approach of the Merton's (1974) model and Black and Scholes (1973) option pricing model. It is based on evaluation of assets in the stock markets, where participants are heterogeneous and diversified, and book values of short-term debts. It measures both solvency risk and liquidity risk. This is an alternative default measure for banks. As stock prices are available almost every business days, the measure is continuously available.

The distance to default measures the number of standard deviations the expected asset value is away from the default. Thus, a high distance to default is associated with a low default probability. The DD is defined by the number of the standard deviation of the market value of assets away from the default point.The larger the DD, the greater is the distance of a company from the default point, and the lower is theprobability of default. For example, a DD of 2.0 means that default within a year is a two-standard deviation event, presuming the fluctuation of the market value of assets follows the recent historical value, using the current market value of assets as a starting point. Even if the DD becomes zero, it does not mean that the bank fails at that point of time. If short-term debts (liabilities with maturity less than a year) are not rolled over, then the bank would need to exhaust assets in order to repay within a year. The DD being 0.0 or even negative means that the bank will be highly likely to fail unless the asset value improves. In this case, the cautious approach is to closely examine any bank that has very high Asset volatility, especially the big banks or those considered systemically important.

4.5.3 Other market data-based default risk measures

According to Curry et al (2003), using market data, the weakest-rated firms exhibit relatively lower returns, increased volatility of returns, lower market valuations, and greater trading volume. As investors become concerned over financial distress and potential insolvency of banks, more variation may appear in return patterns. This relationship indicates that greater stock return volatility will increase the likelihood of insolvency and is directly associated with the likelihood of a downgrade. From Column 2 of Table 4.8, the banks with high estimated volatility seem to have a lower credit rating and hence a higher credit risk.

5.0 GAUGING SUPERVISORY SCREENS AND ECONOMETRIC MODELS AS EARLY WARNING SIGNALS

5.1 Comparative Evaluation of Estimated Default Risk Measures

In Table 5.1, we present the default prediction from various models evaluated in the previous sections. The proposed EWS models are used to predict the failure of the problem banks (Afri, BankPHB, Intercontinental and Oceanic) and First Bank as at June 2009 and July 2009. The predicted health status of these banks for the month of July 2009 predicted as at June 2009 and for the months of Aug and Sep 2009 predicted as at July 2009 are presented below. Table 5.1 below shows the prediction of banks' survivability just before the 2009 banking crisis.

We should consider the credit risk and market data-based models as providing a more cautious rating than those provided by eFASS or logit. Why? According to Harada et al (2010), capital adequacy ratio (CAR) provides how much capital is prepared for risk-weighted assets. However, it was not particularly a good measure predicting bank financial health, as there are many ways for "window dressing." In particular, Japanese banks in the mid-1990s were struggling to maintain a high CAR using various provisions to boost capital and to compress loan loss reserves based on optimistic assumption.

Capital adequacy is a major component of eFASS rating. This ratio can be regarded as a good measure of failure prediction if the banks do not "window dressing" or manipulate it and other ratios while reporting the ratios for bank supervision.

Credit risk model estimate of default, on the other hand, is based on prices as determined by market forces, therefore unbiased. eFASS and logit ratings are computed based on ratios supplied by the banks and may be biased or manipulated by the banks. Market discipline is enforced by those participants with the most stake like major shareholders and sophisticated investors. These participants ensure that risk taking by institutions is quickly reflected in market prices together with their expectations of the banks. The above eFASS and logit ratings will result in Type I error. The cautious rating produced by the credit risk model seems to be more accurate as observed from its high equity volatility and associated asset volatility. We therefore need a framework that involves comparing the predictions from logit model against the credit risk and market data-based models (Merton PoD and Equity Volatility) so as to limit Type I error.

Recall that the whole objective of an EWS is to point to the bank that will likely fail so that detailed on-site examination to ascertain true health status of the bank can take place. The banks that are at-risk and should have detailed examination of their status, including on-site examination, should be scheduled before the rest not very risky ones. This is the purpose of an early warning system. The analyst/reviewer can also include those banks not at-risk but who have suffered rating downgrade of more than three classes within one year (discussed above under probability of Default), as likely to fail.

In conclusion, we can say that the credit risk model (based on market data) therefore seems to outperform the eFASS and logit models by avoiding the incidence of Type I errors. The credit risk model should therefore be used in conjunction with the logit models for bank failure/survival prediction.

5.2 Method For Analyzing Ratings, Analysis And Stress Testing Of Factors

In this section, we investigate the impact and contribution of the various variables/factors used in eFASS on individual bank rating. We also investigate the impact of the variables on the forecasted distress rating using Logit model and stress test the variables using different measures. The key statistics of the variables are presented in Table 5.2.

Table 5.2: Jan-Jul 2012 Statistics Based On Reported EFASS Values

	Minimum	Maximum	Average	Standard deviation
Capital Adequacy	9.23	42.47	19.92	7.51
Liquidity Ratios	37.06	102.15	65.06	19.02
Gross_Cre	0.09	1.40	0.68	0.32
Num_Perf	0.02	152.10	9.06	22.87
Bank Pro	25.55	9702.67	475.40	1440.28
No Perf SH	0.05	118.34	17.72	19.08
RoA	-0.38	1.40	0.21	0.28
RoE	-5.81	10.88	1.58	2.53
Tot Ass	26.11	28.60	27.52	27.27
Composite	51.40	81.78	67.71	7.17

Rating				

Note that banks that have been taken over are considered as outliers and have been removed from the sample.

We also examine simple statistics of banks' ratings with categorization based on eFASS composite score so as to further confirm the changing nature of banking industry data. The average values of ratios from eFASS database are shown in Table 5.3 for two years.

Table 5.3: Average Values Of Ratios Computed From e-FASS Database

Banks rated as	***Cap_Adeq***	***Liq_Rat***	***Gross_Cre***	***Num_Perf***	***Bank Pro***	**NoPerfSH**	***RoA***	***RoE***	**Tot Ass**
Sound, Score 80 and above in 2012	22.02	91.17	0.47	1.17	1004.51	1.04	0.29	2.99	468bn
Sound, Score 80 and above in 2011	Ave=29.89 Max=40.98 Min=18.8	116.21	0.4	5.92	178.57	5.74	2.14	13.82	331bn
Sound, Score above 70 and < 80 in 2012	Ave=21.93 Max=29.02 Min=16.31	66.83	0.67	4.1	445.46	9.45	0.28	2.16	1.2tr
Sound, Score above 70 and < 80 in	23.4	83.19	0.65	3.033	308.58	6.86	0.12	0.98	1.2tr

2011									
Score above 60 and < 70 in 2012	20.09	62.37	0.75	5.55	395.40	15.45	0.19	1.32	824bn
Score above 60 and < 70 in 2011	Ave=20.82 Max=39.81 Min=10.87	56.92	0.95	6.62	106.79	19.63	0.21	1.26	928bn
Score above 50 and < 60 in 2012	13.52	61.54	0.51	23.78	151.95	39.6	0.083	0.5	410bn
Score above 40 and < 50 in 2011, with negative Cap Adeq	-31.8	59.03	0.62	26.64	87.53	63.78	-0.09	-1.23	381bn
Score above 40 and < 50 in 2011, without negative Cap Adeq	15.82	58.4	0.75	27.55	83.49	94.02	-0.14	-1.19	357bn

As we can see from Table 5.3, the values of ratios fluctuate from year to year and even within groups of composite scores (above 80, between 70 and 80, between 60 and 70, between 60 and 50 and between 50 and 40). For instance, the average capital adequacy for composite score above 80 in 2011 is 29.89, while it is 22.02 in 2012. In addition, the same score in 2011 severely fluctuates for capital adequacy with minimum of 16.31 and maximum of 40.98 for different banks. The same variation of data is observed in successive years and across the banks. We can therefore infer that values assigned to ratios should not be static but re-estimated at least yearly so as to capture important structural and other changes in the banking industry. This could be the reason why the SEER/SCOR models are re-estimated based on new call report data.

5.3 Proposed Method for Analysing Ratings

Similar to the US FDIC SCOR and Federal Reserve's SEER models, our proposed bank failure prediction model will be updated every quarter using Call report data. If the relationship between these ratios and probability of survival changes, then it will be reflected in the model through a change in the coefficients. It is therefore essential that the model is re-estimated on a quarterly basis, allowing for different coefficient estimates. This implies that there should be no fixed weight assigned to ratios or variables for predicting bank distress. Rather, the weights assigned to ratios or variables should change if the environment has changed due to structural changes (for example policy that required banks to merge), competition (for example Zenith bank that has now assumed systemic status) or any other reason that has caused a major change in the composition or ratings of the banks.

In Table 5.4 we show the coefficients of our logit model as well as their relative importance in predicting bank failure. From the table, we observe that the ratios with the highest weights, in order of decreasing importance, are log of total assets, return on assets, Gross Credits To Deposit Ratio (*Gross_Cre*), Non-Performing Credits To Total Credits (*Num_Perf*), capital adequacy and liquidity ratios. Others are Change in Net Credit (*Ch Net Ass*), return on equity, Non-Performing Credit To Shareholders Funds % (*No PerfSh*) and *Bank Pro*vision To Non-Performing Credits (*Bank Pro*).

If a bank rating system is to be designed, bearing in mind that the proposed logit model has 93% accuracy scores and the least type I error, then the proposed contribution of each ratio to failure prediction should be followed, until new call report is ready and model coefficients are re-estimated again.

Table 5.4: Ratios and Their Relative Importance In Predicting Distress

Ratio	**Coefficient**	***Failure Prediction Ability***
Cap_Adeq	0.04	*-3.73%*
Liq_Rat	0.02	*-2.11%*
Gross_Cre	-0.09	*9.05%*
Num_Perf	-0.09	*8.98%*
Bank Pro	0.00	*0.05%*
No Perf SH	0.00	*0.24%*
RoA	0.35	*-41.37%*
RoE	0.00	*-0.43%*
Ch Net Ass	0.01	*-0.62%*
Tot Ass	0.35	*-42.12%*

The minus sign in the last column is an indication that the variable does not contribute to failure, rather adds to the strength of the bank. The significance of the variables has already been discussed in the previous sections.

As stated earlier, we advocate using the logit model in conjunction with the credit risk model for Nigerian bank failure/survival prediction so as to eliminate Type I error, as much as possible.

The result further reinforces the call for the combination of credit risk model and the logit models for bank failure/survival prediction.

5.4 Scenario Analysis

We also carried out scenario analysis by estimating the marginal impact of a change in a financial ratio on the probability that a bank will fail, holding all other ratios constant.

We made the following observation based on scenario analysis of the variables:

- We observed that holding all other variables constant while total assets is stressed to 80% of its average Jan-June 2012 value, most banks fail. This underlines the importance of asset size to banks in failure prediction. Surprisingly, return on assets had to be stressed to high levels, -2500% of its Jan-June 2012 value average value before most of the banks failed.
- The ratios that required extremely high stress values of 5000% and more of the Jan-June 2012 value, implying least importance in failure prediction, are return on equity, NoPerfSH and *Gross_Cre*.
- Increasing capital adequacy ratio increases probability of survival. Decreasing the same variable decreases probability of survival, and most banks will fail (probability of survival will be less than 40%) when capital adequacy ratio decreases to about -150% of its Jan-Jul 2012 average. According to the scenario analysis, an increasing capital adequacy therefore increases probability of survival.
- Liquidity ratio also behaves similarly to capital adequacy ratio and most banks will fail (probability of survival will be less than 40%) when this ratio decreases to about -150% of its Jan-Jul 2012 average.
- Banks react to various ratios differently and fail at different points/percentages. However, for most banks, the most important variables for predicting bank distress based on stress testing, in order of decreasing importance, are total assets, liquidity and capital adequacy ratios. Based on this, liquidity and capital adequacy ratios should therefore attract the highest weight in CAMEL ratings or eFASS bank failure prediction then followed whilst *RoE, NoPerfSH* and *Gross_Cre* should have the least weights.

6.0 SUMMARY AND CONCLUSION

6.1 Findings

- All the econometric models (logit, probit and discriminant analysis) used in this paper revealed the same variables (factors) as most significant indicators of bank distress. The factors are Capital Adequacy, Liquidity Ratio, Return on Assets and Total Assets.
- Logit model is the most accurate in predicting distress when using large sample (2 years) to forecast bank failure for longer horizons (from 6 to 18 months) based on econometric and artificial intelligence techniques.
- Using longer sample to forecast from 1 year and further into the future produces more Type II (a false prediction of failure)than Type I errors (the inability to predict an actual failure).
- The accuracy of the four models when used for predicting bank failure is in line with percentage accuracy reported by Andersen (2008), Bellovary et al (2007) and Thompson (1991). The accuracy of the four models is very high for predicting bank distress in Nigeria.
- We observed that the values of ratios (as obtained from eFASS) fluctuate from year to year and even within groups of composite scores (above 80, between 70 and 80, between 60 and 70, between 60 and 50 and between 50 and 40). For instance, the average capital adequacy for composite score above 80 in 2011 is 29.89, while it is 22.02 in 2012. In addition, the same score in 2011 severely fluctuates for capital adequacy with minimum

of 16.31 and maximum of 40.98 for different banks. The same variation of data is observed in successive years and across the banks.

- The reliance on financial data from eFASS has several other effects on the Logit model's performance. It means that the selected model is completely dependent on the accurate reporting of financial information by the banks and on the extent of correctness of data in eFASS. Credit risk models and market data that utilise this data should be used for bank failure prediction, either single-handledly or together with other models.
- Scenario analysis revealed:
  - Holding all other variables constant while total assets is stressed to 80% of its average Jan-Jul 2012 value, most banks fail. This underlines the importance of asset size to banks in failure prediction.
  - Increasing capital adequacy ratio increases probability of survival. Decreasing the same variable decreases probability of survival, and most banks will fail (probability of survival will be less than 40%) when capital adequacy ratio decreases to about -150% of its Jan-Jul 2012 average. Efforts geared towards increasing capital adequacy therefore increases probability of survival.
  - Liquidity ratio also behaves similarly to capital adequacy ratio and most banks will fail (probability of survival will be less than 40%) when this ratio decreases to about -150% of its Jan-Jul 2012 average.

6.2 Recommendations

- Fixed and time-invariant should therefore not be assigned to ratios or variables weights (such as Capital Adequacy ratios given constant 20% weight at all times, each year) for predicting bank distress whether based on econometric, credit risk or eFASS systems. Rather, the weights assigned to ratios or variables should change if the environment has changed due to structural changes (eg policy that required banks to merge), competition or any other reason that has caused a major change in the composition or ratings of the banks. We therefore recommend that failure predictive percentages assigned to ratios should not be static but re-estimated at least yearly so as to capture important structural and other changes in the banking industry. In this wise, all the models used in this paper should therefore be run every quarter based on new Call Report as well as market data (equity/stock prices). This in consonance with the best practice as obtained in other advanced jurisdictions. For instance, the SEER bank distress prediction model of the US Federal Reserve System is run every 3 months with new Quarterly call report data. Similarly, the SCOR model of FDIC is run every quarter on the basis of call report data. Early Warning System of BFG Poland also updates the system every 3 to 6 months.

- We should consider the credit risk and market data-based models as providing a more cautious rating than those provided by eFASS or Logit alone. The advantage(s) of this have been demonstrated in jurisdictions such as Canada. Formal integration of selected market data into the regulatory agencies' analytical systems could substantially improve the quality of the oversight they can provide. Market data comes into being due to the activities of market players where the participants are heterogeneous, well-informed and diversified. They can be savvy individual market players or sophisticated participants like shareholders and corporate investors. These players impose market discipline and ensure that banks are well-managed to a very good extent[4]. The activities of a firm/bank are therefore reflected in the market price. Measures that are obtained from credit risk models, distance-to-default for instance, estimate both solvency risk and liquidity risk. Credit risk model estimate of default is based on prices as determined by market forces, therefore unbiased. As stock prices are available almost every business day, the measure is continuously available and hence credit risk models can be estimated every

[4]The activities of this category of players are recognised in deposit insurance systems where they are needed to impose and ensure market discipline, hence only 90-95% of total number of deposits are insured, while the rest are savvy and influential enough to limit risk-raking.

week if required instead of quarterly frequencies[5] like eFASS-based estimates, in addition to being free of manipulation by banks.

- According to most researchers, because most supervisors prefer investigating too many banks instead of too few, Type I errors (misclassification of distressed banks as healthy) are normally perceived as more serious than Type II errors(a false prediction of failure). A framework that ensures least Type I error should be adopted. In our analysis, the credit risk model seems to outperform the eFASS and logit models by avoiding the incidence of Type I errors through prediction of a more cautious survival score. We therefore propose a new bank failure rating framework for NDIC that compares predictions from logit model against the credit risk and market data-based models (Merton PoD Equity volatility) and if the predictions are similar, then it is accepted as correct, otherwise we analyse the particular case and accept the most pessimistic rating so as to limit Type I error.

- Regulators also need an acceptable and mathematical/statistical way of rating banks that can be compared with the ratings by credit rating agencies. This is because, in spite of their undoubted influence, the recent track-record of rating agencies suggests there is good reason to overhaul their activities. During the middle of the 2007-09 financial crisis, they often gave high ratings to 'risky' collections of loans called Collateralised Debt Obligations as well as to mortgage bank securities. The rating agencies themselves have blamed their mistakes on scarce resources, yet their balance sheets show resources were not a problem. This paper has implemented an alternative way of rating banks using the well-known Merton 1974 credit risk model to rate problem banks. This method is therefore being recommended for use by the NDIC to predict bank distress in Nigeria.

6.3 Conclusion

[5]Recall that credit risk models are also used by FDIC and many other DISs around the world to evaluate the adequacy of their DIF.

The whole objective of an EWS is to indicate the bank that will likely fail so that detailed on-site examination to ascertain true health status of the bank can take place. The banks considered to be at-risk should have a detailed examination of their status, including on-site examination, scheduled before the rest that are not high-risk. This is the purpose of an early warning system. The analyst/reviewer can also include those banks not at-risk but who have suffered rating downgrade of more than three classes within one year (discussed above under probability of Default), as likely to fail.

Similar to the US FDIC SCOR and Federal Reserve's SEER models, our proposed bank failure prediction model will be updated every quarter using Call report data. If the relationship between these ratios and probability of survival changes, then it will be reflected in the model through a change in the coefficients. It is therefore essential that the model is re estimated on a quarterly basis, allowing for different coefficient estimates. This implies that there should be no fixed weight assigned to ratios or variables for predicting bank distress. Rather, the weights assigned to ratios or variables should change if the environment has changed due to structural changes (eg policy that required banks to merge), competition (eg Zenith bank that has now assumed systemic status) or any other reason that has caused a major change in the composition or ratings of the banks.

We advocate using the logit model in conjunction with the credit risk model for Nigerian bank failure/survival prediction so as to eliminate Type I error, as much as possible. The accuracy of the four models when used for predicting bank failure is in line with percentage accuracy reported by Andersen (2008), Bellovary et al (2007) and Thompson (1991). The accuracy of the four models is very high for predicting bank distress in Nigeria.

Banks react to various ratios differently and fail at different points/percentages. However, for most banks, the most important variables for predicting bank distress based on stress testing, in order of decreasing importance, are total assets, liquidity and capital adequacy ratios. Based on this, liquidity and capital adequacy ratios should therefore have highest weight in CAMEL ratings or eFASS bank failure prediction whilst *RoE, NoPerfSH* and *Gross_Cre* should have the least weights.

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APPENDIX

Table 1 Probit Model estimated using full sample. All variables included

Probit Maximum Likelihood Estimates

Dependent Variable = Rating

McFadden R-squared = 0.5185

Estrella R-squared = 0.6209

LR-ratio, 2*(Lu-Lr) = 688.1542

LR p-value = 0.0000

Log-Likelihood = -319.4953

# of iterations = 9

Convergence criterion = 4.6730846e-10

Nobs, Nvars = 1000, 11

# of 0's, # of 1's = 379, 621

****

Variable	Coefficient	t-statistic	t-probability
const	-9.578977	-3.937439	0.000088
Cap_Adeq	0.026783	7.593436	0.000000
Liq_Rat	0.019302	5.699723	0.000000
Gross_Cre	-0.132960	-0.670014	0.503005
Num_Perf	-0.029896	-8.306416	0.000000
Bank Pro	0.000165	0.505695	0.613183
No Perf SH	-0.001135	-2.036420	0.041974

RoA	0.266184	4.856270	0.000001
RoE	0.003444	1.023948	0.306110
Ch Net Ass	0.003068	1.069700	0.285015
Tot Ass	0.346117	3.967915	0.000078

Table 2 Logit Model estimated using full sample. All variables included

Logit Maximum Likelihood Estimates

Dependent Variable = Rating

McFadden R-squared = 0.5410

Estrella R-squared = 0.6442

LR-ratio, 2*(Lu-Lr) = 718.0015

LR p-value = 0.0000

Log-Likelihood = -304.5717

# of iterations = 10

Convergence criterion = 2.7466604e-10

Nobs, Nvars = 1000, 11

# of 0's, # of 1's = 379, 621

****

*****

Variable	Coefficient	t-statistic	t-probability
const	-16.666036	-3.597731	0.000337
Cap_Adeq	0.069251	7.321586	0.000000
Liq_Rat	0.033566	5.140817	0.000000
Gross_Cre	-0.578130	-1.553037	0.120734
Num_Perf	-0.062164	-6.891605	0.000000
Bank Pro	0.000341	0.499657	0.617428
No Perf SH	-0.002859	-2.143521	0.032315
RoA	0.359686	3.396164	0.000711
RoE	0.003030	0.491880	0.622913
Ch Net Ass	0.002492	0.464537	0.642365
Tot Ass	0.604350	3.621873	0.000307

Table 3 Logit, Probit, DT and MDA Model estimated using *One-year* Model with 6 variables

Logit Maximum Likelihood Estimates

Dependent Variable = Rating
McFadden R-squared = 0.5100
Estrella R-squared = 0.6212
LR-ratio, 2*(Lu-Lr) = 199.8653
LR p-value = 0.0000
Log-Likelihood = -96.0044
# of iterations = 10
Convergence criterion = 2.7331111e-10
Nobs, Nvars = 288, 6
# of 0's, # of 1's = 167, 121
****

Variable	Coefficient	t-statistic	t-probability
const	-71.197631	-2.516382	0.012412
Cap_Adeq	0.039626	2.356841	0.019115
Liq_Rat	0.028149	2.787673	0.005670
Num_Perf	-0.071615	-3.483144	0.000574
RoA	0.428288	2.170824	0.030779
Tot Ass	21.382964	2.513497	0.012512

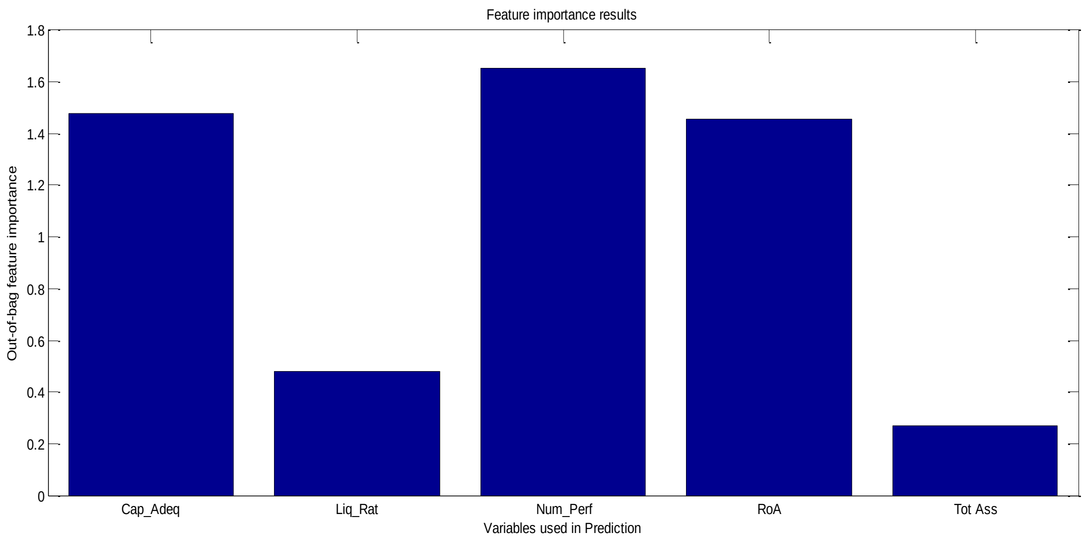
Probit Maximum Likelihood Estimates
Dependent Variable = Rating
McFadden R-squared = 0.4941
Estrella R-squared = 0.6043
LR-ratio, 2*(Lu-Lr) = 193.6132
LR p-value = 0.0000
Log-Likelihood = -99.1304
# of iterations = 9
Convergence criterion = 9.2105778e-12
Nobs, Nvars = 288, 6
# of 0's, # of 1's = 167, 121

****

*****

Variable	Coefficient	t-statistic	t-probability
const	-41.147915	-2.768363	0.006007
Cap_Adeq	0.010178	1.784107	0.075481
Liq_Rat	0.019123	3.525616	0.000493
Num_Perf	-0.039163	-4.338535	0.000020
RoA	0.196158	2.279444	0.023388
Tot Ass	12.389530	2.770526	0.005968

Figure A1



MDA

0.0257

0.0427
-1.0874
-0.0737
0.0551
0.9203