FORECASTING NON-PERFORMING LOANS IN BARBADOS

by

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ABSTRACT

The purpose of this paper is to build various models to forecast non-performing loans in the banking sector of Barbados. Given its association with bank failure and financial crises, the evaluation of non-performing loans is of great importance, and should therefore be of interest to developing countries. Using the estimates from these forecasting techniques, the performance of each model is evaluated to determine which performs best, as well as to facilitate comparison, and discussion of results. Given the forecasting models, the paper is capable of providing insights into the stability of the financial system and is also practical for commercial banks and bank regulators in terms of developing plans to regulate the occurrence of non-performing loans in the future.

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I. 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 may be defined as a loan that has been unpaid for ninety (90) 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 (6) commercial banks, which are currently all foreign owned, and presently the aggregate NPL loan ratio is approximately 3.138%.

The magnitude of non-performing loans (NPLs) is a key element in the initiation and progression of financial and banking crises. Ahmad (2002) in analyzing the Malaysian financial system reports a significant relationship between credit risk and financial crises and conclude 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 of a significant nature. In addition, the current global financial crisis, which began in the United States (US), is also 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 being able to forecast non-performing loans is important. The key issue here is how should we go about forecasting non-performing loans and what approach is most appropriate to do so. 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 GDP and a lagged dependent variable. However, most of these papers use one model to generate forecasts, and evaluate its performance, rather than using a comparative approach.

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 various forecasting techniques to forecast non-performing loans using quarterly data, to facilitate comparison so as to determine which performs best. The use of individual bank data therefore provides a greater basis from which to determine which forecasting technique is preferred. In this study we investigate the performance of the univariate ARIMA model and a multivariate model, as well as a combined model.

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 four 4 then presents the model estimates and results; section five 5 offers a discussion of results and concludes with a summary of the findings, including limitations and policy implications.

II. Overview Of Non-Performing Loans In Barbados

This section reviews the evolution of non-performing loans (NPLs) in the banking system in 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 6 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, 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

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

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 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.

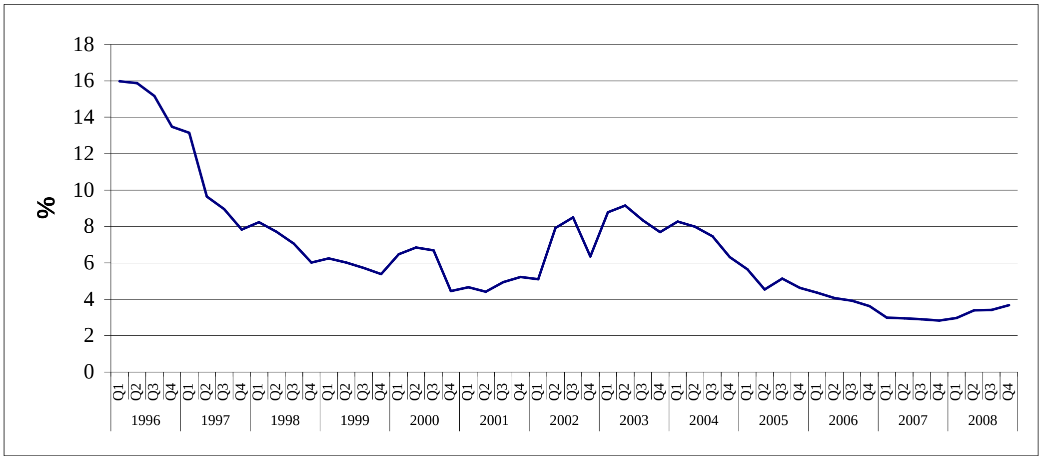
Table 1 presents some descriptive statistics of the aggregate NPL ratio, and indicates that the average ratio during the period 1996 to 2008 is approximately 6.7%, reaching a minimum of 2.8% and a maximum of 16%. Figure 1 gives an idea of how the NPL ratio is distributed across the period.

Table 1: Some Summary Statistics of the NPL Ratio

Mean	0.067
Standard Error	0.005
Median	0.061
Standard Deviation	0.033
Sample Variance	0.001
Kurtosis	1.751
Skewness	1.356
Range	0.132
Minimum	0.028
Maximum	0.160
Sum	3.491
Count	52

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).

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



The initial decreasing trend in the data, for example, can be linked to 5 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 terrorists' 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. 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-primes 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 the non-performing loan portfolio of the bank in 2005, 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.

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 gradually for Bank 6 declined into 2007, with a slight increase in 2008.

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

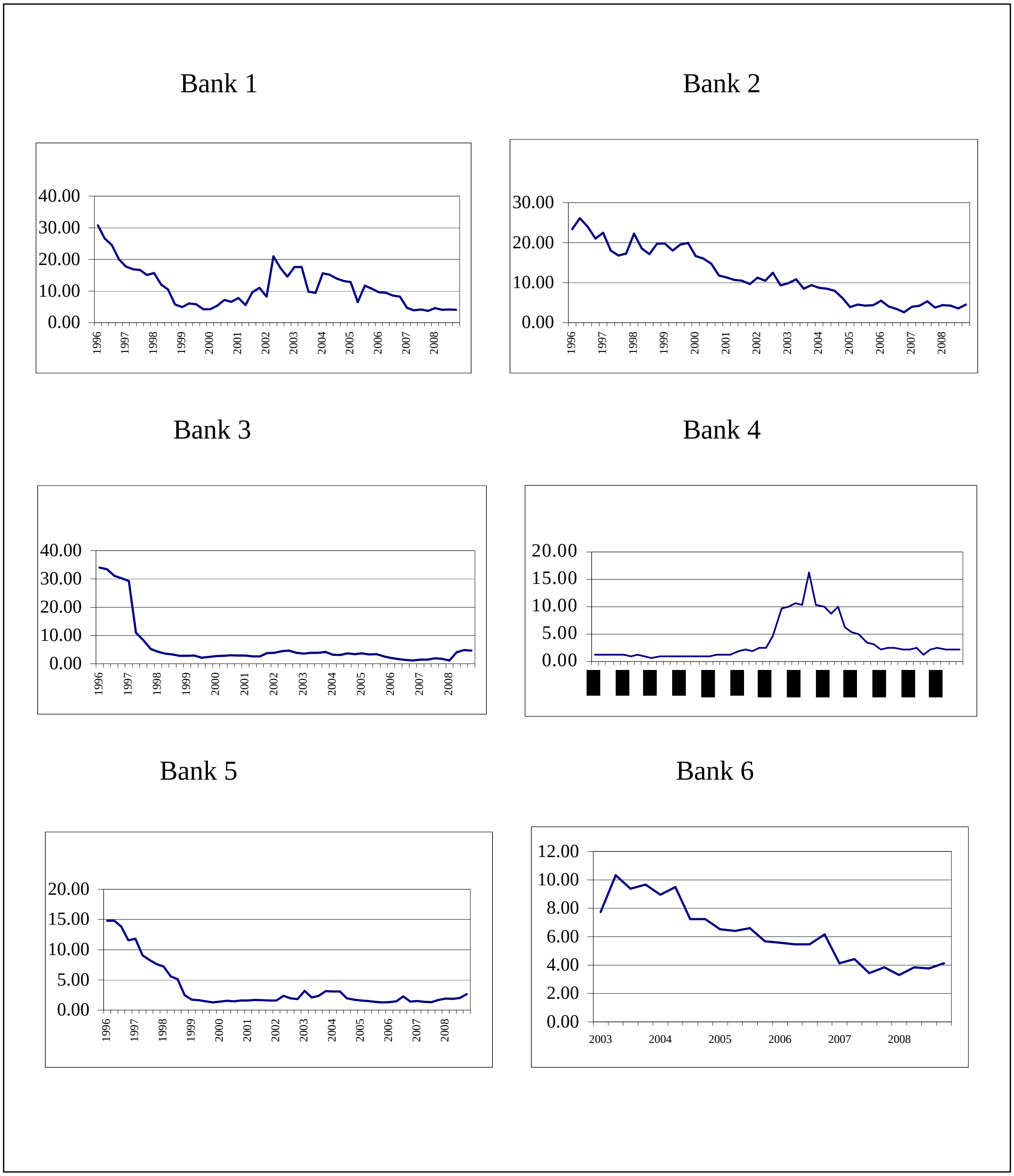
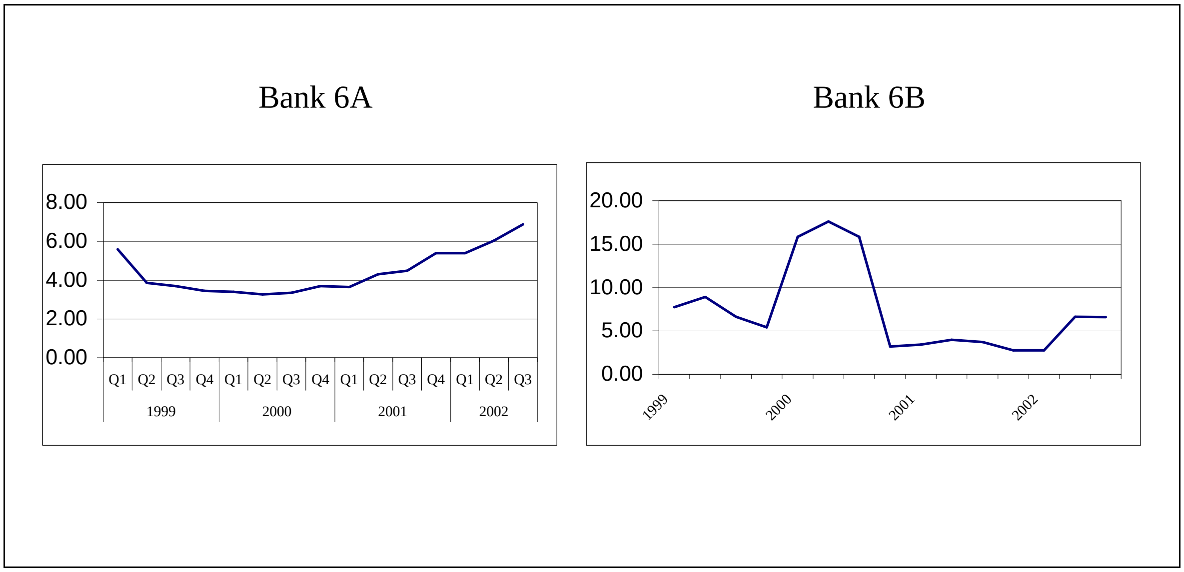


Figure 3: NPL to Total Loan Ratio, 1996 – 2002



III. Literature Review

Despite the importance of the examination and monitoring of non-performing loans, forecasting these ratios has only received moderate attention in literature. The existing theoretical approaches however, suggest a variety of determinants and approaches to be used in the forecasting of non-performing loans. Graham and Humphrey (1978) present one of the early attempts at predicting non-performing loans. The authors suggest that, in general, banks with larger amounts of classified loans 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 evaluate 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) argue that bank failure prediction studies have continually concluded that the efficiency of a bank's management are the leading causes of failure, yet few researchers have attempted to quantify management quality or incorporate it into predictive models. Seballos and Thompson (1990) and Hsing et al. (1991) also support the view that a key determinant is management's ability to operate efficiently and manage risks. Barr et al. (1994) therefore attempt 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 include 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 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.

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 specify 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 findings suggest 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 note 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) notes 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 estimates 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 conclude 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.

IV Model Estimates And Results

In order to accomplish the objectives of the study, forecasts of the NPL ratios will be generated using both univariate and multivariate models. Graham and Humphrey (1978) expressed the view that only using data only on past loans gives more accurate results than less parsimonious models. In light of this observation, we consider the popular Autoregressive Integrated Moving Average (ARIMA) models forecasting. We also present a multivariate forecast model, however, given our available data, we are unable to include management efficiency as a variable as recommended by Bar et al (1994), though their evidence support 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 the model by Chase et al. (2005) for the multivariate analysis, since their model has been proven to work well in the past, and presents a more practical approach[3].

Univariate

The purpose of univariate modelling is to establish a relationship between the present value of a time series and its past values so that forecasts can be made on the basis of the past values alone Wang (2008). Such an approach is useful where data on other determinants that maybe used for forecasting purposes are either not available or of poor quality, and where the time series in question exhibits significant persistence. Thus, in the search for an appropriate forecasting model, univariate analysis must be considered. In this regard, Greenidge and Dalrymple (1998) and Greenidge and McClean (1997) demonstrate that among the various options for univariate forecasting, Autoregressive Integrated Moving Average (ARIMA) models perform well.

ARIMA Models

ARIMA models are developed to model single time series processes and involve the following four steps: identification, estimation, diagnostic checking and forecasting. An important issue is whether the process is stationary, which implies that the distribution of the variable of interest

[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).

does not depend on time. The letter "*I*" (Integrated) indicates that the time series has been transformed into a stationary time series.

The plot of the 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 Augmented Dickey Fuller (ADF) test indicates that the null hypothesis of a unit root can be rejected at the 10% level of significance. The Phillips-Perron test also suggests rejection of the null of a unit root. Finally, 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. In fact, closer examination of Figure 1 shows that prior to the first quarter of 2000, the NPL ratio exhibits a clear downward trend but levels off thereafter. For modelling purposes we proceed as if the NPL ratio is stationary over the entire sample period but also bear in mind that it could be close to 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*	-2.913*	0.446*
Bank 1	-3.297*	-3.337*	0.210
Bank 2	-2.970	-3.755*	0.049
Bank 3	-4.095**	-4.034**	0.440
Bank 4	-1.040	-1.040	0.104
Bank 5	-4.535**	-4.874**	0.542*
Bank 6	-4.039*	-4.016*	0.092

** and * indicate significance at the 1% and 5% levels respectively

An examination of the autocorrelation and partial-autocorrelation functions suggests an autoregressive process of order 1, AR(1), or a moving average process of order 4, MA(4). As such, we estimate both models over the period 1996Q1-2006Q4 and the following results are obtained:

$$NPL_t = 5.637 + 0.843AR(1)$$
$$(4.424) \quad (15.044)$$

R^2	0.847	*Akaike info criterion*	3.133	*D-W*	2.338
$\bar{R}^2$	0.843	*Schwartz criterion*	3.215	*Chow Forecast* [F]	1.572
ARCH [F]	1.307	*Breusch Godfrey* (LM)	1.465	*Norm* [Jarque-Bera]	4.400

$$NPL = 6.778 + 0.707MA(1) + 0.472MA(2) + 0.870MA(3) + 0.680MA(4)$$
$$(10.545) \quad (5.935) \quad (6.231) \quad (15.144) \quad (6.246)$$

R^2	0.876	*Akaike info criterion*	3.236	*D-W*	1.770
$\bar{R}^2$	0.863	*Schwartz criterion*	3.438	*Chow Forecast* [F]	0.490
ARCH [F]	0.480	*Breusch Godfrey* (LM)	1.857	*Norm* [Jarque-Bera]	1.257

The parameter estimates for both models are significant and the ADF test indicates that the residuals are stationary. For neither of these specifications can we reject the null hypothesis that the residuals correspond to a white noise process. The autoregressive model provides a better fit than the moving average model, as suggested by the values of the *Akaike Information* and *Schwartz* criteria. A static in-sample fit over the period 1996Q1-2006Q4, as well as dynamic out-of-sample forecasts for the period 2007Q1-2008Q4 are generated, and the results presented in Table 3.

Table 3: Forecast Evaluation of the ARIMA model of the Aggregate NPL Ratio

	In-Sample Fit Period: 1996Q1-2006Q4		Out-of-Sample Forecast Period: 2007Q1-2008Q4	
	AR(1)	**MA(4)**	**AR(1)**	**MA(4)**
Root Mean Squared Error (RMSE)	1.106	1.089	1.724	3.116
Mean Absolute Error (MAE)	0.790	0.877	1.692	3.014
Mean Absolute Percentage Error (MAPE)	12.028	13.369	55.135	97.580
Theil Inequality Coefficient	0.072	0.069	0.216	0.333
Bias Proportion	0.000	0.000	0.963	0.936
Variance Proportion	0.042	0.315	0.000	0.025
Covariance Proportion	0.958	0.685	0.036	0.040

An examination of the forecast evaluation criteria does not suggest a clear-cut model with regards to the in-sample fit. The RMSE and Theil Inequality Coefficient are in favour of the moving average model, whereas the MAE and MAPE suggest that the autoregressive model is more accurate. This slight discrepancy in the interpretation of the Akaike and Schwartz criteria, as compared to the forecast evaluation criteria could result form the former penalising for an increased number of parameters, in the case of the moving average model. More importantly however, the AR(1) has a greater out-of-sample forecasting accuracy than that of the moving average model, and hence will be used for our comparison purposes A root mean squared error (RMSE) of 1.724 is produced for the out-of-sample AR(1) forecast , which is less than that of the MA(4) model. The other forecasting criteria confirm this result.

We also estimate ARIMA models for the individual banks of the banking sector to facilitate comparison with other forecasting models. The three unit root tests, suggest that the NPL ratio series for Banks 1, 3, 5 and 6 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. However, the Phillips Perron and the KPSS test suggest rejection of the presence of a unit root at the 5% level. 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 also assume the series is I(1). The results of the estimated models are presented in Table 4.

The autocorrelation and partial autocorrelation functions of the NPL ratio for Bank 1 suggests an AR(1) model or MA(4) model. Diagnostic checks of the autoregressive model reveals the existence of non-normality, and hence a dummy variable is incorporated to account for an unusual fluctuation in the data in the second quarter of 2002. The effect on the economy of the September 11 terrorists' attacks is believed to be the cause of the increase in the NPL ratio in this period due to the contraction of real GDP. The significance of the dummy variable led to a satisfactory model on the basis of specification tests, including the Jarque-Bera normality test. The 4^{th} term of the moving average model was insignificant, and hence eliminated from the model, to form a MA(3) model. The AR(1) model provides a better fit on the basis of *Akaike Information* and other criteria. The forecasting statistics of these models also reveal that the autoregressive model has more accurate prediction ability (Table 5).

The low values of the ACF and PACF after differencing make it difficult to identify a pattern for NPL ratio series of Bank 2. Significant lags were found only at period 5 for the ACF and period

2 for the PACF. Hence, an autoregressive model of order 2, and a moving average model of order 5 were estimated. A dummy variable was included in the AR(2) model to account for an irregular deviation in the differenced data in the first quarter of 1998. The first three terms of the MA(5) model were removed due to their insignificance. The AR(2) produces better diagnostic statistics and generally a better fit, however, the MA(5) model with the first three terms removed, has greater forecasting accuracy.

The NPL ratio series for Bank 3 was modelled with an AR(1), as well as a MA(3) model. The sample size in this case was reduced to 1998Q1-2006Q4, in order to achieve normality in the sample. Subsequently, both models passed all diagnostic checks and produced very similar results with regards to the model's fit. However, the moving average model has better out-of-sample forecasting accuracy.

After transformation of the NPL ratio series for Bank 4 to stationarity, both autoregressive and moving average models of order 3 were estimated. The first two terms were removed in each case due to their insignificance, and a dummy variable was added to account for a few irregular variations in the data. Although both models gave very similar results, the AR(3) model fits the data better, but the moving average model forecast slightly better.

An autoregressive process of order 1 or a moving average process of order 5, seems appropriate for the NPL ratio series for Bank 5. A dummy variable was included in the model to account for an unusual deviation in the data in the fourth quarter of 1998, which results from a significant fall in the NPL ratio in that period. This adjustment generates a satisfactory model with performs better than the corresponding MA(5) model in terms of the model's fit. An evaluation of the forecast criteria for both models suggests that the autoregressive model also has better forecasting ability.

An analysis of the autocorrelation and partial autocorrelation functions of the NPL ratio series for Bank 6 suggests an AR(1) model. The model was found to be satisfactory based on all diagnostic checks.

The model with the greatest forecasting accuracy for each bank was selected, and the forecast evaluation criteria are presented in Table 5. To facilitate comparison, multivariate models are estimated for the aggregate NPL ratio series, as well as for the individual banks.

Table 4: Results of the ARIMA models of the individual NPL Ratios

Model 1	**Bank 1**	**Bank 2**	**Bank 3**	**Bank 4**	**Bank 5**	**Bank 6**
Coefficients	9.88**C	-0.624**C	-	-	-	6.602**C
	8.579(DUM)**	4.639(DUM)**	0.954*AR*(1)**	4.693(DUM)**	-1.483(DUM)**	0.826*AR*(1)**
	0.779*AR*(1)**	-0.268*AR*(1)*		-0.291AR(3)*	0.907AR(1)**	
		-0.305AR(2)*				
R^2	0.789	0.342	0.514	0.889	0.963	0.662
$\overline{R}^2$	0.779	0.288	0.514	0.886	0.962	0.636
Akaike info criterion	4.848	3.755	1.884	1.924	2.238	3.036
Schwartz criterion	4.971	3.922	1.928	2.008	2.320	3.131
Durbin-Watson statistic	2.114	1.807	2.543	2.228	2.230	2.145
Norm [Jarque Bera]	1.274	0.295	0.273	2.457	0.444	1.062
ARCH [F]	0.081	0.341	0.470	0.956	0.130	2.141
Breusch Godfrey (LM)	0.874	1.812	1.674	1.055	0.703	1.318
Model 2						
Coefficients	12.179**C	-0.445**C	2.989**C	-	2.736**C	
	0.642*MA*(1)**	-0.300*MA*(4)*	0.809*MA*(1)**	4.711(DUM)**	1.086*MA*(1)**	
	0.671*MA*(2)**	-0.688*MA*(5)**	0.918*MA*(2)**	-0.297MA(3)*	1.063*MA*(2)**	
	0.969*MA*(3)**		0.772*MA*(3)**		1.302*MA*(3)**	
					1.021*MA*(4)**	
					0.650*MA*(5)**	
R^2	0.774	0.304	0.580	0.889	0.962	
$\overline{R}^2$	0.758	0.269	0.540	0.886	0.956	
Akaike info criterion	5.172	3.815	1.906	1.847	2.633	
Schwartz criterion	5.334	3.938	2.082	1.929	2.876	
Durbin-Watson statistic	1.90	2.674	2.096	2.209	1.763	
Norm [Jarque Bera]	2.091	1.481	0.689	4.326	1.141	
ARCH LM test	0.600	1.301	0.248	1.385	0.683	
Breusch Godfrey (LM)	0.401	9.300**	0.335	1.184	9.482**	

** and * indicate significance at the 1% and 5% levels respectively. DUM and C represent dummy variable and constant respectively.

Table 5: Forecast Evaluation of the ARIMA models of the individual NPL Ratios

	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6
In-Sample fit[4] (1996Q1-2006Q4)						
Root Mean Squared Error	2.548	1.520	0.562	0.582	0.707	0.966
Mean Absolute Error	1.860	1.775	0.459	0.344	0.543	0.769
Mean Absolute Percentage Error	19.072	10.846	16.336	8.106	23.608	10.594
Theil Inequality Coefficient	0.098	0.054	0.086	0.054	0.069	0.065
Bias Proportion	0.000	0.001	0.000	0.038	0.004	0.000
Variance Proportion	0.095	0.003	0.046	0.000	0.002	0.103
Covariance Proportion	0.905	0.996	0.954	0.962	0.994	0.897
Out-of-Sample forecast (2007Q1-2008Q4)						
Root Mean Squared Error	4.966	3.226	1.463	0.558	1.403	2.611
Mean Absolute Error	4.917	2.923	1.367	0.420	1.215	2.573
Mean Absolute Percentage Error	118.073	68.144	76.733	27.474	58.137	71.229
Theil Inequality Coefficient	0.369	0.529	0.250	0.129	0.531	0.259
Bias Proportion	0.980	0.820	0.005	0.183	0.749	0.971
Variance Proportion	0.000	0.064	0.766	0.596	0.104	0.014
Covariance Proportion	0.020	0.115	0.229	0.221	0.147	0.015

Multivariate

For the multivariate forecast of non-performing loans in Barbados, we adopt the model of Chase et al. (2005), since, as mentioned earlier, it has been proven to work well with the Barbadian case. In this regard, the aggregate NPL ratio for the banking system is estimated from the following equation:

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

[4] The in-sample forecast period for Bank 3 and Bank 6 is 1998Q1-2006Q4 and 2003Q1-2006Q4 respectively.

where r is the treasury bill rate, 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 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 banks is, the better risk management strategies it is able employ, and hence 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 results of the unit root tests of the bank-specific and macro-economic variables are presented in Table 6. The annual growth rate of loans is stationary for each bank, whereas the relative market share is only stationary for Banks 3, 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 suggest that the size of Bank 2 is I(1), yet the Phillips Perron and KPSS test suggest it is I(0). An examination the series leads us to conclude that the series is indeed I(1). Table 6 also indicates that the GDP growth rate and inflation rate are stationary. The ADF and Phillips Perron tests suggest that the treasury bill rate is I(1), however the KPSS test suggests it is stationary. Inspection of the plot of the treasury bill rate also points that the series may be stationary, and hence we assume that $\dot{r}$ is I(0) .

Table 6: Results of the Unit Root Tests of the Bank Specific Variables

		ADF	Phillips Perron	KPSS
Bank 1	$size_t$	-3.381	-3.328	0.205*
	$\Delta loans_t$	-5.891**	-5.862**	0.147
Bank 2	$size_t$	-1.239	3.276*	0.229
	$\Delta loans_t$	-6.861**	-6.845**	0.226
Bank 3	$size_t$	-4.243**	-4.083*	0.115
	$\Delta loans_t$	-6.186**	-6.241**	0.120
Bank 4	$size_t$	-3.815**	-3.484*	0.278
	$\Delta loans_t$	-4.668**	-4.620**	0.136
Bank 5	$size_t$	-4.831**	-5.597**	0.053
	$\Delta loans_t$	-5.152**	-5.086**	0.100
Macroeconomic	$\dot{y}_t$	-3.542*	-3.607**	0.171
	$\dot{p}$	-2.997*	-0.674	0.171
	$\dot{r}$	-1.04	-1.07	0.0133

** and * indicate significance at the 1% and 5% levels respectively

ARDL Models

Given the mixture of I(0) and I(1) variables, we opt to utilise an 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, just in a simpler more compact form. Hence, the variables removed must not have been contributing to the desirable results of the model.

Initially, a general ARDL model with 5 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 7 presents the results of this model, and both the in-sample and out-of sample forecast results are presented in Table 8.

Table 7: Results of the final ARDL Model of the Aggregate NPL ratio

	Coefficient	**t – Statistic**	
Dependent variable: ΔNPL_{t-1}			
ΔNPL_{t-1}	-0.552	-3.287**	
ΔNPL_{t-2}	-0.386	-1.736*	
ΔNPL_{t-3}	0.267	1.708*	
ΔNPL_{t-4}	0.455	3.906**	
ΔNPL_{t-5}	0.373	3.447**	
$\dot{y}_{t-2}$	-0.280	-4.263**	
$\dot{r}_{t}$	0.324	3.518**	
$\dot{r}_{t-4}$	-0.226	-2.241*	
$\dot{p}_{t}$	-0.559	-4.212**	
$\dot{p}_{t-1}$	0.625	4.214**	
R^2	0.564	Akaike info criterion	2.793
$\overline{R}^2$	0.424	Schwartz criterion	3.310
Durbin Watson statistic	2.020	Breusch Godfrey (LM)	1.972
Norm [Jarque Bera]	2.230	ARCH [F]	1.323

** and * indicates significance at the 1 and 5 percent levels respectively.

Table 8: Forecast Evaluation of the ARDL Model of the Aggregate NPL Ratio

	In-Sample Fit Period: 1996Q1-2006Q4	**Out-of-Sample Forecast** Period: 2007Q1-2008Q4
Root Mean Squared Error	0.765	0.980
Mean Absolute Error	0.573	0.823
Mean Absolute Percentage Error	9.858	29.956
Theil Inequality Coefficient	0.059	0.155
Bias Proportion	0.001	0.006
Variance Proportion	0.021	0.285
Covariance Proportion	0.978	0.709

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 six models. Bank 6 is excluded from this analysis due to the small sample size of its NPL ratio, and thereby the inability to estimate the ARDL model with 5 lags. Due to the non-stationarity of the NPL ratio and size of Bank 2, an error correction model is initially estimated, and subsequently reduced. Dummy variables are included in the models for Banks 1, 3 and 4 to capture irregular spikes in the data and to generate a satisfactory general model, prior to reduction.

The results of the final ARDL models of the NPL ratio of the individual banks are presented in Table 9. Diagnostic checking of the results indicate that the models are satisfactory. The GDP growth rate significantly and negatively impacts the NPL ratio for Banks 1, 3 and 4. The cumulative effect of the inflation rate implies a positive relationship, which is significant for all 5 banks. The treasury bill rate is also significant for all 5 banks, however, the association is negative for Banks 1, 2, and 3, and positive for Banks 4 and 5. The bank's 'size' is only important for Bank 1, whereas 'total loan growth' is significant for Banks 2, 3 and 5. Loan growth bears a negative relationship with the NPL ratio for Bank 2, and a positive relationship otherwise. The results of the forecasts of these models are presented in Table 10.

Table 9: Results of the ARDL models of the individual NPL ratios.

Dependent Variables	**Bank 1** NPL_t	**Bank 2** ΔNPL_t	**Bank 3** NPL_t	**Bank 4** ΔNPL_t	**Bank 5** NPL_t
C	7.533**		2.503**	-1.965**	0.548**
NPL_{t-1}			0.545**	-0.551**	
NPL_{t-3}	0.592**	0.174**		0.242*	0.382**
NPL_{t-4}				0.752**	
NPL_{t-5}		-0.310**		0.339**	-0.157*
$\dot{y}_t$			-0.059*		
$\dot{y}_{t-2}$				-0.209**	
$\dot{y}_{t-3}$	-0.441**				
$\dot{y}_{t-4}$	-0.388**			-0.259**	
$\dot{p}_t$				0.533**	0.069*
$\dot{p}_{t-1}$	0.652**				
$\dot{p}_{t-2}$		0.746**	0.207**	-1.221**	
$\dot{p}_{t-3}$		-1.443**	-0.278*	1.208**	
$\dot{p}_{t-4}$		0.884**	0.143*		
$\dot{r}_t$		0.462**		0.460**	
$\dot{r}_{t-1}$			-0.273**		
$\dot{r}_{t-2}$		-1.049**	0.369**	0.447*	
$\dot{r}_{t-3}$	-1.805**	0.648**	-0.267**	-0.851**	
$\dot{r}_{t-4}$	0.912*				
$\dot{r}_{t-5}$		-0.216*		0.359**	0.134**
$size_{t-2}$	-1.353**				
$size_{t-4}$	1.331**				
$\Delta loans_t$		-0.112**	-0.093**		-0.058**
$\Delta loans_{t-1}$		-0.045*			
$\Delta loans_{t-2}$		2.272**			
$\Delta loans_{t-3}$			-0.037**		
$\Delta loans_{t-5}$					-0.065**
R^2	0.893	0.864	0.959	0.902	0.934
$\overline{R}^2$	0.859	0.806	0.941	0.842	0.921
Norm [Jarque Bera]	0.876	1.495	1.652	0.747	0.707
Durbin-Watson statistic	2.668	2.253	2.010	2.232	1.831
Akaike Info criterion	4.103	2.512	0.604	2.545	1.704
Schwartz criterion	4.534	3.029	1.122	3.191	2.006
ARCH [F]	0.182	1.615	0.001	0.688	0.744
Breusch Godfrey LM	2.592	1.335	0.363	1.033	0.081

** and * indicates significance at the 1 and 5 percent levels respectively.
Dummy variables are not reported in the results table.

Table 10: Forecast Evaluation of the ARDL Models of the individual NPL ratios

	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5
In-sample fit (1996Q1-2006Q4)					
Root Mean Squared Error	1.459	0.620	2.166	0.582	0.553
Mean Absolute Error	1.118	0.529	0.648	0.442	0.431
Mean Absolute Percentage Error	12..360	6.198	9.152	21.462	22.368
Theil Inequality Coefficient	0.062	0.024	0.191	0.051	0.081
Bias Proportion	0.001	0.000	0.002	0.000	0.005
Variance Proportion	0.012	0.041	0.166	0.004	0.049
Covariance Proportion	0.987	0.958	0.832	0.996	0.946
Out-of-Sample (2007Q1-2008Q4)					
Root Mean Squared Error	5.725	5.023	1.107	5.972	0.747
Mean Absolute Error	4.832	4.753	0.935	4.897	0.613
Mean Absolute Percentage Error	111.747	111.169	67.116	256.649	45.852
Theil Inequality Coefficient	0.413	0.863	0.176	0.609	0.171
Bias Proportion	0.666	0.895	0.170	0.672	0.457
Variance Proportion	0.292	0.042	0.553	0.250	0.110
Covariance Proportion	0.043	0.063	0.277	0.077	0.433

Combined Forecasts

The idea of combining individual forecasts in the production of an overall forecast was originally proposed by Bates and Granger (1969). In their paper, they discussed the combination of pairs of forecasts. However, the methodology can easily be extended to the combination of several forecasts Reid (1969). If individual forecasts of a given variable are unbiased, then the combination forecast obtained by regressing the variable on these forecasts without and intercept will also be unbiased if the sum of the beta coefficients is restricted to unity.

Granger and Ramanathan (1984) have argued that biased forecasts may also be successfully combined by fitting the model:

$$NPL_t = \alpha + \sum \beta_i f_{it} + e_{ct}, \forall i = 1,...,k \qquad (3)$$

where f_i represents the forecast values from model *i*, and not restricting either α to be zero or β to sum to unity. This model is fitted by least squares to the available historical record and then projected forward to derive the required composite forecast. We adopt this approach to generate combination forecasts from the preferred univariate ARIMA model and the multivariate model of the aggregate and each of the individual NPL ratios. We regress the actual NPL ratios on the respective forecast combination for the period 1996Q1 – 2006Q4. These equations are then used to forecast the NPL ratio over the period 2007Q1-2008Q4. The results of these regressions and the forecasts are presented in Tables 11 and 12, respectively.

Table 11: Results of the Combined models of the aggregate and individual NPL Ratios

Model 1	**Aggregate**	**Bank 1**	**Bank 2**	**Bank 3**	**Bank 4**	**Bank 5**
Coefficients	0.379 C	-0.521 C	-0.243 C	0.172 C	-0.031 C	0.200 C
	-0.017 f_1	0.215f_1*	0.095 f_1	0.017 f_1	0.459 f_1**	0.129 f_1
	0.962 f_2**	0.838 f_2**	0.926 f_2**	0.931 f_2**	0.516 f_2**	0.784 f_2**
		-3.788(DUM)**		-0.577(DUM)*	1.593(DUM)**	
				-0.563(DUM)*	1.287(DUM)**	
R^2	0.781	0.917	0.989	0.933	0.993	0.939
$\bar{R}^2$	0.768	0.913	0.988	0.924	0.993	0.935
Akaike info criterion	2.448	3.499	1.965	0.127	0.824	1.667
Schwartz criterion	2.578	3.627	2.095	0.347	0.996	1.795
Durbin-Watson statistic	2.432	2.4654	2.421	1.267	2.048	1.798
Norm [Jarque Bera]	1.951	0.420	2.025	0.832	0.693	0.789
ARCH [F]	1.593	0.002	2.989	0.554	0.058	0.270
Breusch Godfrey (LM)	1.196	1.176	2.601	2.715*	0.115	0.004

** and * indicate significance at the 1% and 5% levels respectively. DUM and C represent dummy variable and constant respectively.

Table 12: Forecast Evaluation of the combined models of the NPL ratios

	Aggregate	**Bank 1**	**Bank 2**	**Bank 3**	**Bank 4**	**Bank 5**
In-Sample fit (1996Q1-2006Q4)						
Root Mean Squared Error	0.761	1.279	0.597	1.892	0.328	0.516
Mean Absolute Error	0.579	0.989	0.513	0.493	0.260	0.430
Mean Absolute Percentage Error	10.024	10.963	5.867	7.237	11.020	21.838
Theil Inequality Coefficient	0.059	0.054	0.023	0.175	0.029	0.077
Bias Proportion	0.000	0.000	0.000	0.018	0.000	0.000
Variance Proportion	0.062	0.021	0.003	0.660	0.002	0.016
Covariance Proportion	0.938	0.979	0.997	0.322	0.998	0.984
Out-of-Sample forecast (2007Q1-2008Q4)						
Root Mean Squared Error	0.206	0.299	0.155	0.093	0.082	0.064
Mean Absolute Error	0.206	0.298	0.155	0.089	0.081	0.052
Mean Absolute Percentage Error	6.687	7.122	3.692	5.881	4.197	3.855
Theil Inequality Coefficient	0.032	0.036	0.018	0.015	0.020	0.016
Bias Proportion	0.992	0.994	0.997	0.136	0.976	0.320
Variance Proportion	0.008	0.006	0.003	0.864	0.024	0.680
Covariance Proportion	0.000	0.000	0.000	0.000	0.000	0.000

Comparison of Models

We have estimated ARIMA univariate models and ARDL multivariate models for the aggregate and individual NPL ratios of the banking sector, as well as, a combination of these models to generate static in-sample and dynamic out-of-sample forecasts for the best model of each technique. For the aggregate NPL ratio, an assessment of the forecast evaluation criteria of the chosen AR(1) model as compared to the reduced ARDL multivariate model indicates that the multivariate model produces smaller out-of-sample forecast errors, and hence may be a more reliable forecast option. The RMSE, MAE, MAPE and Theil Inequality coefficient all favour the multivariate model with regards to the in-sample fit, as well as the out-of-sample forecasts. However, the combination model outperforms both models with smaller forecast errors. A RMSE of 0.206 is produced for the out-of-sample combination forecast, compared to 0.980 for the multivariate model.

With regards to the individual bank models, the Akaike and Schwartz criteria of the chosen models reveal that for 4 out of the 5 banks, the multivariate model has a better fit than the univariate model, the exception being Bank 4. The in-sample forecast evaluation produces a similar result. The multivariate model for Banks 1, 2 and 5 has a better fit than the univariate model, where for Banks 3 and 4, the univariate is preferred. The results of the out-of-sample forecasts indicate that for Banks 3 and 5, the multivariate models produce smaller forecast errors with reference to all included forecast measures, however, the univariate model produces more accurate forecasts for Banks 2 and 4. For Bank 1, the RMSE and Theil Inequality coefficient favour the univariate model, whereas, the MAE and MAPE favour the multivariate model. Moreover, combined models outperform both the univariate and the multivariate models for all 5 banks in the banking sector as evidenced by smaller forecast errors for all measures.

V. Concluding Remarks And Policy Implications

This study attempts to utilise univariate ARIMA models and 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 combine the univariate and multivariate forecasts to produce an overall forecast. The inclusion of the individual bank models provides a greater basis for comparison and also allows us to incorporate bank specific variables in our analysis. Overall, it can be said that of the two reasonable options presented here, the multivariate model slightly outperforms the univariate. Nonetheless, the combination forecasting procedure considerably improves the accuracy of the forecasts in all cases, and has proven to be the more superior model.

Our empirical results support the view that macro-economic factors such as growth in real GDP, the inflation rate and the treasury bill rate has 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 are usually more accurate than less parsimonious models, can only be found for 2 of the 6 cases presented. 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 the NPLs.

Note should be made of the inability to utilise Bank 6 in the individual multivariate modelling, due to its small sample size, as well as the unavailability of a larger data set, since prior to 1995 there was no standard treatment of non-performing loans.

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 financial system and the regulation of non-performing loans to occur in the future. Additionally, unexpected increases in NPLs reduce the coverage provided by loan loss reserves, and lead to a deterioration of banks' liquidity. Based on our findings, we suggest that highly accurate forecasts may be obtained though the use of a combination of univariate and multivariate forecasts. The study also implies 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.

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

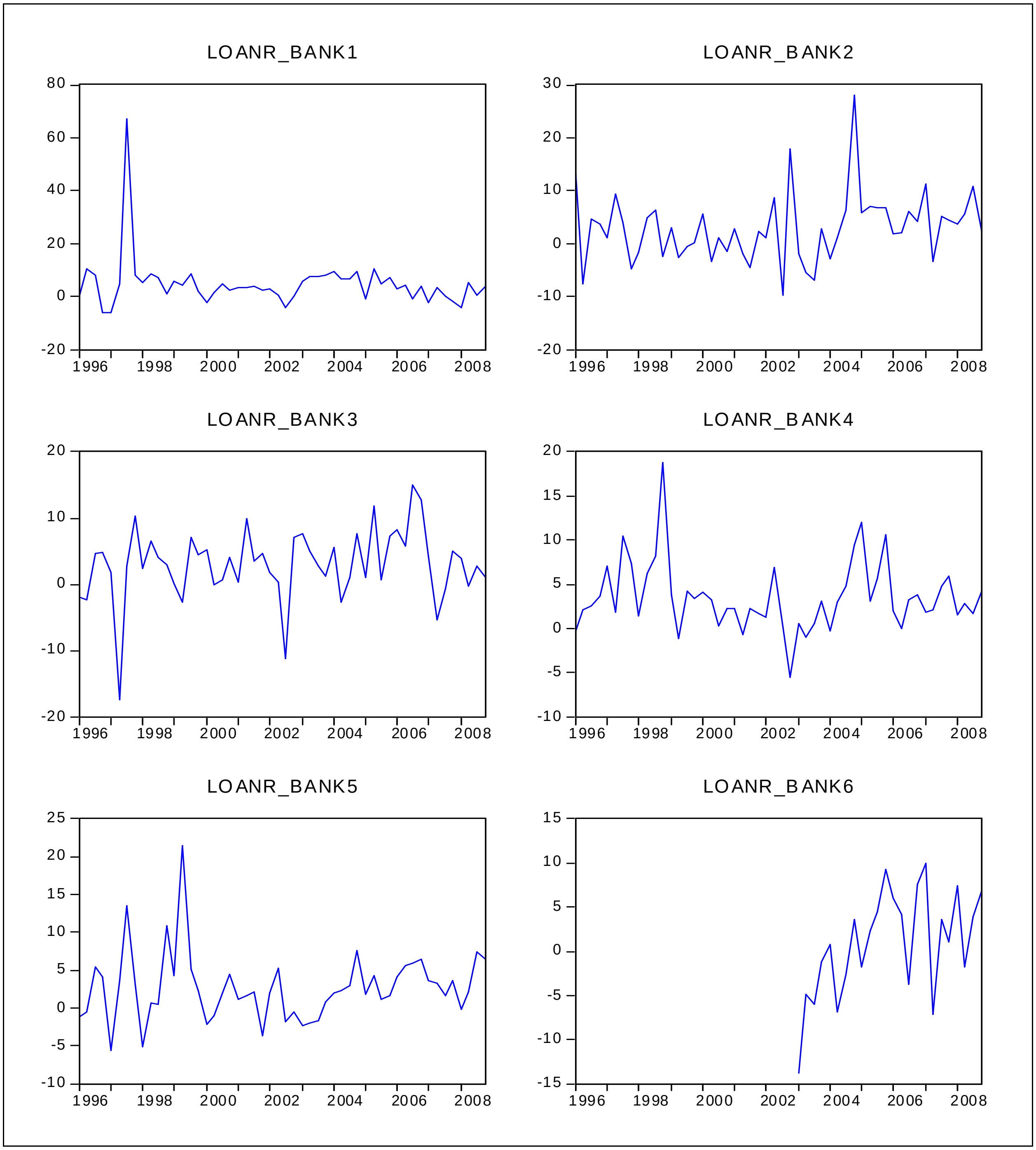

Figure A2: Relative Market Share (Size) of the Individual banks f the Banking Sector

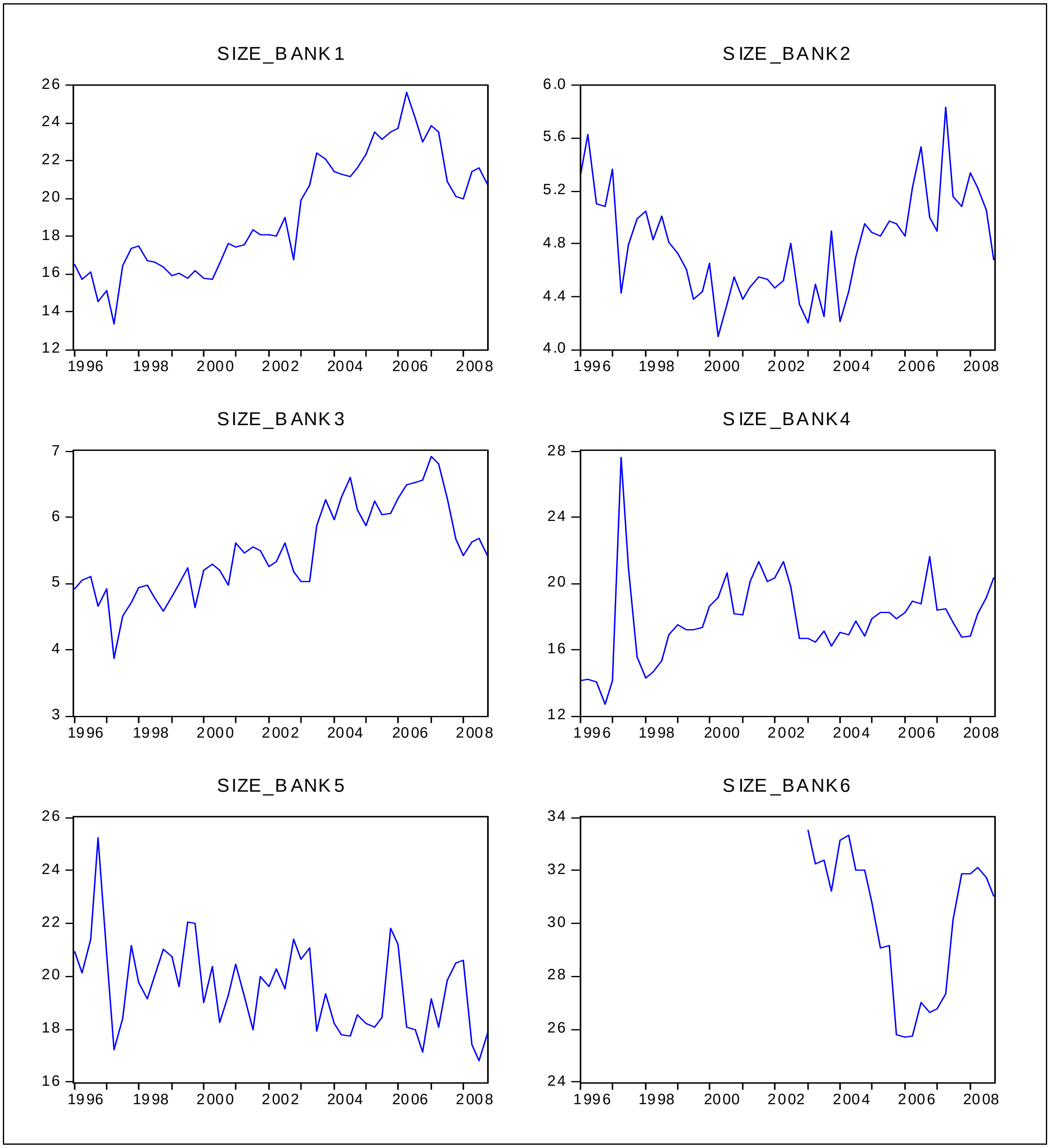
SIZE_BANK1
SIZE_BANK2
SIZE_BANK3
SIZE_BANK4
SIZE_BANK5
SIZE_BANK6
1996
1998
2000
2002
2004
2006
2008

Figure A3: Macroeconomic Variables