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# A REGIME SWITCHING APPROACH TO ANALYZING BANK NON-PERFORMING LOANS IN BARBADOS

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# A Regime Switching Approach to Analyzing Bank Non-Performing Loans in Barbados

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**ABSTRACT**

A frequently used metric associated with bank vulnerability is the non-performing loans ratio (NPLs), and many studies have analyzed and developed frameworks for forecasting this variable. The primary critique against many of the previous work is the failure to account for the nonlinearities inherent in the relationship between bank NPLs and the economic cycle. As a result the generalized conclusions on the linkage between NPLs and gross domestic product (GDP) may be misguided, especially when prudential rules impose natural asymmetries that may cause the association to change along different phases of the economic cycle. This study therefore, reexamines the relationship between NPL and GDP for Barbados using a regime switching approach. In doing so, the authors analyzed bank-impacts from a mix of macroeconomic and idiosyncratic data under different regimes to determine whether NPL outcomes across regimes and across institutions are homogenous. Further, the authors examined whether changes in systemic vulnerabilities are driven by all banks or only a subset. Answers to these critical problems, therefore provides a valuable framework that guides the authorities in developing appropriate policies to help strengthen the banking sector against systemic failures. The overall findings suggest that a non-linear approach to analyzing the NPL-GDP nexus is valid, but the relationship is not homogenous across institutions in different regimes. In addition, some institutions appear to be of greater systemic importance than others.

## INTRODUCTION

Increased attention has been given to analyzing the asset and liability portfolio of banks since the global financial fall-out as the sizeable losses realized by banks across many jurisdictions triggered panic and financial instability, which also affected economies adversely [see Berrospide (2012) and Laeven and Valencia (2012 )]. Policy-makers have intensified their prudential monitoring and analyses, and to some extent have tried to identify factors that can provide early warnings for when banks' stability have been compromised for example Davis and Karim (2008) and Bussiere and Fratzscher (2006). A widely-used variable of interest in this analysis is the non-performing loan ratio (NPL), as high NPLs have been found to be associated with many problem institutions. Several authors, such as Salas and Saurina (2002), Khemraj and Pasha (2009) just to name a few, have adopted various techniques to analyze the factors that might influence the non-performing loan metric, and by consensus the economic cycle – beyond the institutions' operations – has been found to be a major determinant in the overall NPL outcome.

In Barbados, authors like Chase et al (2005), Greenidge and Grosvenor (2010), Guy and Lowe (2012) and Belgrave et al (2012) have advanced the discussion on this subject and in each case there is an underlined assumption of linearity between NPLs and economic growth. This assumption became a target of critique when it was observed by the authors that the analytical framework proposed in Guy and Lowe (2012) constantly produced NPL estimates lower than the actual NPL outcomes at turning points of the economic cycle. For example, as the economy starts to pick-up (following burst periods) in Guy and Lowe (2012) suggest that NPLs would start to improve after four quarters. However, the actual outcomes were consistently higher than the expectations. A further review of the NPL classification process suggest that banks' reporting are governed by prudential rules which create frictions that obstruct the symmetric relationship between the GDP and NPLs at different points of the cycle. For instance, a loan account is generally classified as non-performing if the account has not been kept up to date for three months. On the other hand, the criteria for NPL transition to a regular account are complicated by a series of regulatory guidelines and prudential checks that are not normally completed before one year [see Financial Institutions (Asset Classification and Provisioning) Regulations]. This rule creates a non-linear relationship and it is believed that a non-linear framework for analysis is more appropriate. Adopting such a framework is very critical as it provides a more comprehensive and robust approach to identifying underlying vulnerabilities among institutions during various phases of the economic cycle. To the policy-maker, this provides an early indicator of potential fall-outs in the banking system and provides guidance as to whether the supervisory agency needs to engage the institution on potential vulnerabilities and on whether policy adjustments are required.

This study therefore adopted a regime switching approach to account for the non-linear nature of the data. The study combines a set of institution specific variables and macro variables to explain the impact of economic conditions on NPLs. In doing so, the authors analyzed the relationship for the oligopolistic banking system as a whole as well as for each of the six banks to determine whether the association is homogenous or whether one or two institutions are mainly responsible for systemic outcomes. The results show that the linear assumption of the previous work is indeed faulty and that a non-linear approach is more suitable. In addition, the authors found that the relationship is not homogenous and that systemic outcomes are largely impacted some institutions. The remainder of the paper is structured as follows: Brief literature review, data and stylized facts, methodology, estimation and analysis and conclusion.

## BRIEF LITERATURE REVIEW

The relationship between NPLs and the macroeconomic environment has been well documented, including variables such as gross domestic product (GDP), inflation, interest rates and unemployment. Specifically, the negative association with GDP has been widely established, that is, as economic growth declines, the level of classified debt rises, see Keeton and Morris (1987), Sinkey and Greenawalt (1991), Salas and Saurina (2002), Khemraj and Pasha (2009), Guy and Lowe (2012). In addition, idiosyncratic variables such as loan growth and bank size have also been found to have a significant impact on NPLs (Khemraj and Pasha (2009), Greenidge and Grosvenor (2010) and Guy and Lowe (2012). Most of the methodologies employed in the literature assume some form of linear regression, and only a few utilized some variant of a non-linear approach such as the Markov Chain approach with transition matrices (Betancourt, 1999). These non-linear models have traditionally been less popular due to data requirements since they entail individual loan data, and limit the analysis as it relates to examining the influence of explanatory variables. Nevertheless, much of the general discussion on non-linear models is driven by the business cycle and expansions and recessions are taken as two separate regimes. There are several types of these models usually classified as 'Regime Switching' models, including Self-Exciting Threshold Autoregressions (SETAR, Tong, 1990), Smooth-Transition models (such as LSTAR, Terasvirta, 1994) and Markov-Switching models (Hamilton, 1989).

Studies evaluating banks' NPLs in Barbados emerged only within the last decade, the earliest being Chase et al (2005) who examined the macroeconomic determinants of NPLs, the 3-month treasury bill rate, the inflation rate and GDP growth using a linear regression framework with a view to stressing the entire banking system. Subsequently, an IMF mission to Barbados in 2008 re-estimated the model of Chase et al (2005) in the context of a panel methodology. Greenidge and Grosvenor (2010) also augmented the model of Chase et al (2005) replacing the 3-month Treasury bill rate with the weighted average loan rate. The authors also included individual bank models which employed the bank specific variables, loan growth and the relative size of banks, and found that these variables help to explain banks' idiosyncratic behavior. However, Guy and Lowe (2011) argued that Greenidge and Grosvenor (2010) excluded the largest bank from their analysis due to a merger that occurred in 2002. In an effort to account for this issue, Guy and Lowe (2011) reconstructed the data for this bank and estimated a pooled dynamic heterogeneous panel model. The results found that their aggregate forecasting model produced more accurate results than IMF (2008) and Greenidge and Grosvenor (2010). Subsequently, Belgrave et al (2012) modeled the response of NPLs to macroeconomic shocks by analyzing the sensitivity of NPL shocks to six economic industries in Barbados within the context of a panel Vector Autoregression (VAR). The authors found that that there is some degree of heterogeneity in response to NPL shocks to the individual sectors, as a shock to one industry may induce a different response to another, and that the significance of direct impacts largely depends on the size of the sector.

Although the negative relationship between NPLs and GDP has been well established even for the Barbadian case, each of the aforementioned studies assumes a linear association. However, it is acknowledged that bank behavior can tend to adjust differently at different points of the business cycle. In fact, Gasha and Morales (2004) argue that linear regression models are less robust as they do not account for non-linearities relating to the starting credit quality of bank customers, which is inconsistent with the non-normality of the probability of default.

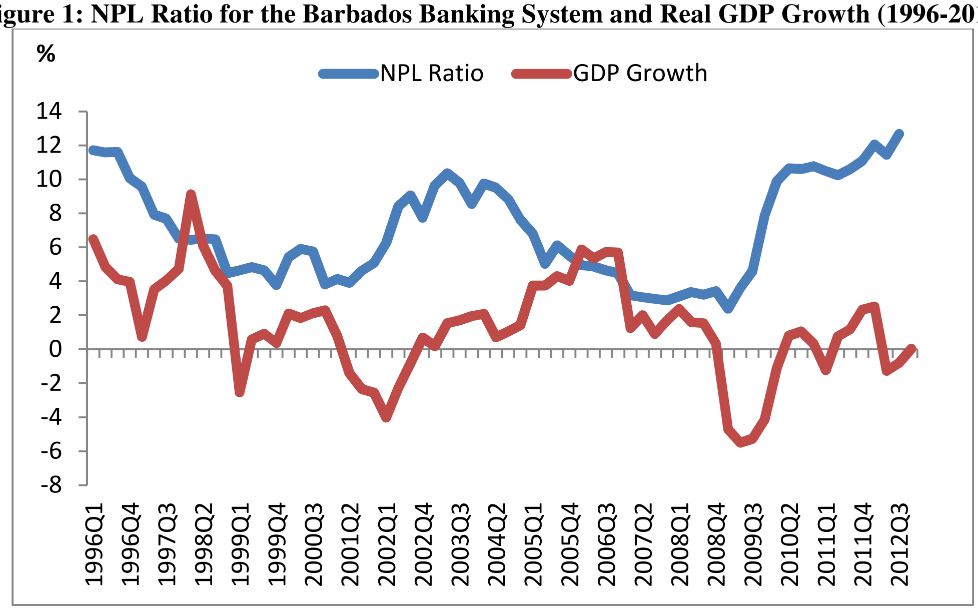
## DATA AND STYLIZED FACTS

Barbados' banking system currently comprises five commercial banks[1], none of which are locally owned. Four banks are subsidiaries of larger banks domiciled in other jurisdictions, while one bank operates as a branch of a foreign institution. Collectively, banks' assets account for approximately 140% of GDP and 80% of the assets of deposit-taking institutions. The banks mainly provide the traditional types of services, with more than half of their assets held in loans, and almost 80 percent of their funding from deposits. The ownership structure has changed significantly over the period of analysis with a series of mergers and government divestments.

Total loans are classified into five categories: pass; specially mentioned; substandard; doubtful and loss. Pass loans are the highest quality of bank loans and reflect loan accounts that are fully up to date. Specially mentioned accounts are generally in good standing but are under a watchful eye due to some late payments or some other special conditions. The sum of the last three categories constitutes the total classified debt which is written as a percentage of total loans to derive the NPL ratio. This ratio normally reflects accounts that are outstanding for more than three months, with a certain time lag distinguishing between the three categories. However, the prudential classification is not symmetric, as observed improvement in an account, over three months for example, does not automatically imply that an account will transition to a higher classification. Consequently, the relationship between the NPL ratio and GDP is likely to change during the economic cycle.

The study employs quarterly data on aggregate and bank-specific NPL ratios (6 banks), as well as quarterly GDP growth rates, 12-month moving average inflation rates, loan growth and bank size. All data was obtained from the Central Bank of Barbados and spans the period 1996Q1 to 2011Q4. Figures 1 illustrates the systemic NPL ratios of commercial banks and GDP growth rates, over the review period. The data confirms that banks experienced three distinct periods where NPLs were above the prudential threshold of 8 percent of total loans. In each case, the upward trajectory of NPLs coincided with episodes of economic downturn, while the subsequent declines in NPLs occurred at the same time economic growth picked up. Guy and Lowe (2011) argued that GDP growth is a useful leading indicator for predicting NPLs as it takes about four quarters for a GDP shock to be reflected in the changes in the NPL ratios. These associations form the basis of this study and they were tested using the regime switching approach.

**Figure 1: NPL Ratio for the Barbados Banking System and Real GDP Growth (1996-2012)**




[1] At the end 2011, the banking system comprised 6 banks; however, an acquisition occurred during 2012, reducing the total to 5 banks.

## METHODOLOGY

Having discussed the properties of the data, this section outlines the methodology of the study. In an effort to explore the effects of non-linearity in the NPL series, a Markov Switching (MS) approach, first introduced by Hamilton (1989, 1990), is employed[2]. These models permit different behavior in different states of nature of the variable in question, while at the same time estimating when there is a movement to another state. While the specification within each regime is linear, the resulting time series is non-linear, as transition probabilities are estimated which govern transition between the different regimes (Doornik and Hendry, 2009).

The general form of a MS model may be written as:

$$y_t = \beta_0(s_t) + \sum_{i=1}^{n} \beta_i X_{it}(s_t) + \varepsilon_t \tag{1}$$

where $s_t$ is the state or regime index. In his seminal work, Hamilton (1989) assumes that the transition between states is governed by a first order Markov process, where $s_t$ denotes the unobserved state of the system. Given two regimes at time periods, $t$ and $t-1$, these transition probabilities may be written as:

$$\begin{aligned} \Pr[s_t = 1 | s_{t-1} = 1] &= p_{1|1} \\ \Pr[s_t = 0 | s_{t-1} = 1] &= p_{0|1} \\ \Pr[s_t = 0 | s_{t-1} = 0] &= p_{0|0} \\ \Pr[s_t = 1 | s_{t-1} = 0] &= p_{1|0} \end{aligned} \tag{2}$$

While a two regime model is estimated here due to the observed nature of the data, the probability matrix for $N$ states is such that:

$$\begin{aligned} p_{i|j} &= \Pr[s_{t+1} = i | s_t = j], \quad i,j = 0, \dots N-1 \\ \sum_{i-0}^{N-1} p_{i|j} &= 1 \end{aligned} \tag{3}$$

For the estimation of systemic NPL model, the equation was specified using the following variables:

$$NPL_t = \beta_0(s_t) + \beta_1(s_t) INF_t + \beta_2(s_t) ALG_t + \beta_3(s_t) GDP_{t-4}(+\varepsilon_t \tag{4}$$

where $\beta_0$ denotes the intercept, $NPL$ is the non-performing loan ratio, $INF$ represents the 12-month moving average inflation rate, $ALG$ denotes average loan growth, and, $GDP^3$ represents growth in GDP and $\varepsilon_t$ is a sequence of $i.i.d. \sim N(0, \sigma^2)$. The switching parameter $s_t$ is imposed in each case to define regime dependent variables, where two estimates would be produced for each parameter, $\beta$.

As suggested by the literature, a negative relationship is expected with GDP as this link has a two-tiered impact. In the first instance, a pick-up in loan growth is usually associated with greater GDP and this increased loan base will tend to pull down the NPL ratio. Secondly, higher income negatively affects borrowers' ability to service loans, thus reducing the growth of loan delinquencies. Additionally, while an elevated price level may suggest an enhanced inability to repay debtors, there is no consensus in the literature on the exact sign that should emerge.

The above specification (4) was augmented to include bank size ($BSZ$) and institutional loan growth($BLG$), for the modeling of individual institutions within the banking system as follows:

$$NPL_t = \beta_0(s_t) + \beta_1(s_t) INF_t + \beta_2(s_t) BLG_t + \beta_3(s_t) GDP_{t-4} + \beta_4(s_t) BSZ_t + \varepsilon_t \tag{5}$$

The MS models are estimated using a Maximum Likelihood procedure, and a likelihood ratio (LR) statistic is utilized to test for the presence of significant non-linearity in the series.

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[2] All estimations were conducted using OxMetrics 6 Software.

[3] $GDP_{t-4}$ was suggested in Guy and Lowe (2011).

## ESTIMATION AND ANALYSIS

Table 1 presents the results for the system estimation while Table 2 (in the Appendices) displays the outcomes for estimations of individual institutions. The primary issue of non-linearity was firstly examined to determine whether this approach was appropriate. If the non-linearity assumption is rejected then this framework would be useless in properly addressing the structural issues discussed earlier that oppose the linearity assumption. The results for the system as well as for each bank, as defined by the Linearity LR-test statistic strongly suggested that the non-linear estimation was a suitable framework. Furthermore, the results show that the NPL cycle for the system is not symmetric over the sample period 1996 to 2011. Periods of low NPLs (Regime 0) are generally longer than those with high NPLs (Regime 1), which approximated to 37 quarters and 23 quarters, respectively, over the sample horizon (see Figure 2 in the Appendices).

The expected negative relationship between NPLs and GDP growth was generally supported by the results in this analysis. Nevertheless, this link was not found to be homogenous across institutions. In particular, the inverse association across regimes was evident for the system and four institutions. This nexus for the other two banks was negative during the low NPL cycle but turned positive under the regime of high NPLs. Only in one case however, was the positive coefficient statistically significant.

Another interesting finding was the magnitude of the impact of GDP under different regimes. For the banking system, the difference is in the region of 8 percentage points, and the results show that the GDP impact is greater in times of low NPLs (Regime 0), compared to periods of high NPLs (Regime 1). In other words, the rate at which NPLs decrease in periods of economic boom is higher than the pace at which NPLs grow during times of recession. This directional impact must be analyzed cautiously because the outcome is in contradiction to the structural frictions that were discussed in the stylized facts, which would naturally suggest that the directional impact should be stronger in times of economic decline. This thesis was supported however, by the analyzing the outcomes of the individual banks. In four banks, the impacts were significantly greater in the recession period to the extent that the difference between the regimes ranged from about 10 percentage points to 60 percentage points. Such variability emphasizes the heterogeneity that exists among the institutions and points to the value to be derived by individual analysis as the system outcome softens the true volatility associated with GDP fluctuations.

**Table 1: Markov Switching Models for Systemic NPLs (1996-2011)[a]**

| Variable [Regime] | Coefficient | P-Value |
|---|---|---|
| Constant [0] | 5.462 | (0.000) |
| Constant [1] | 8.729 | (0.000) |
| GDP(-4) [0] | -0.223 | (0.013) |
| GDP(-4) [1] | -0.146 | (0.016) |
| Inflation [0] | -0.179 | (0.011) |
| Inflation [1] | 0.232 | (0.001) |
| Loan Growth [0] | 0.222 | (0.012) |
| Loan Growth [1] | -0.061 | (0.308) |
| Linearity Test ($\chi^2$) | 69.949 | |
| | (0.000) | |
| Residual Tests: | Normality Test | 2.319 |
| | ARCH (1-1) Test | 0.632 |
| | Portmanteau (12) | 11.70 |

[a] P-values in parentheses

All the other control variables included in the model were particularly important to ensure the stability of the analyzing framework and the diagnostics for both the system and individual models provide this support. Mixed results were observed for inflation and loan growth in the systemic model. While in Regime 0, inflation is negatively correlated with NPLs, in Regime 1, a positive association is indicated, with both effects significant at the 1% level. Alternatively, in periods of high NPLs a higher inflation rate, leads to higher NPLs, while in periods of low NPLs the converse is true, albeit of a lesser magnitude. Loan growth was found to be positively related to NPLs in Regime 0 and negatively so in Regime 1, but insignificant. This outcome may reflect that fact that in periods of low NPLs (usually associated with a boom environment), banks may become less stringent in lending causing and lend to more risky borrowers causing the total loan portfolio to rise and higher NPLs as well.

Beyond the impact in any given regime, this non-linear framework provides an informative innovation that adopts conditional probabilities to determine the likelihood of transitioning from one state to the next, one period ahead. According to the system outcome, there is a 6 percent chance that a period of low NPLs would be followed by a period of high NPLs. On the other hand, the probability of transitioning from high to low NPLs is about 9 percent. Individual bank analysis exhibited a wider dispersion in the transition probabilities, which ranged from 2.5 percent to 20 percent from low to high NPL regime and from 6 percent to 20 percent in the converse. These results are again consistent with the heterogeneous outcomes for the NPL-GDP relationship.

## CONCLUSION

Many studies have found a negative relationship between NPLs and GDP. This paper critiques the assumption of linearity adopted by the models used to assess this relationship for banks in Barbados. It argues that a non-linear approach is better suited given the prudential rules and other frictions that naturally force the association between the variables to change during different phases of the economic cycle. The adoption of a MS framework was used to analyze aggregate bank data as well as the data from individual institutions to determine the nature of the relationship, whether the relationship was homogenous across institutions and whether all entities contributed significantly to NPL vulnerability.

The results show that a regime switching approach is a statistically valid methodology to analyzing banking NPL response to the economic cycle. The negative association is generally maintained but the overall impact was widely dispersed among institutions in the boom phase compared to the periods of downturn. Such dispersion is not captured in the linear models and the system averages does not properly capture true vulnerabilities that may exist in a particular institution. Furthermore, the impact is aggravated significantly in the down period for four banks, even though the system as a whole showed a slightly contrary outcome. The transition probabilities from one state to another state in the future were not homogenous among institutions. Overall, these findings support the arguments for a non-linear framework as it better captures the natural asymmetries in the NPL-GDP nexus, thus providing a better estimate of the directional magnitude in the economic cycle.

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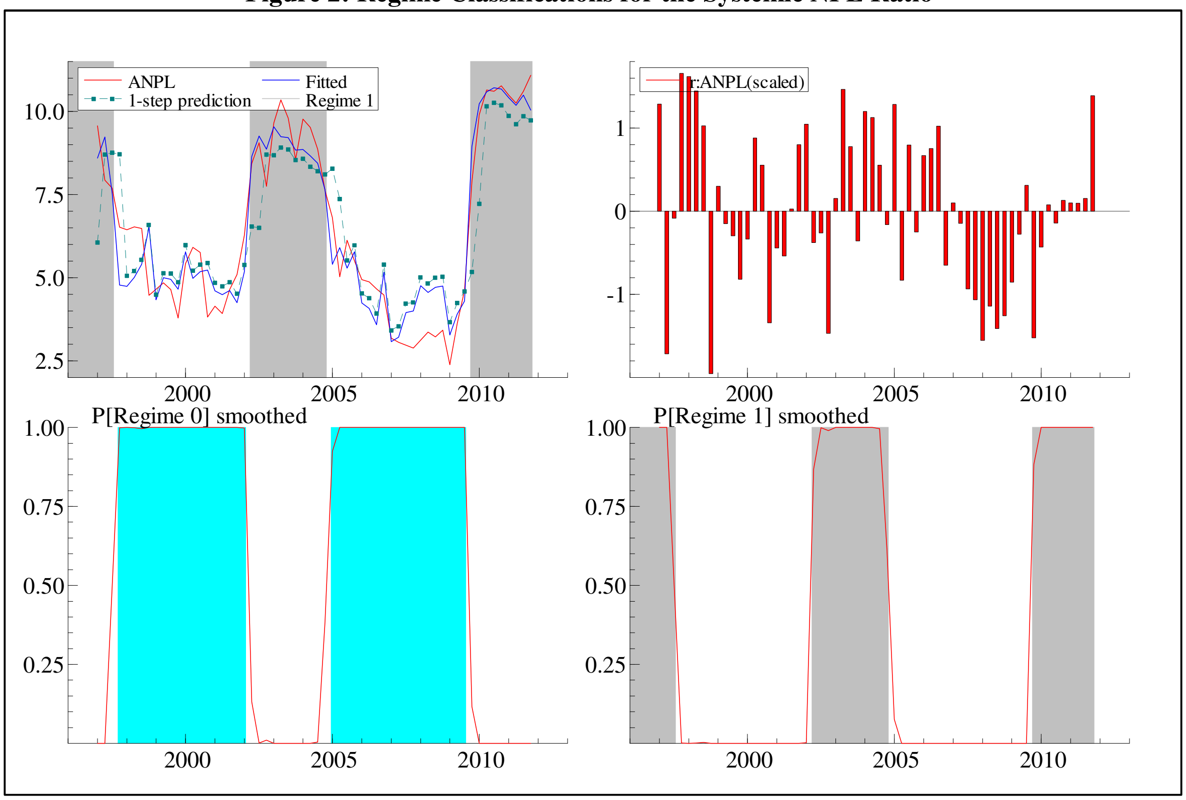
## APPENDICES

**Table 2: Markov Switching Models for Bank Specific NPLs (1996-2011)[a]**

| Variable [Regime] | | Bank 1 | Bank 2 | Bank 3 | Bank 4 | Bank 5 | Bank 6 |
|---|---|---|---|---|---|---|---|
| Constant [0] | | -3.451 | 11.465 | 0.886 | 2.089 | 0.503 | 15.297 |
| | | (0.288) | (0.000) | (0.526) | (0.094) | (0.688) | (0.000) |
| Constant [1] | | 10.142 | 8.164 | 7.713 | 15.690 | 5.578 | 18.334 |
| | | (0.561) | (0.000) | (0.036) | (0.000) | (0.028) | (0.000) |
| GDP(-4) [0] | | -0.637 | -0.248 | -0.146 | -0.155 | -0.112 | -0.084 |
| | | (0.000) | (0.000) | (0.040) | (0.000) | (0.007) | (0.237) |
| GDP(-4) [1] | | 0.809 | -0.428 | -0.780 | -0.304 | 0.312 | -0.186 |
| | | (0.304) | (0.000) | (0.000) | (0.001) | (0.000) | (0.113) |
| Inflation [0] | | -1.029 | -0.186 | 0.096 | -0.252 | 0.033 | -0.521 |
| | | (0.000) | (0.044) | (0.127) | (0.000) | (0.311) | (0.000) |
| Inflation [1] | | -2.874 | -0.134 | 1.498 | 0.398 | 0.595 | -0.741 |
| | | (0.000) | (0.048) | (0.000) | (0.000) | (0.000) | (0.000) |
| Loan Growth [0] | | 0.135 | -0.031 | 0.011 | -0.026 | 0.044 | -0.094 |
| | | (0.176) | (0.288) | (0.810) | (0.226) | (0.042) | (0.002) |
| Loan Growth [1] | | 0.089 | -0.115 | -0.222 | -0.162 | -0.056 | -0.244 |
| | | (0.039) | (0.008) | (0.005) | (0.000) | (0.324) | (0.002) |
| Bank Size [0] | | 0.811 | -1.182 | 0.059 | 0.323 | 0.066 | -1.346 |
| | | (0.000) | (0.006) | (0.409) | (0.160) | (0.290) | (0.021) |
| Bank Size [1] | | 1.144 | -0.014 | 0.030 | -2.231 | -0.135 | -0.919 |
| | | (0.275) | (0.725) | (0.890) | (0.000) | (0.256) | (0.159) |
| Linearity Test ($\chi^2$) | | 44.769 | 41.101 | 152.72 | 52.614 | 130.45 | 51.255 |
| | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Residual Tests: | Normality Test | 0.207 | 2.208 | 5.681 | 5.689 | 4.377 | 4.448 |
| | ARCH (1-1) Test | 0.074 | 0.578 | 0.343 | 0.513 | 0.011 | 0.164 |
| | Portmanteau (12) | 8.942 | 11.97 | 15.62 | 14.09 | 21.34* | 6.352 |

[a] P-values in parentheses

**Figure 2: Regime Classifications for the Systemic NPL Ratio[4]**




[4] Regime Classifications charts for the individual bank scenarios are available upon request from the authors.