Macro-financial Linkages in the ECCU

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ABSTRACT

This study examines the linkages between non-performing loans (NPLs) and macroeconomic performance in the Eastern Caribbean Currency Union through the lens of several complementary approaches. Static and dynamic panel models estimated over the period 1995 – 2013 for commercial banks in the ECCU indicates that the NPL ratio improves following a positive growth shock. By contrast, higher lending rates reduce the quality of the loan portfolio of banks. Less efficient, riskier banks hold higher NPLs on average, while more profitable banks are associated with lower NPLs. The results of panel VAR models suggest robust feedback effects between deterioration in banks' balance sheets and subdued economic activity.

Key words: non-performing loans, panel VAR
JEL Classification: C11, C23, E44

1.0 INTRODUCTION

The banking systems in the Eastern Caribbean Currency Union member states were adversely affected to varying degrees by the global economic and financial crisis, despite the favourable macroeconomic environment that existed in the years preceding the crisis. Real GDP expanded on average by 4.6 per cent in the five year period 2004 – 2008, while domestic credit rose by 13.6 per cent. Favourable macro-economic conditions led to lower non-performing loans (NPLs), which fell from 12.7 per cent in 2004 to 7.6 per cent in 2008. NPLs rose sharply in 2010, and have continued their seemingly inexorable march upwards, attaining a level of 18.3 per cent in 2013. Relatedly, domestic credit growth has stagnated, contracting by 3.7 per cent in 2013.

The current juxtaposition of elevated NPLs and declining credit growth is of concern to regulators and policy-makers alike, given the documented links between deterioration in NPLs, banking failures and financial crises. The loss of interest income from rising NPLs may erode bank profits and thus the capital base of individual banks. Losses may be further magnified if pledged collateral assets cannot be recovered in a timely manner. Moreover, potential spill-over effects to the rest of the banking system and related financial institutions can have destabilizing effects on the financial sector.

The objective of this study is to analyse the determinants of NPLs in the Eastern Caribbean Currency Union. In more detail, the paper employs a variety of empirical frameworks estimated on a balanced panel data set over the period 1995 – 2013 to examine the relationship between NPLs and several macro-economic and bank specific variables. The contribution of the paper is to simultaneously model the feedback effects between rising NPLs, credit constraints and subdued economic activity, using newly developed Bayesian and Panel Vector Auto-regression methods.

The study finds that bank specific and macroeconomic factors determine the loan portfolios of commercial banks in the ECCU. Additionally, the results from the analysis ascribe a central role to NPLs in the link between credit market imperfections and macroeconomic vulnerability. To preview the main results, there is some evidence of a negative relationship between real GDP growth and non-performing loans. Riskier, less efficient banks carry a higher level of non-performing loans than average, while more profitable banks are better incentivized to monitor their loan portfolio and thus hold lower NPLs on average. The results of the study provide some utility, both as a methodological tool in macro-stress testing analysis, and as input in policy debates on the ECCU financial system.

The paper is structured as follows. In the following section the international and Caribbean literature examining the determinants of NPLs is reviewed. Section 3.0 describes the data and the econometric methodology, while section 4.0 contains the empirical results. Section 5.0 offers a brief policy discussion and concludes.

2.0 LITERATURE REVIEW

The literature on the determinants of NPLs has expanded in recent years, in line with the greater incidence of financial and banking crises during the 1990s and 2000s in Latin American, East-Asian, and Sub-Saharan African countries. In this section we make contact with the extant literature, so as to motivate theoretical priors for the investigation of the determinants of NPLs in the ECCU. The literature relates the evolution of NPLs to two distinct factors. The first factor attributes variation in NPLs to external or macro-economic factors that can impinge on the capacity of borrowers to repay loans. By contrast, another strand of literature identifies idiosyncratic or bank-specific factors as the main determinants of NPLs. There is support however for both approaches in the empirical literature.

The link between macro-economic performance and the banking sector has been extensively examined. From the theoretical side, contributions from Diamond and Rajan (2001) and Allen and Gale (1998, 2004) highlight the vulnerability of banks to macro-economic shocks, primarily as a result of the inherent instability of bank's business models. Banks finance illiquid assets with liquid liabilities, and are thus negatively affected by adverse changes in the economic environment. In economic downturns for example, the value of bank assets may be reduced, as well as the value of the collateral pledged by borrowers, giving rise to a negative feedback loop that may increase the likelihood of a banking crisis.

Similarly, the empirical literature has documented considerable evidence on the relation between macroeconomic factors and banking performance. An early study that gave rise to a wide and varied literature is Keeton and Morris (1987). Using a sample of almost 2500 banks in the mid-western United States, the authors found that a substantial part of loan losses can be attributed to local economic conditions. Keeton and Morris (1987) additionally suggested that loan losses were also associated with variations in the business practices of banks, with some banks being more aggressive in their lending practices and taking greater risks than other banks. Pesola (2001) highlighted the role played by adverse macro-economic shocks in exacerbating loan losses during the banking crisis in four Nordic countries in the early 1990s[1]. The deterioration in loan quality in these countries was attributed to high levels of household and corporate indebtedness, increasing interest rates, and worse than anticipated GDP growth. Berge and Noye (2007) document the sensitivity of NPLs in Sweden to variations in real interest rates, oil prices, and domestic demand. An important precursor to the present study is Nkusu (2011), which analysed the links between NPLs and macroeconomic performance using panel data regressions and a panel VAR. Nkusu documents a negative feedback loop, whereby elevated NPLs weaken macroeconomic performance, that in turn exacerbates macro-financial vulnerabilities.

A related strand of the literature considers both macroeconomic and bank specific factors in the determination of NPLs. In a study of Italian banks, Quagliariello (2007) find that loan loss provisions are strongly pro-cyclical, using static and dynamic panel data me thods. Quagliariello (2007) note that the impact of recessionary conditions was significant and long-lasting. Bank profits and capital adequacy both decline during such periods, giving credence to the belief that poorly-capitalised banks may be forced to reduce credit supply in periods of subdued economic activity. In an innovative study, Bofondi and Repelle (2011) examined the determinants of household and commercial NPLs in Italy, over the period 1990 Q1 to 2010

[1] The Nordic countries studied included Denmark, Finland, Sweden, Norway.

Q2. Both household and commercial NPLs are negatively affected by shocks to real GDP growth, and positively related to the interest rate and unemployment rate. The temporal reactions of household and commercial NPLs to macroeconomic variables differ however, with commercial NPLs responding relatively faster. In a similar vein Louzis, Vouldis and Metaxas (2011) investigated the drivers of NPLs separately for consumer loans, business loans and mortgages in the Greek banking sector. The authors documented that both macroeconomic fundamentals and the quality of management significantly influenced loan quality. Moreover, mortgage loans were the least responsive on average to macroeconomic shocks.

A relatively new strand of the literature has attempted to uncover the feedback loop between NPLs and macroeconomic variables through panel vector auto-regressions. Espinoza and Prasad (2010) considered the relationship between elevated NPLs and the wider macro-economy using a panel VAR on Gulf Cooperation Council (GCC) countries. The panel VAR model suggested robust but short-lived feedback effects on non-oil GDP growth. Nkusu (2011) utilised a panel VAR model on a large sample of advanced countries, and in contrast to Espinoza and Prasad (2010), documented long lasting effects between NPLs and macroeconomic performance. A similar methodology was followed by Love and Ariss (2013), in their investigation of macro-financial linkages in Egypt. A positive shock to capital inflows and real GDP growth leads to an improvement in the loan portfolio quality of banks, while increases in lending rates presage a decline in the quality of loans extended.

There is a healthy Caribbean literature on the determinants of NPLs. Chase et al (2005) and Greenidge and Grosvenor (2010) considered the drivers of NPLs for Barbados. Chase et al (2005) focussed on three key macroeconomic variables, namely the nominal interest rate, inflation, and real GDP growth and - in line with the international literature - found that the expected directional impacts were significant. Greenidge and Grosvenor (2010) expanded the model of Chase et al (2005) to include loan growth and bank size as bank specific determinants of NPLs. The results were similar to the previous study, but in contrast to the literature, larger banks were found to hold higher levels of NPLs. An important variation was conducted by Belgrave, Guy, and Jackman (2012) on the banking system in Barbados. The authors examined the relationship between industry-specific income shocks and NPLs. The results of a VAR model implied some degree of heterogeneity in the response of NPLs to sector specific income shocks. For example, positive shocks to the distribution, professional and tourism industries lead to a reduction in NPLs. Shocks to the mining, quarrying and construction industries by contrast, tend to increase NPLs. Guy and Lowe (2012) utilised idiosyncratic bank variables and macro-economic factors to forecast NPLs in Barbados. The findings of the study gave equal credence to macro and micro variables in explaining the behaviour of NPLs. In a stress testing exercise, Guy and Lowe (2012) estimated that the banking system in Barbados was resilient to significant shocks in the real economy. In a study on the Guyanese banking system, Khemraj and Pasha (2009) document that the loan to asset ratios of banks as well as credit growth – in addition to the standard macroeconomic variables – significantly determined the NPL ratio. Jordan and Tucker (2013) investigated the linkages among economic growth and NPLs in the Bahamas, by constructing a Vector Error-correction VAR model. The main finding of the paper was that growth in economic activity leads to a reduction in NPLs on average during the time period considered. Additionally there was small but significant feedback effects from non-performing loans to output.

3.0 DATA AND METHODOLOGY

In this section we describe the data and econometric methodologies adopted to generate the empirical results in section 4. The study utilizes annual bank-level data on banks operating in the ECCU, as well as data on several macroeconomic variables over the period 1995 – 2013. The choice of the sample size was data dependent – although observations on macroeconomic variables are available from the early 1980s, data on non-performing loans date from 1995. The macroeconomic variables utlised reflect those considered in the extensive NPL literature, and thus include real GDP growth, the lending rate, and the rate of inflation. As an indicator of the general state of the economy, real GDP growth is anticipated to be negatively related to non-performing loans; a growing economy is likely to be associated with rising incomes, increasing borrower's capacity to repay their debt obligations. Conversely, an increase in interest rates is hypothesised to weaken repayment capacity, leading to a positive relation between NPL's and interest rates. The impact of inflation on non-performing loans can be considered ambiguous: on one level, price stability is usually deemed a prerequisite for sustained economic growth. However, increases in inflation may assist borrowers by eroding the real value of debt.

The choice of the bank specific variables also follows the empirical literature, accounting for bank efficiency, riskiness, size, and profitability (see for example Salas and Saurina 2002; Quagliariello 2007). The ratio of loans to total assets is taken as a measure of the risk appetite of banks. A higher proportion of assets allocated to loans increases credit risk exposure, which may lead to problem loans (Love and Ariss, 2013). The expected sign of the loan/asset ratio is thus positive. Bank efficiency is proxied by the cost to income ratio. A relatively higher cost to income ratio suggests that banks may be less effective in screening borrowers, and in turn may make higher provisions. Size is constructed as the logarithm of total assets. The empirical evidence on bank size and its relation to NPLs in somewhat ambiguous in the literature. There are some studies that suggest that larger banks may have better risk management and compliance frameworks, leading to a negative relation between size and NPLs. Some authors however argue that larger banks do not necessarily possess a comparative advantage in risk practices, and thus size and NPLs may also be positively related (Rajan and Dahl, 2003). More profitable banks are anticipated to have higher loan loss provisions, which can be used to smooth income flows and improve the incentives to monitor the credit risk portfolio. It is expected that better profitability will improve loan quality, leading to a negative relation with NPLs.

3.1 Panel Regressions

The base line multivariate model used to determine the drivers of loan portfolio quality is as follows:

$$npl_{it} = Y'_{it}\beta + \theta_i + \lambda_t + \varepsilon_{it} \tag{1}$$

Where Y_{it} is a vector of endogenous and predetermined variables, including lags of the dependent variable; β is the coefficient vector, while θ_i and λ_t reflect bank fixed effects and time fixed effects respectively. Lags of the dependent variable are included to account for omitted variable bias, as well as the persistence of NPLs. The starting point for the empirical analysis is pooled OLS, followed by a standard panel fixed effects model, and two variants of a generalised method of moments (GMM) estimator. The model in equation (1) is dynamic, in the sense that the set of right-hand side variables includes the lagged dependent variable. Estimation of such a model is subject to substantial complications, arising from the fact that the lagged dependent variable is correlated with the error, which can create an endogeneity bias. Equation (1) contains a country specific individual effect, η_i, which – as is the norm in the panel data literature - can be eliminated by a first difference transform:

$$y_{i,t} - y_{i,t-1} = \alpha(y_{i,t-1} - y_{i,t-2}) + \beta'(X_{i,t} - X_{i,t-1}) + (\varepsilon_{i,t} - \varepsilon_{i,t-1}) \tag{2}$$

The lagged dependent variable is still endogenous however, as the $y_{i,t-1}$ term in $(y_{i,t-1} - y_{i,t-2})$ is correlated with $\varepsilon_{i,t-1}$ in $(\varepsilon_{i,t} - \varepsilon_{i,t-1})$ by construction. The standard way to overcome this difficulty is to use instrumental variables, utilising second lags of $y_{i,t}$ as instruments. Two maintained assumptions are that (1) the error term is free from serial correlation and (2) the explanatory variables are weakly exogenous (that is, they are not correlated with future realisations of the error term). Formally,

$$E[y_{i,t-s}.(\varepsilon_{i,t} - \varepsilon_{i,t-1})] = 0 \quad \text{for } s \geq 2; t = 3,...T \tag{3}$$
$$E[X_{i,t-s}.(\varepsilon_{i,t} - \varepsilon_{i,t-1})] = 0 \quad \text{for s} \geq 2; t = 3,...T \tag{4}$$

The GMM dynamic panel estimator using these moment conditions is referred to as the difference estimator in the literature. There are statistical shortcomings with the difference estimator however: the estimator eliminates the country specific effect, making cross-country comparisons difficult. More importantly, Alonso-Borrego and Arellano(1999) and Blundell and Bond (1998) demonstrate that if the regressor's are persistent, the lagged levels $(y_{i,t-2})$ being used as instruments may be weak, which may serve to bias the coefficients in small samples. Arellano and Bover (1995) and Blundell and Bond (1998) derive a new estimator that combines in a system the regression in levels and the regression in differences (equations (1) and (2)), which they christened system GMM. By utilising a larger set of moment conditions, system GMM is potentially more efficient than standard two-stage least squares estimators and the difference GMM estimator discussed above. Identification of model (2) requires that the error term be free of serial correlation, an essential condition for consistency of the estimator as it instruments the lagged dependent variable with further lags. Additionally, the procedure hinges on the validity of the chosen instruments. It is standard to use the Sargan-Hansen test of the over-identifying restrictions, which assesses the contemporaneous correlation between the set of instruments and the error term. Both specification tests are reported in the empirical results detailed in section 4.

3.2 Bayesian Panel VAR

To further assess the impact of macroeconomic conditions on NPLs – and more importantly to uncover feedback effects - a Bayesian panel vector auto-regression (Bayesian PVAR) was constructed and estimated. As with the dynamic panel data model in equation (1), several important econometric issues arise from estimating a panel VAR. The presence of the lagged dependent variable induces correlation between the regressor's and the error term, but that can be alleviated somewhat by using a GMM estimator. A further challenge with the VAR in a panel setting is the issue of homogeneity. The dynamics of a VAR system are governed by the full set of parameters: if the lags are homogenous, impulse responses will be identical for each country. In many cases, this may be too strong an assumption. Another way to proceed is to assume that the cross sections are similar, but not identical, which is the assumption utilized in this study. This can be motivated in the case of the ECCU by appealing to similar production and trade sectors, a single currency, and a common central bank.

The assumption of similar – but not homogenous - dynamics of the VAR system makes the estimation process a bit more involved. This study relies upon the work of Swamy (1970), who estimated a model with explicit allowance for coefficient vectors that were "similar" in some way. The Random Coefficients Model (RCM) introduced by Swamy (1970) was equation (1) above combined with:

$$\beta_i = \beta + v_i, v_i \sim N(0, \Delta) \tag{5}$$

The RCM allows the slope coefficients to differ from the central (or average) β. The difficulty in using the RCM for the purposes of this paper is that unlike the univariate panel regression in equation (1), the choice for the variance (Δ) is not as straightforward: the variance will be affected by the different scales of the variables in each equation. As a result this study embeds the insights of Swamy (1970) in a Bayesian PVAR model. Bayesian techniques allow for the calibration of the variance-covariance matrix Δ above by explicit use of prior information about the lag coefficients in the VAR system. The priors are adopted from the extensive time series literature on Bayesian VAR's, and are specified in the "Minnesota" tradition[2]. A Minnesota prior is placed on the difference between the central β and the individual β_i, so as to impart heterogeneity on the lag dynamics of the VAR. With the Minnesota prior, each equation of the VAR can be estimated by univariate OLS. The standard error of the estimate of these regressions (s_i) are used to rescale the standard deviation of the prior for a coefficient on the lag of variable j in equation i by s_i/s_j.

To make the prior operational, it is normally assumed that the prior distributions on the lags of endogenous variables are independently normal, and the means of the prior distributions for all coefficients are zero (Litterman, 1980). This prior specification incorporates the belief that the more recent lags should provide more reliable information than more distant lags, and that "own" lags in an equation should explain more of the variation of a given variable than the lags of other variables in the equation. An exception is the first own lag of the dependent variable in each equation, which is given a prior mean of one by default. This relies on the assumption that most macroeconomic time series can be reasonably described as random walk processes. These assumptions reduce the information required in specifying the prior to a few "hyper-parameters", which are governed by the expression:

$$E[(A_k)ij] = \begin{Bmatrix} \delta_i, & j = i, k = 1 \\ 0, & \text{otherwise} \end{Bmatrix} \;\; ; V[(A_k)ij] = \begin{Bmatrix} \frac{\lambda^2}{k^2}, & j = 1 \\ \vartheta \frac{\lambda^2}{k^2} \frac{\sigma_i^2}{\sigma_j^2}, & \text{otherwise} \end{Bmatrix} \tag{6}$$

[2] Early work on Bayesian VARs was conducted by researchers at the University of Minnesota and the Federal Reserve Bank of Minneapolis (see Doan et al, 1984; Litterman, 1986)

The hyper parameter λ controls the overall tightness of the prior distribution around a random walk (or white noise, if the variables display substantial mean reversion) and governs the relative importance of the prior versus the information contained in the data (Banbura, Giannone and Reichlin, 2010). For $\rightarrow 0$, the prior is imposed exactly and the data do not influence the estimates; as $\lambda \rightarrow \infty$ the prior becomes loose and the prior information does not influence the estimates, which will converge to standard OLS. The factor $1/k^2$ dictates the rate at which the prior variance decreases with increasing lag length, and the factor σ_i^2/σ_j^2 is a scaling parameter which accounts for the different scale and variability of the data. The coefficient $\vartheta \in (0,1)$ governs the extent to which the lags of "other" variables are less important than "own" lags.

To complement the Bayesian analysis, the study also uses a panel vector auto-regression estimated in the classical tradition developed by Love and Zicchino (2006). The general form of the VAR can be written as:

$$y_{it} = \theta_i + \Theta(L)y_{it} + \varepsilon_{it} \tag{7}$$

Where $\Theta(L)$ is a polynomial in the lag operator and y_{it} is a vector of macroeconomic and bank level variables. Love and Zicchino (2006) get around the problem of biased coefficients resulting from the correlation between the fixed effects and the regressor's by using the Helmert procedure. The Helmert procedure removes the forward mean – that is the mean of all future observations – instead of the usual standard differencing to remove fixed effects. The procedure is useful in that it preserves orthogonality between the transformed variables and the regressor's, allowing the use of the lagged regressor's as valid instruments (Love and Ariss, 2013). In both VAR models a Cholesky decomposition was used to identify orthogonal shocks. The macroeconomic variables are placed first in the VAR, followed by non-performing loans. Thus macro-economic shocks are assumed to have a contemporaneous impact on all other variables, while being affected by shocks to NPLs with a lag. The results however are insensitive to the choice of ordering.

4.0 DETERMINANTS OF NON-PERFORMING LOANS

The results of various panel estimators of equation (1) are given in table 1 below. The pooled OLS and fixed effect models explain a fairly high percentage of the variation in NPLs, but the estimates are likely to be biased as a result of the presence of the lagged dependent variable. The estimates indicate that NPLs are highly persistent, with an auto-regressive parameter of 0.65 in the preferred System GMM specification. The GMM estimates are more robust, in that they account for the endogeneity bias introduced by lagged NPLs in the equations. The consistency of the coefficient estimates obtained using dynamic panel GMM estimators hinges on the models being free of serial correlation, and that the instrumenting variables are 'valid' in the sense that they are mutually correlated with the conditioning variables but are uncorrelated with the error term. The study utilizes the Arellano-Bond statistic (Arellano and Bond, 1991) for this purpose, and as shown in table 1, the test is not rejected for both differenced and system GMM specifications. To verify the validity of the instruments, the Hansen test of over-identifying restrictions was conducted; the results indicate that the restrictions are not rejected

Table 1: Macroeconomic and Bank-Specific Determinants of NPLs

	Pooled OLS	Fixed Effects	Difference GMM	System GMM
$npl_{(-1)}$	0.674***	0.491***	0.654***	0.651***
$loan/asset$	0.202***	0.433**	1.015***	0.234***
$cost/income$	0.194***	0.107*	-0.147	0.154**
$size$	0.006	-0.030	-0.467**	-0.009
$profitability$	-0.318***	-0.413***	-0.981***	-0.352***
$gdp\ growth$	-0.022***	-0.017**	-0.019**	-0.015***
$interest\ rate$	0.043**	0.039**	-0.087*	0.034
Observations	645	645	608	645
R-squared	0.57	0.55		
Number of instruments			35	54
Hansen test p-value			0.70	0.92
A-B AR(1) test p-value			0.00	0.01
A-B AR(2) test p-value			0.35	0.19

$*** \ p < 0.01, ** \ p < 0.05, * \ P < 0.10$

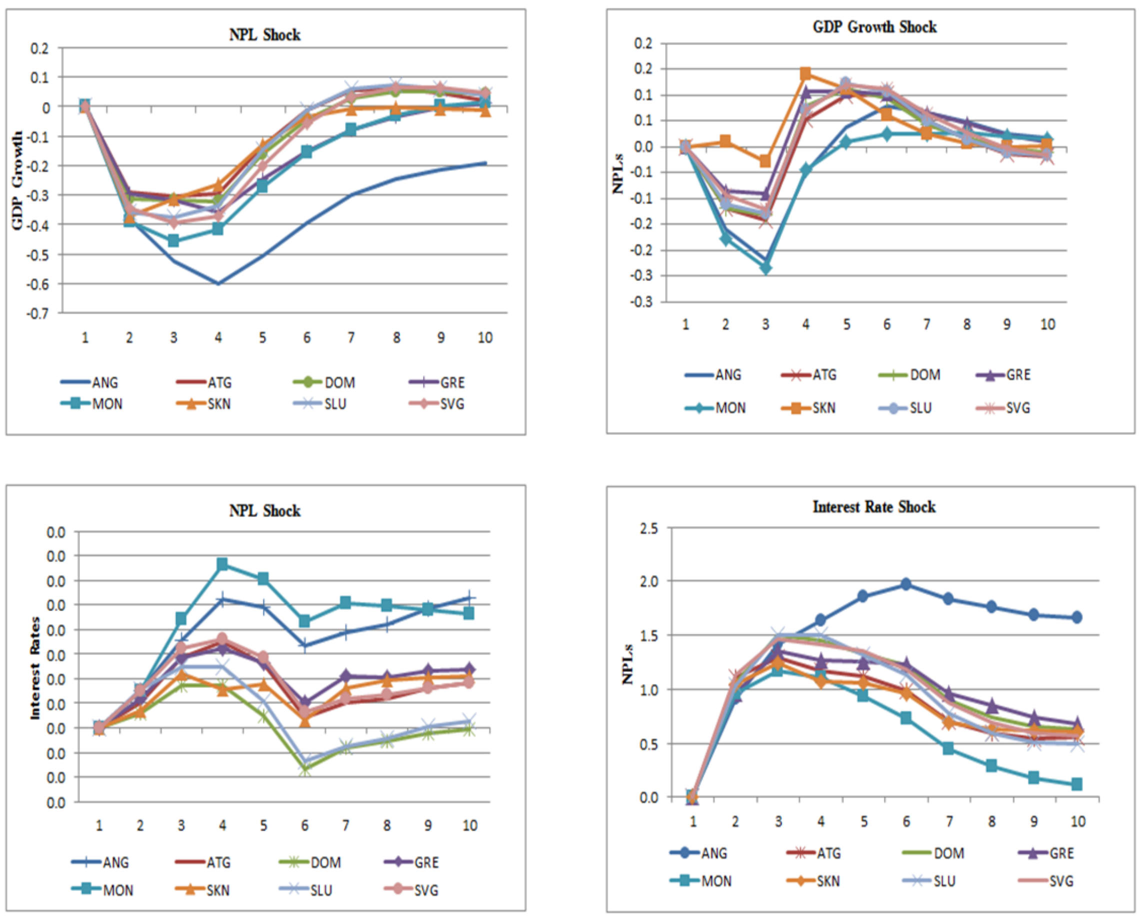
The analysis shows that both macro-economic and bank-specific variables contribute to the increase in NPLs in the ECCU. The loan to asset ratio – which proxies the risk appetite of commercial banks – is positive and highly significant in all specifications. An interpretation of this result is that banks that are high risk takers are likely on average to incur higher levels of NPLS (Sinkey and Greenwalt, 1991). Banks that are less efficient – typified by a higher relative cost to income ratio - are also less effective in screening borrowers and thus hold higher NPLs on average.

In accordance with some aspects of the literature, larger banks appear to have better risk management frameworks, in that there is an inverse relationship between bank size and NPLs (see Rajan and Dhal, 2003, Salas and Saurina, 2002, and Hu et al 2006). However, the effect of size is not significant in the majority of specifications. Higher profits are associated with an improvement in loan quality, providing bank managers with an incentive to monitor the performance of the credit portfolio.

The results displayed in table I also suggest that macro-economic aggregates are significant determinants of loan quality. The coefficient on real GDP growth is negative and significant in all specifications considered. Higher rates of growth induce a decline in NPLs, as well as improving the repayment capacity of borrowers, leading to an improvement in the quality of the loan portfolio. An increase in the lending rate leads on average to higher NPLs, in most specifications. The estimated positive relationship between the lending rate and NPLs suggests that higher interest rates weaken the debt servicing capacity of borrowers.

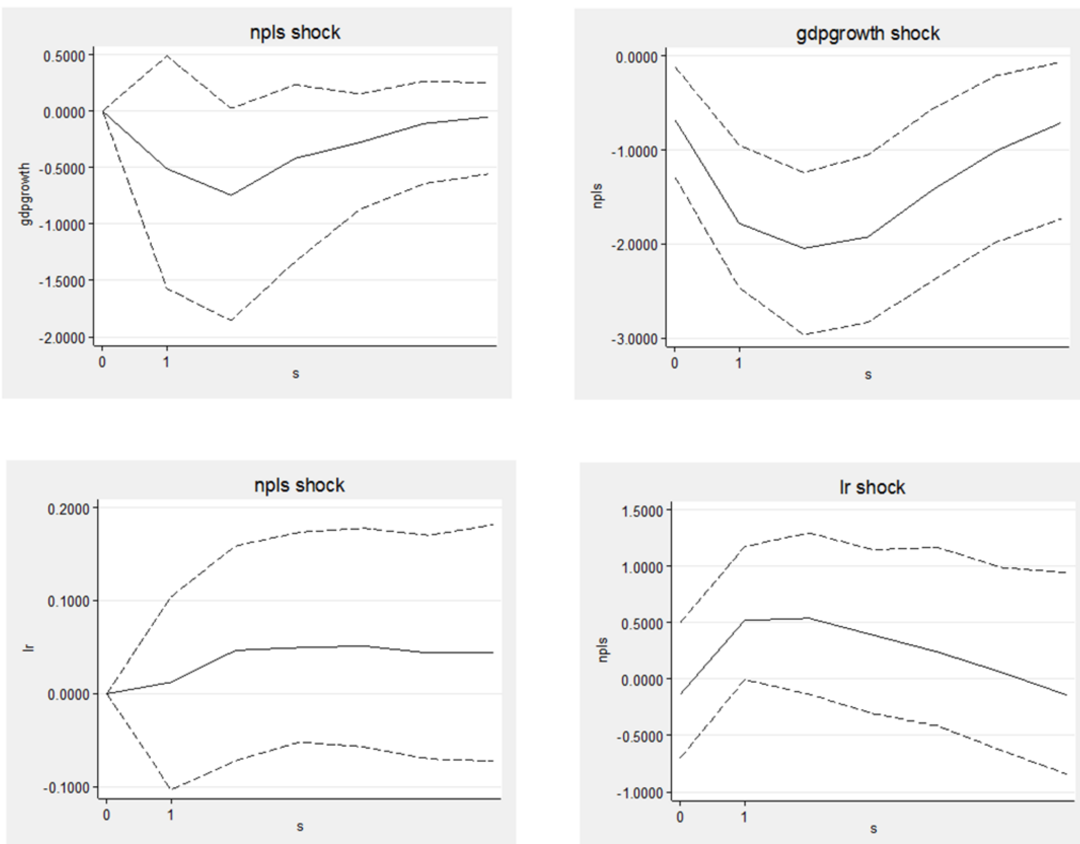
The results of the Bayesian Panel VAR are displayed as impulse response functions (IRFs) in Figure 1 below. There is some heterogeneity among ECCU countries. The first panel in the chart shows the response of real GDP growth to a one unit shock in NPLs. The IRF is significant, with real GDP declining by 0.3 percentage points on average. The largest reaction – in terms of magnitude – is found in Anguilla, followed by Montserrat. This result is intuitive, as NPLs in Anguilla increased by 41.0 per cent on average over the period 2009 – 2013. The impact of an increase in real GDP growth on NPLs is also significant, with the responses being led once again by Anguilla and Montserrat. There is considerably more variation in the response of the lending interest to a unit shock in NPLs. The magnitude of the response is however minimal. The non-performing loan ratio reacts strongly to unit shocks in the lending interest rate. The impact is also relatively persistent, with shocks to the NPLs in Anguilla remaining elevated for approximately 5 years after the shock.

Figure 1: Impulse Response Functions – BVAR



As a robustness check on the results of the Bayesian PVAR, figure 2 displays the results of the panel VAR constructed by Love and Zicchino (2006). The IRFs are qualitatively similar to those derived from the Bayesian PVAR. Note however that figure 2 displays the *average* impulse responses, instead of the country specific IRFs shown in figure 1. The feedback effect of higher NPLs on real GDP growth is shown in the first panel of figure 2. A one standard deviation shock to NPLs results in a reduction of 0.7 of a percentage point in real GDP growth after 2 years. The impact of real GDP growth on NPLs is somewhat stronger, with NPLs declining by 2.0 percentage points in the two years after the initial impulse.

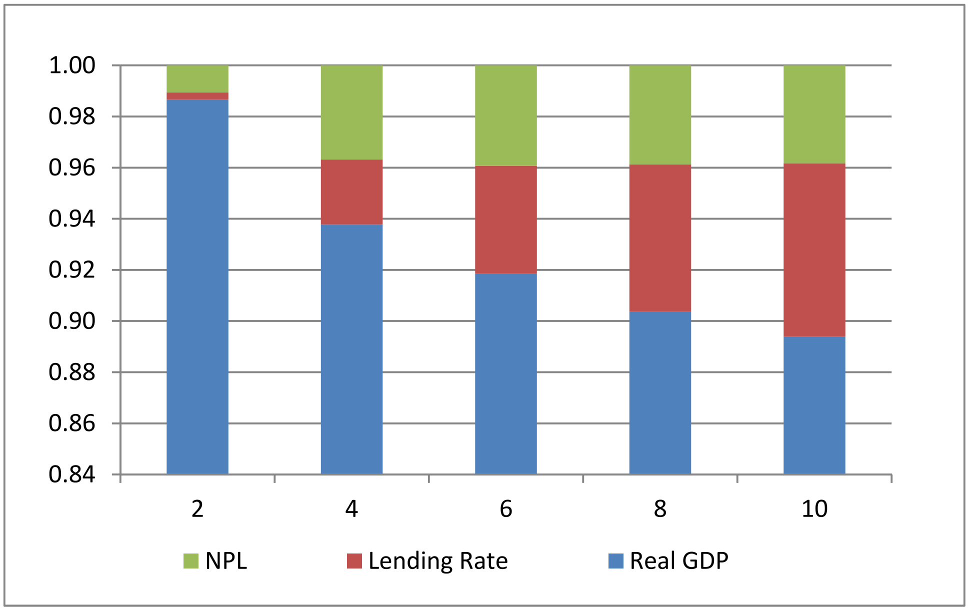
Figure 2: Impulse Response Functions – Normal VAR



In summary, the results of both panel VARs suggest a relatively robust feedback effect of NPLs on real GDP growth. Impulse responses can be used to determine whether a variable is statistically significant; to measure economic significance, forecast error variance decompositions are computed. The ordering of the variables are the same as that used to cnstruct the IRFs. However, the results are not materially affected by the choice of ordering.

The forecast error decomposition shows that shocks to NPLs explain a small variation in real GDP growth: on average, NPLs explain approximately 4.0 per cent of the variance over the medium-term.

Figure 3: Variance Decomposition – Real GDP Growth



5.0 POLICY DISCUSSION AND CONCLUSION

Despite a rich empirical history, an examination of the determinants and consequences of high and rising NPLs continue to be an important avenue of research. A possible reason may be the importance of the commercial banking system for the smooth functioning of modern economies. Relatedly, repeated occurrences' of banking and financial crises ensure that the subject of credit risk and the interaction with macroeconomic variables remain high on the policy agenda. This study investigated the determinants of NPLs in the ECCU banking system using a bank-level data set and several panel estimators. The empirical results suggest that macro-economic factors and bank-specific characteristics affect the level of non-performing loans. There is some evidence of a robust negative relationship between real GDP growth and non-performing loans. Higher lending rates are correlated with an increase in NPLs, suggesting that borrowers face tighter financial constraints as interest rate rise. Riskier, less efficient banks carry a higher level of non-performing loans than average, while more profitable banks are better incentivized to monitor their loan portfolio and thus hold lower NPLs.

A contribution of this study was to assess the feedback effects among increasing levels of NPLs and the real economy using Panel Vector Auto-regressions. Panel VARs are useful in this context for uncovering the dynamic inter-relationships among NPLs and macro-economic indicators. The results of the panel VARs suggest robust feedback effects on real GDP growth in the ECCU from elevated NPLs. Conversely, there are also non-zero effects from increasing real GDP growth rates to lower levels of non-performing loans. The results of the Bayesian PVAR also suggest considerable heterogeneity in macro-financial linkages among ECCU countries. Countries that experienced higher levels of credit growth during the pre-crisis years, or with higher than average NPLs post 2009 were most responsive to shocks in NPLs or real GDP.

The main findings of the paper have broad practical and policy relevance. From a practical standpoint the models constructed in this paper can be utilized in forecasting and stress testing exercises. Used jointly with assumptions on the likely evolution of macroeconomic variables, macro-stress testing scenarios and sensitivity analyses can be conducted to assess the potential impact on NPLs and the banking system and feedback effects to the macro-economy. The policy implications of the analysis highlight the central role of NPLs in contributing to credit constraints and subdued economic activity. The pro-cyclicality of credit growth and non-performing loans suggest added focus on macro-prudential tools such as loan to value ratios, leverage ratios and dynamic provisioning to alleviate somewhat the increase in leverage and credit growth in cyclical upswings.

There are several interesting avenues for future research. While the relationship between aggregate NPLs and economic activity was useful, a granular examination of sector specific NPLs can provide additional insights. Secondly, the output effects of bank balance sheet quality may be non-linear; exploring the possibility of threshold effects may be a useful extension of the results presented in this study.

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