FORECASTING NON-PERFORMING LOANS IN BARBADOS

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ABSTRACT

The evaluation of non-performing loans is of great importance given its association with bank failure and financial crises, and it should therefore be of interest to developing countries. The purpose of this paper is to build a multivariate model, incorporating macroeconomic and bank-specific variables, to forecast non-performing loans in the banking sector of Barbados. On an aggregate level, our model outperforms a simple random walk model on all forecast horizons, while for individual banks, these forecasts tend to be more accurate for longer prediction periods only.

JEL: C22, C53, G21
Keywords: Non-performing Loans; Forecasting; Banking System

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1.0 Introduction

One of the main tasks of commercial banks is to offer loans, and their main source of risk is credit risk, that is, the uncertainty associated with borrowers' repayment of these loans. A non-performing loan (NPL) may be defined as a loan that has been unpaid for ninety days or more. For the purpose of this study, we analyse the non-performing loan ratios of the commercial banking sector calculated by dividing gross classified debt by total loans. The commercial banking sector of Barbados consists of six commercial banks which are currently all foreign owned, and presently the aggregate NPL ratio is approximately 3.138%.

The magnitude of non-performing loans is a key element in the initiation and progression of financial and banking crises. Ahmad (2002), in analyzing the Malaysian financial system, reported a significant relationship between credit risk and financial crises and concluded that credit risk had already started to build up before the onset of the 1997 Asian financial crisis, and became more serious as NPLs increased. Li (2003) and Fofack (2005) also found this relationship to be significant. Further, the current global financial crisis, which began in the United States, is attributed to the August 2007 collapse of the sub-prime mortgage market. In fact, there is evidence that the level of NPLs in the US started to increase substantially in early 2006 in all sectors. NPLs are therefore a measure of the stability of the banking system, and thereby the financial stability of a country.

Given the above discussion, it is not difficult to see why the ability to forecast non-performing loans is important. Generally, previous empirical studies have modeled NPLs through the use of various multivariate analyses. For example, Chase et al. (2005) used OLS to forecast non-performing loans using the treasury bill rate, the consumer price index, real gross domestic product (GDP) and a lagged dependent variable. This study contributes to the existing literature by modeling the NPL ratio of the commercial banking sector in Barbados, not only on an aggregate level but also on an individual bank level. This research paper therefore attempts to use a multivariate model to forecast non-performing loans using quarterly bank specific data, as well as macroeconomic factors

The structure of the paper is as follows: section 2 provides an overview of non-performing loans in Barbados; section 3 provides a review of existing literature; section 4 then presents the model estimates and results; section 5 offers a discussion of results and concludes with a summary of the findings, including limitations and policy implications.

2.0 Overview of Non-Performing Loans in Barbados

This section reviews the evolution of NPLs in the banking system of Barbados. As a precursor to the discussion, it should be noted that the Barbadian financial sector is well developed and encompasses a wide range of financial institutions. There are currently six commercial banks, 13 non-bank financial institutions, 34 credit unions, 11 life insurance and 16 general insurance companies[2]. At end-2008, assets of commercial banks accounted for 142% of GDP and about 80% of the assets of all deposit-taking institutions. In addition, commercial banks accounted for 82% of all deposits and around 74% of loans and advances.

Our study utilises quarterly data spanning the period 1996 to 2008. Prior to1995 there was no standard treatment or interpretation of non-performing loans. Information was received on past-due loans that did not include all the features of what is now termed as classified debt. Each bank employed its own rating system, and some still retain their own internal classification system which runs parallel to that instituted by the Central Bank of Barbados. The Asset Classification and Provisioning guidelines, which are based on the Basle Committee's Core Principles, were written into law in 1996. Over time there has been general adherence to these guidelines and standardisation has been largely achieved. Therefore, figures on classified debt are available on a quarterly basis from 1996. However, since complete adherence to the new provisioning guidelines was not immediately achieved, figures may have been

2 See Chase et al. (2005) and IMF (2009) for a more detailed discussion on the composition of the financial sector in Barbados.

misrepresented in the earlier stages. In fact, during this period, it was not unusual for examiners to adjust the level of classified debt reported by banks on conclusion of an on-site examination. However, these adjustments were usually minor.

Table 1 presents descriptive statistics for the aggregate NPL ratio over the period 1996 to 2008, and for the sub-periods 1996 to 2002 and 2003 to 2008. The average NPL ratio was approximately 7.96% in the first sub-period and fell to 5.21% during the period 2003 to 2008. As a result the average NPL ratio was 6.7% over the entire period. The maximum ratio over the entire period was 16%, which occurred during the first sub-period. On the other hand the lowest ratio (2.83%) occurred during the second sub-period. Figure 1 gives an idea of how the NPL ratio is distributed across the period.

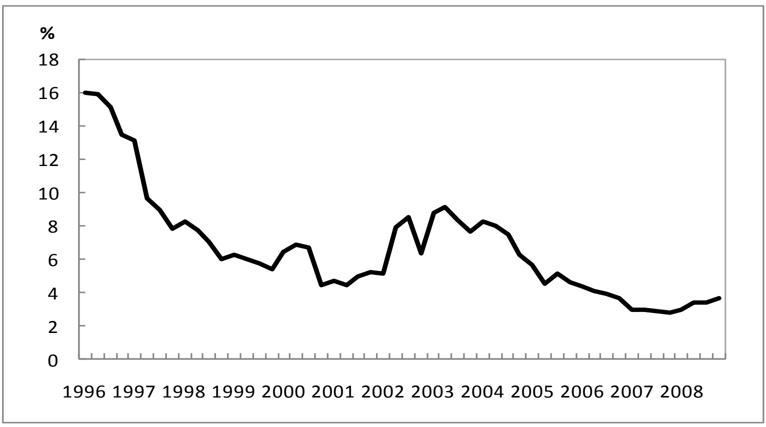
Table 1: Some Summary Statistics of the NPL Ratio

	1996Q1-2008Q4	1996Q1-2002Q4	2003Q1-2008Q4
Mean	6.70	7.96	5.21
Median	6.00	7.00	4.50
Maximum	16.00	16.00	9.00
Minimum	2.83	4.00	2.83
Standard Deviation	3.25	3.53	2.14
Skewness	1.30	1.15	0.54
Kurtosis	4.44	3.22	1.81
Observations	52	28	24

Overall, the plot indicates a general downward trend in classified debt over the sample period. The NPL ratio was recorded at 15.98% at the end of the first quarter of 1996, and steadily declined into 2000; however the quality of the portfolios weakens after 2001, as illustrated in Figure 1. There is significant empirical evidence to suggest that local economic conditions explain to some extent, the variation in non-performing loans experienced by banks, including Keeton and Morris (1987), Sinkey and Greenwalt (1991), Salas and Saurina (2002), and Rajan and Dhal (2003).

The initial decreasing trend in the data, for example, can be linked to five years of consecutive growth for the Barbadian economy from 1996 to 2000. Following these consecutive years of growth, real GDP contracted by 2.6% in 2001, with a small recovery in 2002, which is in line with an increased NPL ratio over that period. This short economic recession reflected the effects on the tourism industry of the global downturn following the September 11 terrorist attacks in the USA. According to the International Monetary Fund (2003), discussions with local commercial bank representatives indicate that banks were starting to see an increase in delinquencies, and requests for restructuring loans in early 2002.

Figure 1: NPL to Total Loan Ratio, 1996 – 2008



However, the economy quickly recovered and continued to grow over the next six years, which is reflected in the improvement of the NPL ratio into 2007. There is evidence of a pick up in the NPL ratio in 2008, which may be attributed to the current global financial crisis that originated in the USA with the 2007 collapse of the sub-prime mortgage market. Although the Barbadian financial market did not experience an immediate impact of the crisis in 2008, it is likely that this deteriorating trend in the NPL ratio is a consequence of the effects the crisis is having on the real economy, particularly on the tourism sector. Thus, this pick up in the NPL ratio is likely to continue into 2009, and even into 2010, depending on the extent of the global financial crisis.

Not only do external factors influence the loan loss rate, but also internal bank-specific factors. Hence, the individual banks in the banking sector are examined. For the purpose of this study, the six commercial banks are labelled Bank 1 to Bank 6.

Figure 2 presents the NPL ratio for the individual banks. Consistent with the aggregate data, there is a common decreasing trend in the NPL ratio from 1996 to 2000 for Banks 1, 2, 3 and 5, which, in addition to being reflective of GDP growth, may also be a result of banks' actions to regulate their loan portfolios. Bank 1, for example, completed a review of their non-performing loan portfolio in 1995, which was part of an on-going restructuring process, and was necessitated because the non-performing loans had represented more than 30% of the bank's total loan portfolio. Subsequently, many of the bank's non-performing loans have been restructured, and have significantly decreased in volume.

However, unlike others, the NPL ratio for Bank 4 was relatively low from 1996 to 2001, with an average of 1.26%. It then increased sharply in 2002, reaching a peak of 16.14% in 2003, and gradually declined thereafter. This significant jump in 2002 was due to a considerable increase in non-performing loans in the third quarter of 2002, followed by another substantial increase in the third quarter of 2003.

Bank 6 was formed through the merger of two other banks (Bank 6A and Bank 6B), and began operations in the fourth quarter of 2002. Figure 3 presents the NPL ratio for these banks from 1999 to 2002 and illustrates the common decreasing trend until 2001 for Bank 6A. However, the NPL ratio for Bank 6B began with a reasonably low ratio of 7.74% in 1999 and increased to 17.61% in the second quarter of 2000, and fell sharply in the fourth quarter. Following the merger the NPL ratio for Bank 6 gradually declined into 2007, with a slight increase in 2008.

Figure 2: NPL to Total Loan Ratio (%) for Individual Banks of Barbados Banking Sector

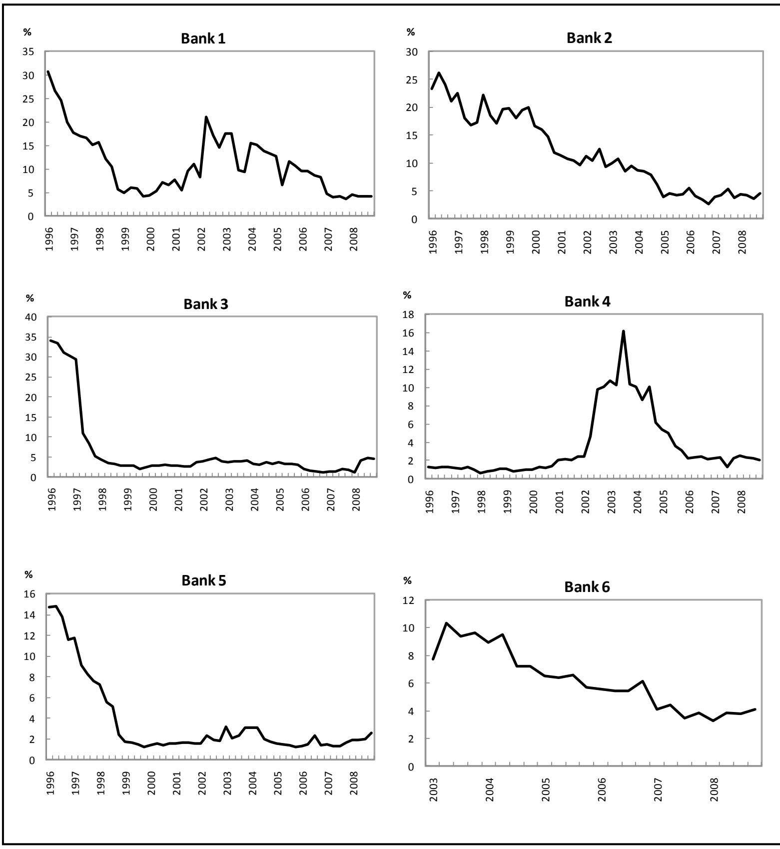
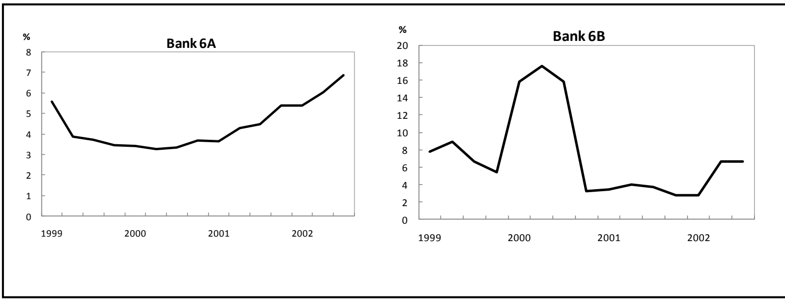


Figure 3: NPL to Total Loan Ratio (%) for Bank 6



3.0 Literature Review

Despite the importance of the examination and monitoring of non-performing loans, forecasting these ratios has only received moderate attention in the literature. There is a general consensus that the level of NPLs experienced by banks is determined by internal and/or external factors. For instance, Keeton and Morris (1987) pointed out that local economic conditions and the poor performance of certain industries explain the variation in loan losses. However, commercial banks with greater risk appetite and that are more willing to make loans with a higher probability of default, tend to record higher losses. Sinkey and Greenwalt (1991) also shared this general view, and posited that NPLs reflect realized credit risk for banks arising either from external factors such as depressed economic conditions, or internal factors such as poor lending decisions or both. The study found a significantly positive relationship between the level of loan defaults and high interest rates, excessive lending and volatile funds.

The existing literature however suggests a variety of determinants and approaches to be used in the forecasting of non-performing loans. Graham and Humphrey (1978) presented one of the early attempts at predicting non-performing loans. The authors suggested that, in general, banks with larger amounts of classified loans (loans with more than normal risk) will experience greater amounts of future losses, and hence classified loan data should be included as an indicator of these loan losses. The authors therefore evaluated whether taking classified loan data into account improves forecasts of future net loan losses.

Three models are used to predict loan loss levels. Model A is a simple prediction model and assumes that the ratio of net loan losses (*N*) to total loans in the present period *t* continues to hold in a future period *t + 1*. Model B uses coefficients from the estimated relationship between net loan losses in periods *t* and *t – 1* from the regression, $N_t = \beta_0 + \beta_1 N_{t-1} + \varepsilon_t$, where ε_t is an error term, to predict future net loan losses. Model C utilises classified loan data generated through on site examination, categorised as doubtful, substandard or specially mentioned, to define the level of net loan losses in period *t + 1*, as a linear function of classified and unclassified loans in period *t*. Since the amount of losses from unclassified loans is likely to be small, compared to losses from classified loans, it is assumed that losses from unclassified loans are randomly distributed and as such are captured in the error term of the model. The coefficients are estimated from a regression equation, for the year just prior to the forecast year. The root-mean-squared error (RMSE) of these models indicated fairly accurate results. The findings suggest that although the addition of current classified loan data improves the fit of the regression model, forecasts based upon the augmented model often yield less accurate forecasts than a simpler model employing data only on past loans. In other words, a simple univariate model outperforms their multivariate model.

Subsequent models are of a more complex nature and include a greater selection of variables for the forecasting of non-performing loans. For example, Barr et al. (1994) argued that bank failure prediction studies have continually concluded that the level of efficiency of a bank's management is the leading cause of failure, yet few researchers have attempted to quantify management quality or incorporate it into predictive models. Seballos and Thomson (1990) and Hsing et al. (1991) also supported the view that a key determinant is management's ability to operate efficiently and manage risks. Barr et al. (1994) therefore attempted to incorporate management quality as an explanatory variable through the use of a data-envelopment analysis (DEA), which combines multiple inputs and outputs to compute a scalar measure of efficiency. In addition, the authors included variables representing Capital Adequacy, Asset Quality, Earnings Ability and Liquidity Position, to complete the CAMEL rating, as well as a proxy for local economic conditions. The performance of the DEA management variable is assessed using a Probit regression model to develop one- and two-year ahead forecasts. Their results supported the claim that management's efficiency is indeed important in forecasting bank failure.

More recently, Chase et al. (2005) modelled non-performing loans using the Treasury bill rate, the consumer price index, real GDP and a lagged dependent variable. The authors use a similar technique to Graham and Humphrey (1978), where Ordinary Least Squares (OLS) is employed to forecast the NPL to total loans ratio for the banking system in Barbados. All of the explanatory variables were found to be significant. Subsequent research conducted in the Caribbean includes that of Khemraj and Pasha (2009), who examined the determinants of non-performing loans in Guyana. Using a panel dataset and a fixed effect model, the authors regressed the NPL ratio on the GDP growth rate, inflation rate, real effective exchange rate, and the bank specific variables, loans to total assets ratio, size, real interest rate and annual growth in loans. The empirical results revealed that with the exception of the inflation rate and bank size, all other factors have a significant relationship with the NPL ratio.

However, note should be made of an earlier argument by Smith and Lawrence (1995) that macroeconomic variables have limited predictive powers in explaining loan defaults, and that explicitly including them in the forecasting model is unlikely to improve its effectiveness for forecasting purposes. They specified a mortgage-loan-default forecasting model based on a Markovian structure, as an extension of the work of Lawrence et al. (1992), who examined the determinants of default risk for mobile home loans. Smith and Lawrence's findings suggested that payment history, the geographical area in which the home is located, and the number of months expired and remaining in the loan's term, are the main contributions to loan default. The authors also noted that several papers have concentrated on the identification of factors that help in the prediction of default, but neglect issues in the development of long-term forecasts of losses on loan portfolios.

Nonetheless, Betancourt (1999) remarked that although the Markov Chain technique is a reasonable approach for estimating loan losses, a common problem with these models is the requirement of very strong assumptions regarding stationarity and homogeneity, which are not usually satisfied. The author estimated loan losses from a portfolio of mortgages, where in any month, a mortgage could be classified into one of the following categories: (1) Active, (2) Thirty days delinquent, (3) Sixty days delinquent, (4) Ninety plus days delinquent, (5) foreclosure, (5) Real estate owned (REO) and (6) Paid off. If B_0 represents a start vector of mortgages at time 0, then multiplying the vector B_0 times the transition matrix P yields a forecast B_1 of how the mortgages in the start vector will be distributed at time 1. A forecast of loan losses (REO acquisitions) at time *t* can be generated by simply observing the number of loans expected to transition to REO at time *t*. The authors concluded that when using the most recent information on transition probabilities, the Markov Chain approach could provide a more accurate forecast of loan losses than a random walk model.

4.0 Model Estimates and Results

In order to accomplish the objectives of the study, forecasts of the NPL ratio will be generated using a multivariate model on an aggregate level, as well as for each individual bank. . Bank 6 is excluded from this analysis due to the small sample size of its NPL ratio. Graham and Humphrey (1978) expressed the view that using data only on past loans gives more accurate results than less parsimonious models. However, since non-performing loans must essentially be driven by factors external to its past, we concentrate on multivariate modelling. Given our available data, we are unable to include management efficiency as a variable as recommended by Barr et al. (1994), although their evidence supports the claim that it is an important determinant in forecasting bank failure. Also, the Markovian structure suggested by Smith and Lawrence (1995) is inappropriate for our purpose due to the common problem of restrictive assumptions, as noted by Betancourt (1999). In addition, the models used in both studies utilise data that is currently unavailable for Barbados such as payment history and geographical area in which the home is located. Finally, despite the argument by Smith and Lawrence (1995) that macroeconomic variables have limited predictive power, we adopt a modified version of a model by Chase et al. (2005) for the multivariate analysis, since their model has been proven to work well in the Barbadian case, and presents a more practical approach[3].

In this regard, the aggregate NPL ratio for the banking system is estimated from the following equation:

$$NPL_t = f\left(\underset{+}{r_{t-1}},\ \underset{+}{\dot{p}_t},\ \underset{-}{\dot{y}_t},\ \underset{+}{NPL_{t-1}} \right) \tag{1}$$

where r is the weighted average loan rate and is taken as a proxy of interest rates in the banking system instead of the Treasury bill rate used by Chase et al. (2005), p is the consumer price index, y is real GDP, a superimposed dot denotes the variable's growth rate and a +/– sign below the variable indicates its expected impact on the NPL ratio. Given that higher interest rates make it more costly for borrowers to pay off loans, the interest rate is expected to have a positive relationship to the NPL ratio. High levels of inflation create an uncertain economic climate and therefore lead to a higher level of non-performing loans. Growth in real GDP increases the capability of borrowers to repay their debts and should contribute to a lower NPL ratio. Lastly, the lagged dependent variable is included in the model to account for inertia in the process of dealing with non-performing loans.

In addition to the macroeconomic variables, some bank specific variables are also included in the individual bank forecasting models based

3 The model of Chase et al. (2005) has been adopted in the stress testing analysis of the IMF for Barbados (see IMF 2003 and 2009).

on the literature review of Khemraj and Pasha (2009). As such, the individual bank regression equation takes the form:

$$NPL_t = f\left(\underset{+}{r_{t-1}},\ \underset{+}{\dot{p}_t},\ \underset{-}{\dot{y}_t},\ \underset{+}{NPL_{t-1}}, \underset{+}{\Delta LOANS},\ \underset{+/-}{SIZE}\right) \tag{2}$$

where $SIZE$ is the relative market share and $\Delta LOANS$ is the annual growth in loans of each bank. It is expected that loan growth will be positively related to the level of NPLs since rapid credit growth is often associated with a higher NPL ratio. Khemraj and Pasha (2009) note that empirical evidence relating to the effect of bank size on the NPL ratio is mixed. A negative relationship between the NPL ratio and bank size may signify that the larger the bank is, the better risk management strategies it is able to employ, and hence has a lower level of non-performing loans compared to a smaller bank. However, it may also be the case that larger banks take on more risk, increasing the magnitude of non-performing loans, thus resulting in a positive relationship. Nonetheless, the authors report that no significant relationship exists between the size of a banking institution and the level of NPLs. Plots of the bank-specific variables are presented in Figures A1, A2 and A3 in the Appendix.

The plot of the aggregate NPL ratio series for the banking sector in Barbados indicates the existence of a downward trend in the data and hence suggests non-stationarity. However, the sample autocorrelation plot "dies out" fairly quickly which is an indication that the data may be stationary. In addition, the Phillips-Perron test suggests rejection of the null of a unit root at the 5% level of significance. However, the Augmented Dickey Fuller (ADF) test indicates that the null hypothesis of a unit root cannot be rejected at the 5% level of significance. Yet the KPSS test indicates that the null hypothesis of stationarity cannot be rejected. Thus, the evidence, though not definitive, points towards the aggregate NPL ratio being stationary. However, given the strong downward trend in the series depicted in Figure 1, for modelling purposes we proceed as if the aggregate NPL ratio is a unit root process. The results of the unit root tests are presented in Table 2.

Table 2: Results of the Aggregate and Individual NPL Ratio Unit Root Tests

NPL Ratio	ADF	Phillips Perron	KPSS
Aggregate	-2.794 (c)	-2.913 (c)*	0.446 (c)
Bank 1	-3.297 (c)*	-3.337 (c)*	0.210 (c)
Bank 2	2.970 (t)	-3.755 (t)*	0.826 (c)**
Bank 3	-4.095**	-4.034**	0.440 (c)
Bank 4	-1.040	-1.040	0.363 (c)
Bank 5	-4.535**	-4.874**	0.542 (c)*

Note: ** and * indicate significance at the 1% and 5% levels respectively (c) and (t) indicate that unit root tests were conducted with a 'constant' and 'constant and trend' respectively.

With regard to the individual models, the three unit root tests suggest that the NPL ratio series for Banks 1, 3, and 5 are stationary, whereas there is no consensus on Banks 2 and 4 (See Table 2 above). The ADF test of the NPL ratio for Bank 2 indicates that the null hypothesis of a unit root could not be rejected, while the KPSS test suggests a similar result, rejecting the null hypothesis of stationarity at the 1% level. The Phillips Perron test suggests rejection of the presence of a unit root at the 5% level, but only with a deterministic trend included. Earring on the side of caution, we assume that this series is I(1). Similarly, both the ADF and Phillips Perron tests statistics were insignificant for the NPL ratio of Bank 4 and hence we assume the series is also I(1).

The results of the unit root tests of the other bank-specific and macro-economic variables are presented in Table 3. The annual growth rate of loans is stationary for each bank, whereas the relative market share is only stationary for Banks 4 and 5. For Bank 1, the ADF and Phillips Perron tests indicate that the null of a unit root cannot be rejected, and the KPSS test rejects the null of stationarity, and hence the size variable for Bank 1 is assumed to be non-stationary. The ADF test suggests that the size of Bank 2 is I(1), yet the Phillips Perron and KPSS test suggest it is I(0). An examination of the series leads us to conclude that the series is indeed I(1). The tests with a unit root null hypothesis only indicate rejection when a deterministic trend is included for the relative market share of Bank 3, while the KPSS test soundly rejects stationarity. We therefore proceed under the assumption that the series is I(1). Table 3 also indicates that the GDP growth rate and inflation rate are stationary. The ADF and Phillips Perron tests suggest that the weighted average loan rate is I(1), whereas the KPSS test suggests it is stationary. Inspection of the plot of the weighted average loan also suggests that the series may be non-stationary, and hence we assume that r is I(1) .

Table 3: Results of the Unit Root Tests of the Bank Specific Variables

		ADF	Phillips Perron	KPSS
Bank 1	$size_t$	-3.381 (t)	-3.328 (t)	0.205 (c)*
	$\Delta loans_t$	-5.891 (c)**	-5.862 (c)**	0.147 (c)
Bank 2	$size_t$	-1.239 (t)	3.276 (c)*	0.229 (c)
	$\Delta loans_t$	-6.861 (c)**	-6.845 (c)**	0.226 (c)
Bank 3	$size_t$	-4.243 (t)**	-4.083 (t)*	0.115 (c)
	$\Delta loans_t$	-6.186 (t)**	-6.241 (t)**	0.497 (c)*
Bank 4	$size_t$	-3.815 (c)**	-3.484 (c)*	0.278 (c)
	$\Delta loans_t$	-4.668 (c)**	-4.620 (c)**	0.136 (c)
Bank 5	$size_t$	-4.831 (t)**	-5.597 (t)**	0.620 (c)*
	$\Delta loans_t$	-5.152 (c)**	-5.086 (c)**	0.100 (c)
Macroeconomic	$\dot{y}_t$	-3.542 (c)*	-3.607 (c)**	0.171 (c)
	$\dot{p}$	-2.997 (c)*	-1.634(c)	0.171 (c)
	r	-0.645	-0.645	0.666

Note: ** and * indicate significance at the 1% and 5% levels respectively (c) and (t) indicate that unit root tests were conducted with a 'constant' and 'constant and trend' respectively.

ARDL Models

Given the mixture of I(0) and I(1) variables, we opt to utilise Autoregressive Distributive Lag (ARDL) models, to forecast the NPL ratios, which is more suited for such cases. Since the specific lag structure of the variables is not known, the general-to-specific approach is used where initially a general model is estimated, and subsequently reduced in size and complexity. The idea behind this approach is that once the general specification is adequate to model the data including diagnostic checks, any model that is more parsimonious is considered to be an improvement, as long as it conveys the same information, in a simpler more compact form. Hence, the variables removed must not have been contributing to the desired results of the model.

Initially, a general ARDL model with five lags on each variable is estimated for the aggregate NPL ratio. Subsequent to satisfactory diagnostic checking of the model, it is then reduced to produce a more parsimonious model, and used to forecast the aggregate NPL ratio. Table 4 presents the results of this model, and indicates that GDP growth, the inflation rate, and the weighted average loan are significant in determining the aggregate NPL ratio of the banking system in Barbados.

A similar procedure follows for the individual banks of the banking sector. However, the bank specific variables, 'relative size' of each bank measured as the relative market share of bank *i* at time *t*, and 'growth rate of total loans' at each bank are included in each of the models. Dummy variables are included in the models for Banks 2, 3, 4 and 5 to capture irregular spikes in the data and to generate a satisfactory general model, prior to reduction of the NPL ratio of the individual banks. Results are presented in Table 5.

Table 4: Results of the Final ARDL Model of the Aggregate NPL Ratio

	Coefficient	t – Statistic	
Dependent variable: ΔNPL_{t-1}			
ΔNPL_{t-1}	**-0.412**	-2.81**	
ΔNPL_{t-2}	**-0.337**	-2.24**	
ΔNPL_{t-3}	**0.269**	1.30	
ΔNPL_{t-4}	**0.318**	2.36**	
ΔNPL_{t-5}	**0.249**	2.36**	
$\dot{y}_{t-2}$	**-0.002**	-3.37**	
$\dot{r}_{t}$	**-0.898**	-1.79*	
$\dot{r}_{t-2}$	**0.737**	1.62	
$\dot{p}_{t}$	**-0.522**	-2.69**	
$\dot{p}_{t-1}$	**0.617**	2.56**	
R^2	0.479	Akaike info criterion	3.001
$\overline{R}^2$	0.311	Schwartz criterion	3.439
Durbin Watson statistic	2.118	Breusch Godfrey (LM)	0.773
Norm [Jarque Bera]	2599	ARCH [F]	0.004

Note: ** and * indicate significance at the 5 and 10 percent levels respectively

The diagnostic tests indicate that the models are satisfactory. The GDP growth rate significantly and negatively impacts the NPL ratio of all banks. The cumulative effect of the inflation rate implies the expected positive relationship, which is significant for all banks except for Bank 3, whereas the weighted average lending rate is only significant for Banks 4 and 5. With regards to the bank specific variables, the bank's 'size' is important for all five banks, with the exception of Bank 4, and bears a positive relationship in each case. Total loan growth is negatively and significantly related to the NPL ratio for each respective bank, which is contrary to our prior expectations. One explanation for this result is that periods of loan growth are usually associated with an expansion in economic activity, when employment and incomes are increasing; however, during recessionary times, the reverse takes place, resulting in slower loan growth, and possibly arrears and NPLs.

In-sample and out-of-sample forecasts are generated from the estimated models over the period 1996Q1 to 2006Q4 and 2007Q1 to 2008Q4 respectively, for both the aggregate and individual NPL ratios. The Diebold-Mariano (D-M) (1995) statistic is employed to evaluate the forecasts of the NPL ratio. A simple random walk model is utilised as the benchmark for comparison and the D-M statistic is computed using the root mean squared error (RMSE), mean absolute error (MAE) as loss functions at each horizon. The Diebold-Mariano statistic aims to test the null hypothesis of equality of expected forecast accuracy against the alternative of forecasting ability across models (Cuaresma et al 2004). One limitation to note of this non-parametric approach is its inapplicability to one-step ahead forecasts (Mariano and Preve 2008)

Table 5: Results of the ARDL Models of the Individual NPL Ratios

Dependent Variable	Bank 1 NPL_t	Bank 2 ΔNPL_t	Bank 3 NPL_t	Bank 4 ΔNPL_t	Bank 5 NPL_t
C	**3.715****		**1.231****	**17.312****	
NPL_{t-1}			**0.669****		**0.463****
NPL_{t-2}					
NPL_{t-3}	**0.713****	**0.366****			**0.297***
NPL_{t-4}				**0.315****	
NPL_{t-5}		**-0.263****			
$\dot{y}_t$		**-0.121***			
$\dot{y}_{t-1}$		**0.142****			
$\dot{y}_{t-3}$	**-0.515****	**-0.116****			
$\dot{y}_{t-4}$	**-0.508****			**-0.243****	
$\dot{y}_{t-5}$			**-0.047****	**-0.217****	**-0.112****
$\dot{p}_{t-1}$	**0.463****				**0.070****
$\dot{p}_{t-2}$		**1.002****		**-0.404****	
$\dot{p}_{t-3}$		**-1.929****		**0.470****	
$\dot{p}_{t-4}$		**1.142****			
$\dot{r}_{t-2}$				**1.007***	
$\dot{r}_{t-5}$					**0.835****
$size_{t-2}$	**-0.848***	**1.482****			
$size_{t-3}$			**0.456****		**0.021****
$size_{t-4}$	**1.120****	**1.957****			
$\Delta loans_t$			**-0.089**		
$\Delta loans_{t-1}$				**0.068****	
$\Delta loans_{t-2}$		**-0.092****	**0.050**		
$\Delta loans_{t-3}$					**-0.027****
$\Delta loans_{t-5}$				**-0.120****	

Table 5: (Continued)

Dependent Variable	Bank 1 NPL_t	Bank 2 ΔNPL_t	Bank 3 NPL_t	Bank 4 ΔNPL_t	Bank 5 NPL_t
R^2	0.710	0.868	0.930	0.905	0.971
$\overline{R}^2$	**0.654**	**0.797**	**0.914**	**0.867**	**0.962**
Norm [Jarque Bera]	**1.380**	**0.591**	**0.517**	**0.099**	**1.756**
Durbin-Watson statistic	**1.946**	**1.849**	**1.865**	**2.034**	**2.035**
Akaike Info criterion	**6.560**	**2.582**	**0.920**	**2.308**	**1.027**
Schwartz criterion	**6.647**	**3.185**	**1.265**	**2.819**	**1.458**
ARCH [F]	**1.219**	**1.881**	**0.605**	**1.461**	**1.513**
Breusch Godfrey LM	**0.273**	**1.014**	**0.420**	**0.134**	**0.293**

Tables 6 and 7 present RMSE, MAE and other relevant in-sample forecast evaluation statistics for the multivariate models, as well as the benchmark (random walk) models. With regards to the in-sample fit, the forecast evaluation criteria, indicates that our model for the NPL ratio consistently out-performs the random walk model in each case, with smaller forecast errors.

Table 6: Forecast Evaluation of the ARDL Models of the NPL ratio

	Aggregate	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5
In-sample fit (1996Q1-2006Q4)						
Root Mean Squared Error	0.837	2.431	0.609	1.815	0.564	0.324
Mean Absolute Error	0.638	2.061	0.501	0.514	0.425	0.234
Mean Absolute Percentage Error	10.749	22.578	6.258	10.863	20.469	12.266
Theil Inequality Coefficient	0.065	0.103	0.024	0.204	0.050	0.048
Bias Proportion	0.027	0.002	0.000	0.025	0.000	0.002
Variance Proportion	0.000	0.037	0.004	0.686	0.005	0.010
Covariance Proportion	0.973	0.961	0.996	0.290	0.995	0.987

Table 7: Forecast Evaluation of the Random Walk Models of the NPL ratio

	Aggregate	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5
In-sample fit (1996Q1-2006Q4)						
Root Mean Squared Error	**1.106**	**3.034**	**1.803**	**2.455**	**1.723**	**0.770**
Mean Absolute Error	**0.790**	**2.029**	**1.393**	**1.181**	**0.803**	**0.556**
Mean Absolute Percentage Error	**12.028**	**20.433**	**12.407**	**21.235**	**14.095**	**24.239**
Theil Inequality Coefficient	**0.072**	**0.116**	**0.064**	**0.123**	**0.164**	**0.075**
Bias Proportion	0.000	0.000	0.000	0.005	0.015	0.004
Variance Proportion	0.042	0.088	0.016	0.011	0.012	0.002
Covariance Proportion	0.958	0.912	0.984	0.985	0.973	0.994

In order to evaluate the out-of-sample forecasts, Table 8 presents the ratios of forecasting error for the aggregate NPL ratio, for one to eight quarters ahead, where the columns RMSE/ RMSE (RW) and MAE/MAE (RW) represent the ratios of the root mean squared error and the mean absolute error respectively to those of the simple random walk models of the NPL ratio. A ratio less than one indicates greater forecasting accuracy of the multivariate NPL ratio model relative to the random-walk model. The results of the test of equal forecasting accuracy are also included in Table 8, while the results for the individual banks are presented in Table 9.

Table 8: Out-of-sample Forecast Results of the Aggregate NPL Ratio

Horizon	Aggregate NPL ratio RMSE/RMSE (RW)	MAE/MAE (RW)
1 quarters	0.712	0.712
2 quarters	0.749*	0.028
3 quarters	0.827**	0.813
4 quarters	0.721**	0.710*
5 quarters	0.641**	0.621**
6 quarters	0.592**	0.541**
7 quarters	0.575**	0.530**
8 quarters	0.556**	0.510**

Notes: ** and * indicate significance at the 5 and 10 percent levels respectively.

To evaluate the out-of-sample forecasts, we examine which model performs better and whether there is indeed a significant difference in forecast accuracy between the two models. The forecast evaluation of the aggregate NPL ratio using the RMSE and the MAE ratios suggest that the multivariate model out-performs the simple random walk model at each forecast horizon. This model rejects the null of equal forecast accuracy for two to eight quarters ahead for when using the RMSE as the loss function, and four to eight quarters ahead when using the MAE. Performance of the multivariate model on an aggregate level is therefore quite satisfactory.

Table 9: Out-of-sample Forecast Results of the Aggregate NPL Ratio

	Bank 1		Bank 2		Bank 3		Bank 4		Bank 5	
Horizon	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
1 quarter	1.63	1.64	1.02	1.02	2.95	2.77	2.59	2.59	0.85	0.85
2 quarters	1.67*	1.67*	1.36	1.30	2.62**	2.38**	1.90*	1.94*	0.65	0.54
3 quarters	1.31**	1.16*	1.13	1.15	1.88**	1.88**	4.02	3.48*	0.55*	0.44*
4 quarters	1.18**	1.08*	1.07	0.99	1.61**	1.60**	3.84**	3.49**	0.62**	0.53**
5 quarters	1.29**	1.19**	1.15**	1.08*	1.67**	1.68**	3.12**	3.04**	0.61**	0.56**
6 quarters	1.15**	1.00**	1.04**	0.89	0.89**	1.07**	3.12**	3.06**	0.63**	0.59**
7 quarters	1.05**	0.90*	0.99**	0.81	0.71	0.87**	3.03**	2.99**	0.68**	0.63**
8 quarters	1.10**	0.96*	0.92*	0.76	0.64	0.77*	2.97**	2.93**	0.64**	0.62**

Notes: ** and * indicate significance at the 5 and 10 percent levels respectively.

For the individual banks however, the results are less consistent. Firstly, the multivariate model only out-performs the random walk model at all horizons using both the RMSE and the MAE loss functions for Bank 5. These results are significant for three to eight quarters ahead in both cases. For Bank 1, the D-M test rejects the null hypothesis of equality two to eight quarters ahead. Nonetheless, the multivariate model performs better than the random walk model only over seven to eight horizons when using the MAE as the loss function. The results for Bank 2 indicate significance for five to eight quarters ahead on the basis of RMSE, and five quarters ahead on the basis of MAE, while the multivariate model only outperforms the random walk model six to eight quarters ahead. For Bank 3, the model rejects the null of equal forecasting accuracy over the two to eight quarter horizon for the MAE and the two to six quarter horizon for the RMSE. Similar to Bank 2, the model for Bank 3 only performs better six to eight quarters ahead. With regards Bank 4, the random walk model actually outperforms the multivariate model at each forecast horizon. Additionally, these results are significant two to eight quarters ahead on the basis of MAE, and two and four to eight quarters ahead for RMSE. Thus, overall, the multivariate models of the individual banks tend to provide more accurate forecasts than the simple benchmark models, for predictions spanning longer time periods.

5.0 Concluding Remarks and Policy Implications

This study attempts to utilise multivariate ARDL models to estimate the aggregate NPL ratio of the banking sector as well as the NPL ratio of the individual banks. Additionally, we employ a random walk model as a benchmark for comparison purposes. The inclusion of the individual bank models provides a greater basis on which to evaluate the chosen model and also allows us to incorporate bank specific variables in the analysis. For the aggregate NPL ratio, the multivariate model consistently produced more accurate forecasts. Although it can be said that the multivariate model performs better than the naïve model to produce forecasts of the NPL ratio overall, it should be noted however that for the individual banks, these forecasts tend to be more accurate only over longer prediction periods.

Our empirical results support the view that macro-economic factors, such as growth in real GDP, the inflation rate and the weighted average loan rate, have an impact on the level of NPLs, and should therefore be included in the forecasting models as suggested by Chase et al. (2005). It follows therefore that our results are contrary to the argument by Smith and Lawrence (1995) that macroeconomic variables have limited predictive power in explaining loan defaults. Evidence to support the view of Graham and Humphrey (1978) that forecasts employing data only on past loans which are usually more accurate than less parsimonious models, is not found in our study. In addition, the bank specific variables, growth in total loans and relative market share, adopted from the models of Khemraj and Pasha (2009), are moderately significant, in contrast to the authors' reports that there is no significant relationship between the size of a banking institution and its level of NPLs.

Forecasting NPLs has major implications for the commercial banking sector of Barbados, and for the financial system as a whole, including the provision of insights into the stability of the banking system and the regulation of non-performing loans to occur in the future. Additionally, unexpected increases in NPLs require banks to increase provision for loan losses, which tends to reduce a bank's profitability, thereby threatening it financial soundness. Based on our findings, we suggest that forecasts of the aggregate NPL ratio may be obtained though the use of a multivariate model employing both macro-economic and bank-specific factors. The study also supports the convention that commercial banks should pay attention to the performance of the real economy when providing loans so as to reduce the magnitude of non-performing loans. In an effort to control the magnitude of NPLs in Barbados, bank regulators should seek to implement measures designed to ensure that banks maintain adequate provisions and conservative credit standards during instances of economic growth in order to mitigate the effects of increased NPLs during periods of recession.

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APPENDIX

Figure A1: Total Loan Growth Rates (%) for the Individual Banks of the Banking Sector

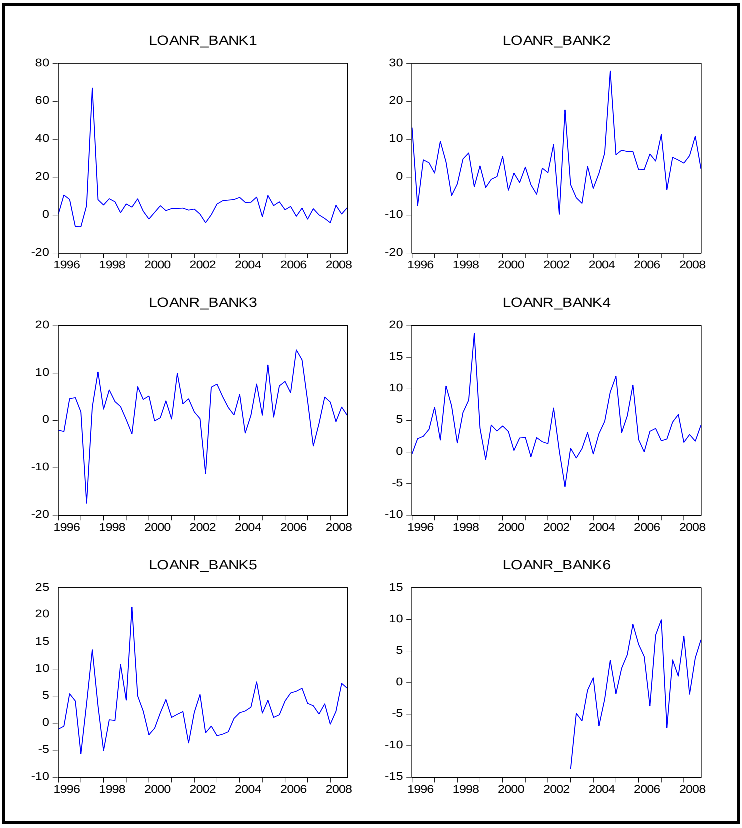

Figure A2: Relative Market Share (%) of the Individual Banks of the Banking Sector

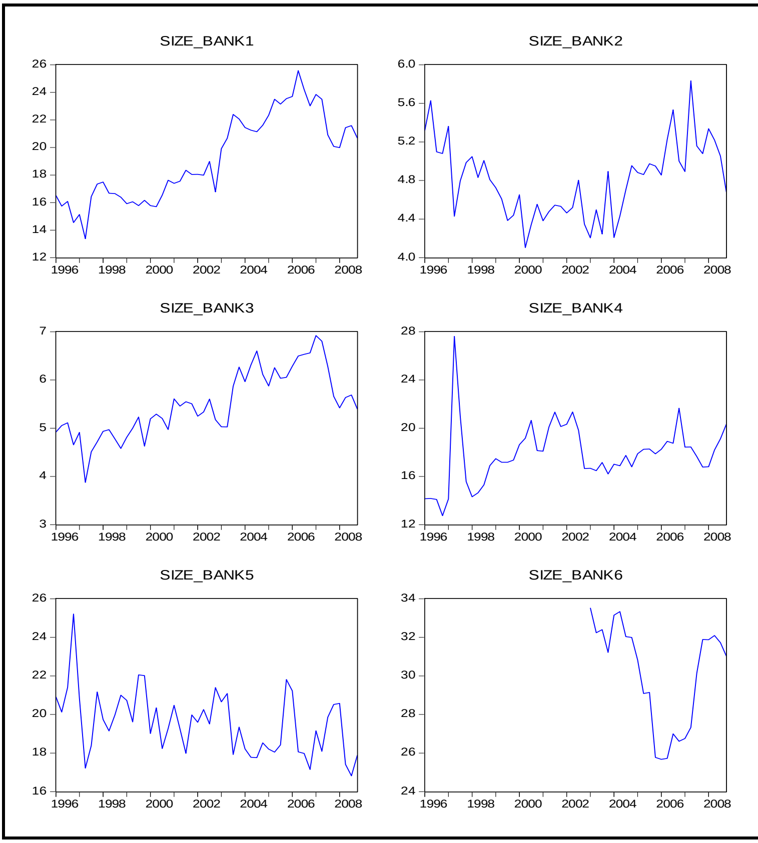

Figure A3: Macroeconomic Variables (%)