Draft

A VAR Analysis of the Effects of Macroeconomic Shocks on Banking Sector Loan Quality in Jamaica

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Abstract

Bank solvency is susceptible to credit risk shocks as a consequence of poor loan quality. These shocks could also have significant destabilizing impacts on a banking system. Given the potential for banking system instability, this paper uses unrestricted VAR models to uncover the main macroeconomic indicators influencing the performance of the credit channel for Jamaica's banking sector, specifically for commercial banks, building societies and FIA institutions, over a ten year period. The model is able to predict changes in loan quality across all sets of institutions. The results suggest that both monetary and structural influences play a role in the accumulation of non-performing loans. As a key innovation, impulse response functions are underpinned by stress testing analysis to assess the stability of the banking system. Stress tests reveal that the relatively good early warning indicators of loan quality depletion are rising prices and real interest rates. However, worst-case scenario analysis provides little evidence of a systemic threat to the banking system from extreme macroeconomic shocks over the next three years.

Keywords: Non-performing loans, Procyclicality, Stress testing, VAR

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I. INTRODUCTION

Banking crises have beset many countries over the past two decades and have resulted in the closing or restructuring of several distressed institutions. In particular, the Jamaican financial crisis of the mid-1990s was estimated to consume resources of over 40.0 per cent of GDP.[2] As a consequence of the crisis, regulatory bodies have taken significant steps to mitigate any likely recurrence of such crises.

The strength of a lending institution lies in the quality of its loan portfolio, making credit risk exposure a key indicator of financial vulnerability in Jamaica. Credit risk is usually measured in terms of the stock of non-performing loans (NPLs) and loan-loss provisions vis-à-vis total loans.[3] The NPL ratios for commercial banks, institutions licensed under the Financial Institutions Act (FIAs), building societies and a weighted overall NPL ratio have exhibited significant improvement over the period 1997 to 2006 (see Figure 1 in Appendix **A2**). The late 1990s was marked by poor loan quality as an aftermath of the financial crisis. However, since 2000, following a period of asset reconstruction within the banking sector, the loan portfolio quality improved across all groups of banking institutions. It is conjectured that the Jamaican macroeconomic environment may have also contributed to the improvement in the NPL ratio.

This paper therefore focuses on quantifying the effects of Jamaica's macroeconomic performance on banking sector's loan portfolio quality. Specifically, the paper seeks to uncover those interrelated macroeconomic factors (such as interest rate, GDP growth, exchange rate, *inter alia*) that influence the evolution of loan portfolio quality for commercial banks, building societies, FIAs and the overall banking sector.[4] Since the results from the literature indicate that exposure to credit-risk shocks are country-specific or regional, the underlying dynamics of loan portfolio quality in Jamaica's banking sector must be explored.[5] The Jamaican economy is particularly susceptible to foreign trade and,

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[2] This is an estimate from the World Bank.
[3] NPLs are defined here as those loans whose payment of principal and interest is past due for 90 days and over.
[4] The overall banking sector defined in this paper does not include credit unions. The banking sector is estimated as the weighted average of commercial banks, FIAs and building societies.
[5] County specific factors refer to the specific structural, legal, regulatory or institutional factors.

in recent times, has also been exposed to frequent weather related shocks such as hurricanes. Hence the paper will include these variables as possible determining factors of loan quality.

A review of the literature reveals that several techniques have been applied to estimate and forecast the effects of macroeconomic shocks on banking sector credit risk and the likelihood of banking distress. Earlier studies have primarily employed single-equation regression models. However, these models suffer from two chief drawbacks. First, it is difficult to distinguish correlation from causality. Second, they are unable to capture the inter-relationships among economic factors and their subsequent overall impact on the performance of loan portfolios. To account for this shortfall, more advanced techniques involving the use of vector autoregression (VAR) analysis are widely used in contemporary empirical macroeconomic studies.[6] This paper applies this VAR methodology and impulse response analysis to investigate the causal relationships between the economic variables and credit quality by tracing out the loan quality time paths in response to macroeconomic innovations.[7]

In addition, similar to Baboucek and Jancar (2005), sensitivity and scenario-based stress testing will also be applied to examine their impact on the loan portfolio quality of banks in Jamaica. Stress testing simulations are performed under exceptional but plausible events of both a hypothetical and historical nature to assess the vulnerability of banks' loan portfolio quality to adverse macroeconomic factors. The idea of these simulations is to provide a forward-looking assessment of the banking sector's level of credit risk exposure in order to safeguard financial stability.

The remainder of the paper is organized as follows. Section II presents a review of the literature covering studies that have attempted to delineate the determinants of loan quality. Section III describes the VAR model, the data and variables to be included in the analysis.

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[6] VAR analysis was proposed by Sims (1980) as an outcome of the criticism of the 'incredible identification restrictions' as a natural part of structural models.
[7] Stock and Watson (2001) agree that VAR is a powerful tool for describing data and forecasting but has limited value when it use for structural inference (since that depends on the ordering) and policy analysis.

Section IV examines the empirical results, including the model forecasts, impulse responses and stress testing. The paper concludes with Section V.

II. REVIEW OF LITERATURE

A large body of research exists which empirically investigates the dynamic relationship between macroeconomic factors and the quality of loan portfolios. Gavin and Hausmann (1996) examined the macroeconomic developments that contributed to banking crises in Latin America during the 1990s. The study found that domestic interest rates, expected inflation, terms of trade, domestic income, growth of bank loans and the specific monetary and exchange rate regime, among others, were important constraints on loan servicing capacity. In extreme cases, the study found that deterioration in these macroeconomic factors usually precedes banking crises.

Demirgüç-Kunt and Detragiache (1998) and Hardy and Pazarbasioglu (1998) also found that the emergence of a banking failure could be attributed to macroeconomic shocks. In particular, Demirgüç-Kunt and Detragiache (1998) theorized that banks face insolvency due to falling asset values when bank borrowers are unable to pay their debt as a result of adverse shocks to economic activity. As such, the authors estimated the macroeconomic determinants of banking crises using four different specifications of a multivariate logistic model for a large sample of developing and developed countries for the period 1980 to 1994.[8] Of particular interest, inflation and the real interest rate were found to be positively associated with a banking crisis, whereas the level of GDP had an inverse association. Also, of note, external vulnerability, proxied by the M2 to reserve ratio, increased the likelihood of a banking crisis.

Hardy and Pazarbaşıoğlu (1998) focused on identifying the macroeconomic and financial conditions which are indicative of banking distress. The authors analyzed a panel of 38 countries using also a multinomial logit model framework. Their main findings were that

[8] The different specifications were due to the inclusion and exclusion of specific financial variables, such as M2/FX reserves and credit growth, as well as institutional variables, such as a deposit insurance dummy and a law and order index. These specifications were estimated over two time periods, during the crisis and after the first crisis.

the likelihood of banking sector failures was largely in accord with declining economic growth. Further, capital inflows and credit expansion to private sector, associated with rising consumption and real interest rates, typically preceded banking crises. Sharp cyclical movements in the inflation rate, adverse trade shocks and declines in real effective exchange rate also tended to precipitate banking crises.

However, in contrast, studies have found that it is typically the case that macroeconomic performance affects the dynamic components of banks' financial variables which then contribute to bank failures. As such, Gambera (2000) employed a bivariate VAR model to assess the impact of regional and national macroeconomic variables on two categories of problem loans, including NPLs and loan delinquencies, using data from US commercial banks categorized as large, medium and small.[9] The explanatory variables included the unemployment rate, farm income, housing permits, state annual product, bankruptcy fillings and car sales. The study found that all variables, except, car sales were significant predictors of bank asset quality. Further, the results from out-of-sample forecasts suggested that this model had accurate predictive power.

Over a complete business cycle, 1991 to 2001, for all 29 OECD countries sampled, Bikker and Metzemakers (2002) attempted to capture the dynamics of loan quality, measured by the stock of loan loss provisions, with respect to changes in macroeconomic and bank-specific variables.[10] The study conjectured that a cyclical downturn would deteriorate asset quality resulting in banks' restricting lending so as not to further exacerbate the increasing stock of problem loans. The authors estimated the following OLS regression: [11]

$$\begin{aligned} LLP_{i,j,t}/TA = &-0.0016 + 0.4131 LLP_{i,j,t}/TA_{-1} - 0.0005\,\Delta \ln GDP_{j,t} + 0.00 UE_{j,t} + 0.2784\, EARN_{i,j,t} + \\ &0.0003\,\Delta \ln LOANS_{i,j,t} + 0.0038(LOANS/TA)_{i,j,t} - 0.0329(CAP/TA)_{i,j,t} \end{aligned}$$

All variables except the unemployment rate significantly (at all conventional significance level) impacted the loan-loss provision rate. These results affirmed the procyclicality of

[9] Loan delinquencies are loans whose payments are past due and still accruing between 30 and 89 days.
[10] The use of bank provisions alternatively to a direct measure of loan quality such as loan losses is due to (i) inadequate time series data on loan losses for many countries and (ii) a strong correlation between loan losses and their provisions. Loan-loss provisions reflect expected loan defaults and so increases in provisions can be interpreted as a decline in loan quality due to expected credit losses.
[11] Several country-specific dummy variables were also apart of the estimated model.

loan quality, the riskiness of credit growth and the autoregressive nature of loan loss provisions. The results also highlighted that bank-specific variables lend support to the income-smoothing hypothesis. This empirically supports the idea that individual banks will make provisions in times of high business activity as a buffer stock for low activity periods to control for income smoothing. An earlier study by Arpa et al. (2001), which also examined bank procyclicality and used a similar methodology, supported these findings. The study also determined that inflation and real estate prices were positively related to loan loss provisions.

Kearns (2004) employed a fixed effects framework on a panel of 14 Irish credit institutions to examine the relationship between loan-loss provisions and explanatory variables, including GDP, unemployment rate and the earnings ratio. The study concluded that unemployment and GDP growth significantly increased the level of provisioning.

Baboucek and Jancar (2005) applied a comprehensive unrestricted VAR to quantify the effects of macroeconomic shocks on the loan quality of the Czech banking sector using monthly series from 1993 to 2006. Using the NPL ratio as an indicator of loan quality, robust causal relationships were found to exist with loan quality and a number of macroeconomic variables based on impulse response analysis.[12] Unemployment, CPI inflation and credit risk shock were found to have negative influences on the NPL ratio, confirming theory and related empirical studies. However, other macroeconomic variables, such as the loan stock, real exchange rate and M1 (as a proxy for GDP) failed to concur with economic theory as innovations in all variables except M1 improved loan quality.[13] Further, stress testing analysis was executed to assess the vulnerabilities of the Czech banking sector with regard to extreme macroeconomic shocks. An accelerating NPL ratio, high unemployment and inflationary tendencies were cited as important early warning indicators of credit portfolio deterioration. Other stress testing results suggested that banking stability was dependent on price stability and economic growth.

[12] Concerns were raised about the NPL ratio being a lag indicator of loan quality, that is, its deterioration is usually evident at the point when problem emerges.
[13] Baboucek and Jancar (2005) used an ARMA(1,4) model to regress real money onto final consumption, investment and the trade deficit.

One of the more recent studies, Filosa (2007) examined stress tests conducted on the Italian banking system through the modeling of three VARs. The study identified the default rate, the NPL ratio and the interest margin (as a measure of profitability) as indicators of banking distress.[14] Each VAR included the output gap and the inflation rate, *inter alia,* as well as three exogenous variables, the interest rate, the exchange rate and a linear trend.[15] The results were that procyclicality of these endogenous and exogenous indicators were not an important feature of the Italian banking system and the hypothetical tightening of monetary conditions, through stress testing, induced significant exposure to credit shocks.

The abovementioned studies, in general, corroborate theoretical postulates with respect to the macroeconomic influences on loan portfolio quality and, consequently, on banking sector credit risk. In effect, good economic conditions seem to be commensurate with good loan quality measured by either the NPL ratio or loan loss provisions. Furthermore, it was notable that most studies tended to employ standard regression analyses to examine this relationship. However, the VAR methodology proposed by Sims (1980) and used by the more recent studies in the literature, were found to be the more appropriate approach. VAR analysis treats each variable symmetrically without relying on *a priori* information to choose dependent or independent variables as opposed to single linear regression equations. Since macroeconomic variables are commonly interrelated, a VAR model conveniently incorporates these feedbacks. In fact, a key benefit to using VAR lies in its ability to forecast the effects of a shock to another variable. In this context, the effects of macroeconomic shocks to banks' loan quality can be easily discerned.

III. EMPIRICAL METHODOLOGY

The VAR Model

[14] The study defined the default rate as the log of the ratio of the *flow* of non performing loans (NPLs) for the last twelve months to the stock of performing loans outstanding at the beginning of the period.

[15] The choice of these variables as exogenous by the author was motivated by the fact that EMU determine movements in those variables as against Italy alone.

The VAR model employs a system of linear equations to capture the dynamic feedback relationships between two or more endogenous variables. VAR treats all variables as symmetrical without theoretically presupposing whether a variable is independent or dependent. All endogenous variables are affected by contemporaneous and past realizations of other variables. The structural form of the model is as follows:

$$\begin{bmatrix} 1 & b_{12} & \cdots & b_{1n} \\ b_{21} & 1 & \cdots & b_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ b_{n1} & b_{n2} & \cdots & 1 \end{bmatrix} \begin{bmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{nt} \end{bmatrix} = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} + \begin{bmatrix} \Gamma_{11}(L) & \Gamma_{12}(L) & \cdots & \Gamma_{1n}(L) \\ \Gamma_{21}(L) & \Gamma_{22}(L) & \cdots & \Gamma_{2n}(L) \\ \vdots & \vdots & \ddots & \vdots \\ \Gamma_{n1}(L) & \Gamma_{n2}(L) & \cdots & \Gamma_{nn}(L) \end{bmatrix} \begin{bmatrix} y_{1t-1} \\ y_{2t-1} \\ \vdots \\ y_{nt-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \vdots \\ \varepsilon_{nt} \end{bmatrix} \qquad [1]$$

or in a compact form:

$$By_t = A + \Gamma(L)y_{t-1} + \varepsilon_t \qquad [2]$$

where B is an $n \times n$ matrix of contemporaneous coefficients of n endogenous variables in the vector y_t. A denotes the $n \times 1$ vector of constant, $\Gamma(L)$ is the $n \times n$ matrix of lag operator polynomials which captures the lags of the endogenous variables and ε_t is the $n \times 1$ vector of white noise processes, that is, $\varepsilon_t \sim N(0,\Omega)$. The model in [2] can be adjusted to include exogenous variables specified as

$$By_t = A + \Gamma(L)y_{t-1} + \Pi x_t + \varepsilon_t \qquad [3]$$

In this case, Π is a $n \times p$ coefficient matrix and x_t is the $p \times 1$ vector of exogenous variables such as weather and/or a dummy variable. Simultaneous structural forms are difficult to estimate because of the problem of endogeneity. Therefore, VAR circumvents this problem by estimating the model in reduced form, as a function of predetermined variables and residuals. Premultiplying [3] by B^{-1} gives the reduced-form VAR as

$$y_t = C_0 + C_1(L)y_{t-1} + C_2 x_t + e_t \qquad [4]$$

where $C_0 = B^{-1}A$, $C_1(L) = B^{-1}\Gamma(L)$, $C_2 = B^{-1}\Pi$ and $e_t = B^{-1}\varepsilon_t$. Since e_t is a function of ε_t, it consists of serially uncorrelated residuals but are correlated across equations. As [4] is symmetrical, OLS estimation can produce consistent and asymptotically efficient parameter estimates.

Lag length selection for VAR models is a critical decision for time series analysis so as to capture the actual data generating process. In addition, it is important not to overfit (and thereby increase forecasting errors) or misspecify the model (that may lead to residual serial correlation) as the consequences will bear out in the forecasts and the impulse response functions. Macroeconomic VAR models are typically overparametized to take account of long lag relationships and so the appropriate lags must be chosen to preserve sufficient degrees of freedom. For this paper, the likelihood ratio (LR) test in conjunction with the Akaike Information Criterion (AIC) are used to inform choice of lag lengths. The LR test facilitates cross-equation restrictions to test shorter lags versus longer lags. It is uncommon to use the AIC - as oppose to the Schwartz Bayesian Criterion (SBC) – for arguments of inconsistency and biasedness towards choosing an overparametized model. However, according to Ozcicek and McMillin (1999), AIC is relatively better at selecting lags for models that the true data generating process is one of long lags.[16] Based on this theoretical formula, it is not unlikely that macroeconomic VAR models have a true long lag.

This paper interprets the results of the VAR estimation through the use of impulse response functions. These functions trace out the time path of a variable in response to an impulse\shock in another variable and therefore, indicate which shocks incite variability in an endogenous variable. The VAR framework makes it possible, for instance, to forecast the effects of pure macroeconomic shocks on loan quality. To execute this, structural innovations must be *identified* from the reduced form residuals.[17] For this paper, identification[18] will take the form of Choleski decomposition that imposes zero restrictions

[16] The authors employed Monte Carlo simulations of 1000 draws to assess the performance of various lag selection criteria for bivariate VAR models of short and long lag structure.
[17] Why use structural innovations as oppose to error terms in the VAR? The idea is that structural innovations capture pure shocks where as regression residuals are usually not contemporaneously independent and so its use would mean that a shock in one variable is likely to be accompanied by a shock in another variable. So when forecasting the response of a shock to one variable while assuming that a shock occurs in one variable at a time, the use of the VAR regression residuals would have misleading outcomes. In short, since error terms from the VAR may be correlated, setting other residuals to zero would be an invalid assumption.
[18] See Enders (2004) for further reading on identification.

assumption on all coefficients in the B matrix above the principal diagonal of ones (i.e. triangularizing). The B matrix from [1] is restricted as

$$\begin{aligned} b_{12} = b_{13} = b_{14} = \ldots = b_{1n} &= 0 \\ b_{23} = b_{24} = \ldots = b_{2n} &= 0 \\ b_{34} = \ldots = b_{3n} &= 0 \\ \ldots \\ b_{n-1n} &= 0 \end{aligned} \qquad [5]$$

The resulting asymmetry exactly identifies the system by forcing $(n^2 - n)/2$ coefficients to be zero, that is, the total elements of n^2 minus the n elements of the leading diagonal and then halved gives the total restrictions. Following from [4], e_t is a composite of the structural innovations ε_t which can be rewritten as $\varepsilon_t = Be_t$. After applying [5], in extended form, the orthogonal structural innovations can be recovered as follows

$$\begin{aligned} \varepsilon_{1t} &= e_{1t} \\ \varepsilon_{2t} &= b_{21}e_{1t} + e_{2t} \\ \varepsilon_{3t} &= b_{31}e_{1t} + b_{32}e_{2t} + e_{3t} \\ &\vdots \\ \varepsilon_{nt} &= b_{n1}e_{1t} + b_{n2}e_{2t} + \ldots + e_{nt} \end{aligned} \qquad [6]$$

The covariance matrix of the resulting structural shocks is then used to derive the impulse responses. Note that Choleski decomposition constrains the system to yield a specific ordering of the contemporaneous relationships between the endogenous variables (that is, a *recursive system*). Higher ordered variables are assumed to be contemporaneously correlated with lower ordered variables and the latter variables are said to affect the former with only lags. This ordering is informed by *a priori* knowledge but if improperly assumed may lead to unreliable results. Any significant correlations between the residuals of each VAR equation will increase the importance of this ordering in recovering the structural innovations. This will have implications on the results of the impulse responses. In such instances, testing the sensitivity of the impulse responses under different reordering (base on the significantly correlated variables) is necessary to assess the robustness of the relationships (Enders, 2004).

Macroeconomic stress testing is applied to banks' loan portfolio to detect risk-bearing capacity under extreme but plausible events. The key aspects of carrying out stress tests involve designing and calibrating stress shocks. Firstly, for this paper, both single (sensitivity analysis) and multiple (scenario analysis) risk factors are shocked. The combination of events selected for the scenarios are both of a hypothetical and historical nature. Secondly, the magnitudes of the shocks are calibrated base on the 99.5th quantiles of each variable's distribution, therefore avoiding any strict assumptions of normality (Sorge, 2004).

Data and Variable Inclusion[19]

Monthly data series spanning the period 1997 to 2006 were collected which including a sufficient indicator of banking sector loan quality as well as core macroeconomic variables for Jamaica. The NPL ratio (calculated as NPLs to total loans) was used as a direct loan quality indicator for banks and was the main measure of credit risk. The existing literature and economic theory informed the choice of seven endogenous variables that were selected for the study. The variables selected were the real effective exchange rate (REER), the consumer price index (CPI), the terms of trade index (TOT), the ratio of public to private loans for commercial banks (CPPL), the loan stock (LOAN), the real 180-day Treasury bill rate (RI) and the growth rate of real money measured as M1 deflated by CPI (RM1), (see Appendix **A2**).[20] A rainfall variable (RF) representing the amount of rainfall in millimetres was included in the model as an exogenous factor of a third-order polynomial structure given nonlinearity in the effects of rainfall. The VAR model was estimated over the period January 1997 to December 2005 in order to facilitate out-of-sample forecasting over the remaining sample.

[19] Due to data unavailability, variables such as unemployment and the ratio of public to private loans for building societies and FIA were excluded. However, the main supplier of loans to government services is commercial banks and so it is sufficient to consider only commercial banks.
[20] The idea is that money demand is a function of wealth as proposed by Fisher. The crux of the results is that movements in real GDP lagged three quarters reproduce fluctuations in real money. For further perusal, an ARIMAX (1, 4) model for real money (M2) was estimated by Baboucek and Jancar (2005) for the Czech economy. Due to the lack of a monthly series for GDP, the M1 proxy accommodated for this shortcoming.

The ratio of NPLs for the banking sector drastically declined post the 1996 financial crisis, attributed to steps taken by the Government to mitigate the effects of the financial crisis. These events support the marked declines in the NPL ratio at end-June 1998, March 1999 and November 1999 for the commercial banks, FIAs and building societies, respectively. These structural breaks supported the inclusion of dummy variables (DUM) to account for their effects on the estimated model coefficients.

This paper incorporates stationary variables in the VAR model. Stationary variables evade the problem of spurious regression and enable hypothesis testing to be performed using the standard t and F distributions.[21] The Augmented Dickey-Fuller (ADF) test was used to test for stationarity in order to determine the order of integration, denoted as I(d).

Granger causality tests were performed to determine whether lags of one endogenous variable significantly improved the forecasting performance of another variable for each group of institutions and the system as a whole. Specifically, these are pairwise tests of the null hypothesis that the coefficients $C_{ij}(L)$ of an endogenous variable in equation [4] equal zero and thus *Granger causes* it. Therefore, rejection of the null hypothesis through a standard F-test (since all variables are stationary) attests to the inclusion of the particular variable in the equation of another variable.

IV. ESTIMATION AND EMPIRICAL RESULTS

A Priori Expectation

According to the theoretical and empirical literature, the following relationships are expected to be reflected in the empirical results: (i) the NPL ratio as an indicator of credit risk should be autoregressive; (ii) the NPL ratio should be pro-cyclical;[22] (iii) higher real

[21] Sims, Stock and Watson (1990) assert that "individual coefficients in the estimated autoregressive equations are asymptotically normal with the usual limiting variance, unless they are coefficients of a variable which is nonstationary …"

[22] This means that in times of economic booms marked by rising income levels economic agents' ability to service debt is likely to increase and vice versa.

interest rate should increase the cost of borrowing and hence accelerate loan defaults; (iv) inflationary pressures should worsen the quality of banks' loans;[23] (v) depreciation in the real exchange rate is expected to have a positive effect on loan quality;[24](vi) A more favourable terms of trade (TOT) should improve debt servicing capacity, (vii) a rise in the ratio of public to private loans is expected to increase loan defaults;[25] and (viii) credit expansion is expected to amplify the likelihood of bad loans. In addition, loans to the agriculture sector are typically adversely impacted by severe weather conditions, resulting in reduced disposable income and hence loan servicing capacity.[26] The effect of rainfall on the NPL ratio is estimated by including the following polynomial relationship: $\alpha_1 x + \alpha_2 x^2 + \alpha_3 x^3$, with α_2 expected to be negative and α_1 and α_3 expected to be positive values. The coefficient α_2 captures the effects of moderate rainfall (good for farming) and the coefficients α_1 and α_3 capture the effects of minor and heavy rainfall, respectively.

Preliminary Results

Unit root tests of the rainfall series and the TOT index revealed that these variables were level stationary (see Table 1). Unit root tests also revealed that all other variables were I(1) except FLOAN.[27]

The results of the pairwise Granger causality tests revealed that granger causality runs from 11 endogenous variables (i.e. all but loans and NPL ratios of building societies and FIAs) to at least one other endogenous variable at eleven lags. This finding attests to the relevance of majority of the variables in explaining changes in credit quality. Importantly, at least one endogenous variable helps to forecast future values of loan quality for each group of institutions with the exception of the system NPL ratio. A lag of eleven

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[23] Aside from increasing nominal interest rate, increases in inflation creates a climate of high uncertainty, rises in informational asymmetry and hence promote adverse selection in bank lending.
[24] Depreciations in the real exchange rate should enable price competitiveness in terms of exports.
[25] Expansion in public sector loans crowds out loans to the private sector causing a rise in loan interest rates and hence constrains loan repayment.
[26] Although agriculture output accounted for just over 7.0 per cent of GDP, the sector employs about 21.0 per cent of Jamaica's labour force,
[27] Although, TOT was stationary at levels, there is a good economic reason to include it as a logarithmic difference series since this achieves the growth rate of the index.

corroborates theoretical predictions that the effects of changes in macroeconomic variables usually take three or four quarters to be observed.

Table 1: ADF Test for Stationarity

Variables	ADF test statistics		
	Level	Transformed series*	Order of Integration
CPI	2.05	-6.84	I(1)
RM1	-0.92	-12.24	I(1)
REER	-1.57	-7.82	I(1)
RF	-9.12	-	I(0)
RI	-1.71	-9.31	I(1)
TOT	-3.72	-12.88	I(0)
CLOAN	2.73	-6.88	I(1)
FLOAN	9.63	-9.87	I(2)
BLOAN	0.56	-15.98	I(1)
LOAN	2.3	-7.04	I(1)
CPPL	-1.47	-8.76	I(1)
CNPL	-0.65	-8.58	I(1)
FNPL	-1.02	-10.55	I(1)
BNPL	-0.76	-13.5	I(1)
NPL	-0.53	-7.93	I(1)

*All I(1) variables are log differenced except RI which is differenced.

Notes: Augmented Dickey-Fuller critical value = -2.89

The letters C, B and F preceding LOAN and NPL signifies commercial banks, building societies and FIA. LOAN and NPL by themselves are system variables.

The Estimated Model

Similar to the approach of Baboucek and Jancar (2005), an incomplete lag structure was used to capture the short and long run dynamics of the estimated equations while avoiding over-parametising. The number of parameters to estimate is a function of the available sample size in each VAR specification for the commercial banks, FIAs, building societies and the system. The lag lengths selected are lags 1, 2, 8 and 11; 1, 2, 8, 9 and 11; 1, 2, 8, 10 and 11; and 1, 2, 8 and 11, respectively. These lag lengths were informed by the LR test, the AIC and the lag exclusion test which jointly substantiate the relevance of the selected lags.

The results of the diagnostic checking of residuals for VAR models for all groups in banks, using the correlogram and the VAR LM serial correlation tests, both conformed to the hypothesis of serially uncorrelated residuals. Further, White's test for independently and identicaly distributed error terms indicated that there was evidence of homoskedastic error terms. Hence, these results confirm unbiasedness and points to the level of efficiency of the parameter estimates as well as to the validity of the specifications.

The results of the VAR estimations reveal significant impacts on loan quality of commercial banks arising from changes in M1 (GDP proxy), real effective exchange rate, public to private loan ratio, credit risk shocks and commercial banks aggregate loans. However, there is little statistical significance of these macroeconomic variables impacting on the loan quality for the other types of institutions or the system. In addition, structural change dummy variables portrayed significant effects on the NPL ratio for all categories of banks. The rainfall variable was generally insignificant. However, its impact on the terms of trade (TOT) and GDP growth (GDP) were statistically significant and were of the expected signs. That aside, the typical overparamatization of an unrestricted VAR model coupled with some significant collinearity among the many regressors may have reduced the reliability of some of the *t*-statistics. Despite this, the objective of the paper is to capture the inter-relationships among the variables to inform loan quality forecasts. Hence, although inference into the dynamism of the VAR may be difficult to make directly from coefficient estimates, forecasting and impulse response analyses should be improved.[28]

In-sample and Out-of-sample Forecasts of the NPL ratio

The VAR models were tested for accuracy in predicting the path of the NPL ratio (in-sample) over the estimation period 1997–2005 as well as the evolution up of the NPL ratio to the end of the year 2008 (out-of-sample) (see Figures 2.1 to 2.4 in Appendix A7). The VAR model for each group performed well in terms of in-sample forecasting as most of the variability in NPL series were accurately predicted. However, out-of-sample projections for January 2000 to December 2005, revealed weaker performance with regard to the models'

[28] Sims (1980) pointed out that it is difficult to interpret VAR coefficients, particularly because "coefficients on successive lags tend to oscillate" and there exist "complicated cross equation feedbacks".

forecasting capabilities. Nevertheless, despite the fact that the VAR projections deviate from the actual series over a wide portion of the series, the magnitude of the deviations were quite small and delineated the deterministic downward trend in the NPL ratio reasonably well (see second column of Figures 2.1 to 2.4 in Appendix A4). Further, the out-of-sample forecasts appear to capture the general trend of the actual values of the NPL ratio for 2006. Thereafter, the likely outlook for the NPL ratio up to December 2008 is a continued downward movement to about 1.6 per cent for the banking sector.[29]

Impulse Response Analysis

Structural innovations in the VAR model were *identified* by Choleski decomposition. The theorized ordering of the variables was:

$$\text{TOT} \rightarrow \text{CPI} \rightarrow \text{RM1} \rightarrow \text{RI} \rightarrow \text{REER} \rightarrow \text{CLOAN} \rightarrow \text{CPPL} \rightarrow \text{NPL} \qquad [7]$$

The variable CPPL was excluded from this ordering in the case of FIAs, building societies and the sector due to data unavailability. The terms of trade (TOT) was assumed to be contemporaneously correlated with all other variables. For all banking groups, at most 33.3 per cent significant correlations were discovered among the reduced-form residuals. Since impulse responses may be sensitive to these correlations, some variables in [7] were reordered based on those strong correlations. Based on the cumulative values of impulse responses at six period intervals, the general directions and magnitudes of the responses appear fairly consistent under all re-orderings considered.[30]

The results indicate that, on average, the NPL ratio was strongly autoregressive over the forecast horizon. In addition, growth in credit was *not* found to foster increases in the NPL ratio while innovations in the real interest rate and the price level were found to increase loan quality depletion. On average, the results indicate that depreciation in the REER tends to generally improve credit quality. Of significance, the net effect of an expansion in

[29] It should be noted that these simulations are based on the assumption of correctly predicting the exogenous variables. Firstly, it is assumed that there would be no structural development in terms of classifications rules or interventions over the forecast horizon. Secondly, rainfall for years 2007 and 2008 were assumed to maintain the same pattern as in the previous two years.

[30] It is a good descriptive tool to consider the cumulated sum of effects because the VAR models use log differences and accumulating the response of the log differences would describe the change in the level of the variables.

money supply and GDP growth rate were found to improve the NPL ratio, validating the procyclicality theory of loan quality. The effect of a higher terms of trade (TOT) ratio on loan quality appears to be quite positive particularly over the longer horizon, consistent with *a priori* predictions.

In the case of commercial banks, faster loan growth was found to reduce the growth in the NPL ratio (see table 2 in Appendix **A5**). A possible explanation for this result is that commercial banks extend a large share of personal loans which are typically diversified across a number of individual borrowers. This diversification of small loans may have deterred default risks. The improvement in loan quality due to a depreciation in the REER are perhaps as a result of loans being cheaper to finance from increase export earnings following from trade theory. A priori expectations of higher real interest increasing the probability of default risk and the hypotheses of the procyclicality of loan quality were also confirmed by the impulse response results. In addition, the results do not provide evidence of a credible threat to loan portfolio quality due to public sector crowding out. The simulations also imply that price innovations accelerates the NPL ratio for about the first one and a half years but thereafter leads to a fall in the NPL ratio which eventually dissipates. The former trend is consistent with expectations.

Results from the impulse response analysis also indicate relatively significant effects of inflation and a credit risk shock on the preponderance of loan quality deterioration for the FIAs (see Table 3 in Appendix **A5**). However, the adverse movements in the NPL ratio induced by both the terms of trade (TOT) and the real effective exchange rate (REER) are not consistent with *a priori* expectations. The effect of the TOT for FIAs is similar to the commercial banks.[31] Associated with impulses from real money growth (RM1) is evidence of the procyclicality view of the impact of GDP growth on loan quality. After one year the pro-cyclicality sets in that fosters an upswing in loan quality in the remaining years. The responses of the NPL ratio to real interest rate innovations after 18 months are in line with

[31] It can be argued that the build up in the NPL ratio resulting from a depreciating currency can be accredited to increase import cost (particularly since Jamaica is import dependent). Higher import costs make it difficult for importers to make loan repayments.

a priori expectations. The projected responses induced by RM1 and RI appearing in the later periods support the claim of the NPL ratio being a lagged indicator of loan quality.

With regard to building societies, the findings confirm the relatively strong autoregressive response of the NPL ratio, that is, the preponderance of credit risk shocks (see Table 4 in Appendix **A5**). Also, the response of the NPL ratio to shocks to the loan stock along with CPI and RI impulses were all consistent with a priori expectations. Further, the countercyclical views on loan quality seem to hold firmly in this case. The idea is that good economic conditions stimulate credit lending which then fuels the likelihood of loan defaults. The innovations in the REER on loan quality again seem consistent with the argument of higher import cost constraining debt servicing capacity. With respect to TOT, the impulses are reflected in an improved NPL ratio in the earlier periods up to six months but thereafter are inconsistent with *a priori* notions. Similarly in this case, the forecasted outcome may be tantamount to a deteriorating competitive trade advantage.

In general, monetary influences whether as a result of a positive shock to real interest rates (RI) or real money supply (RM1) influence loan quality determination. However, rising RI was the overriding monetary factor inducing loan quality deterioration. Each set of institutions responded differently in terms of economic growth performance while the system effect of rising growth in GDP is favourable. The impact of REER depreciation tended to ameliorate loan quality for commercial banks and the system at large but had the opposite effect on smaller DTI's.

Based on the results, loan growth appears to be heterogeneous in its effect on loan quality, though the results based on the system indicates an improvement in loan quality for the sector. Also, high inflation was found to lead to poor loan quality for the sector. This is probably due to price distortions which catalyze adverse selection problems for bank lending.

Stress Testing Exercises [32]

According to Sorge (2004), systemic risks are perceived to be derived from sustained adverse shocks to the system for an extended period of time. Whereas, sensitivity analysis is used to evaluate the impact of one-time abnormal but plausible movements in macro variables of a hypothetical nature, this paper also employs scenario analysis by looking at a combination of extreme events of both a historical and hypothetical nature.

Extreme events with a 0.5 per cent probability of occurring are considered. Of note, the distributions of the endogenous variables in the VARs are all leptokurtic and heavy-tailed and therefore extreme values of two standard deviations or more under normality assumptions cannot be used. As such, 99.5 per cent quantiles were constructed to capture the extreme values of the actual time series distributions (see table in appendix **A6**).

Sensitivity Analysis

Pre-shocks and post-shocks[33] were conducted using one standard deviation innovations and the 99.5 per cent quantiles (see Figure 1 below and Figures 1-3 in Appendix **A8** for illustrations of the cumulative stress responses of the NPL ratio up to 100 periods for pre and post shocks). This analysis facilitated the comparison of the sensitivity of the responses for the relative magnitudes (in percentages) of the NPL ratio responses to each abnormal impulse so as to differentiate the early warning indicators.

With respect to the banking system, the sensitivity of the responses was evident in the wide discrepancy between the responses pre- and post-stress shocks (see Figure 1). This outcome mirrored the developments in the NPL ratio for the individual set of institutions (see Appendix **A8**). Sensitivities are particularly large for the real interest rate, inflation, terms of trade and the NPL ratio. The cumulative responses reflect stabilization or convergence to a long run finite non-zero value, representing the net impact on loan quality over time. Further, deterioration in the banking sector loan quality can be primarily detected by early

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[32] See Blaschke et al (2001) and Sorge (2004)

[33] Note that pre-shocks are one standard deviation innovations and post-shocks are the abnormal but plausible impulses.

warning indications of credit risk shocks, rising interest rate, rising prices and falling growth in loans (see Table 2).

Figure 1: System Pre and Post Stress Test Results

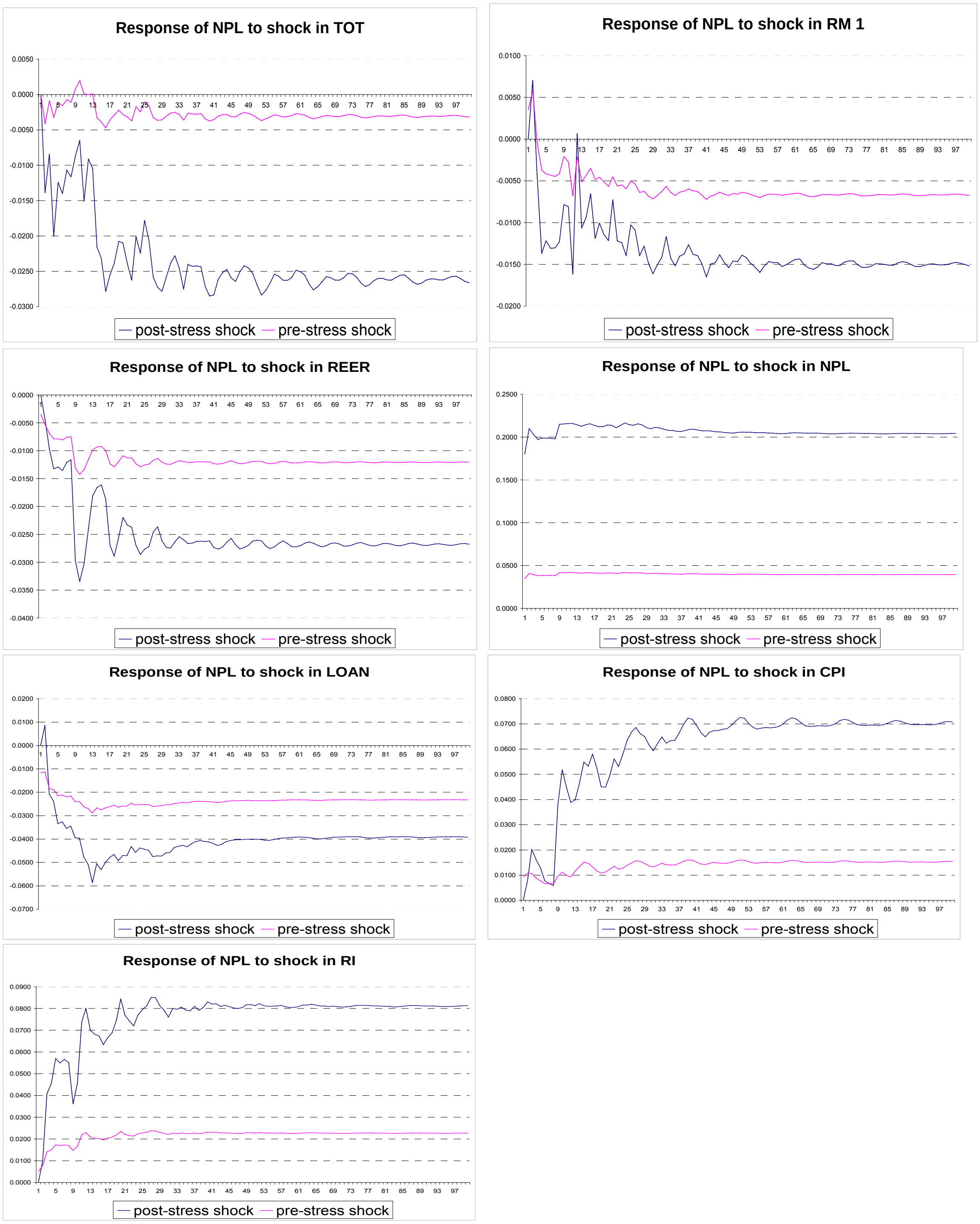


Table 2: System– cumulative stressed responses of the NPL growth rate (DL_NPL)*

Months	Impulses						
	DL_TOT	DL_RM1	DL_REER	DL_NPL	DL_LOAN	DL_CPI	D_RI
6	-1.40	-1.31	-1.35	19.88	-3.26	0.77	5.50
12	-0.91	0.06	-2.40	21.57	-5.08	3.89	8.01
18	-2.39	-1.14	-2.89	21.22	-4.65	5.24	6.89
24	-2.24	-1.03	-2.86	21.64	-4.38	5.79	7.71
30	-2.58	-1.50	-2.73	20.98	-4.60	6.18	7.92
36	-2.43	-1.38	-2.66	20.68	-4.19	6.35	7.90
40	-2.85	-1.49	-2.62	20.91	-4.13	7.18	8.30

* DL_NPL is the differenced log of the NPL ratio for the system. These are cumulative responses measured as percentage changes in the level of the NPL ratio for the given period.

In addition, the augmentation to the innovations, for the most part, propelled significant reinforcing movements in the NPL ratio across all institutions (see Tables 1 to 3 in Appendix **A8**). The growth rate of the NPL ratio is susceptible to abnormal movements in all variables particularly in the case of the FIAs.

The overriding early warning indicators of deterioration in loan quality includes, for commercial banks: a rising NPL ratio, declining loan growth, rising real interest rate and appreciation. In terms of FIAs, early warning signs include higher terms of trade, depreciating REER, a rise in prices and the real interest rate. For building societies rising real interest rate, inflationary tendencies worsening terms of trade and credit expansion, complete the set of early warning signals.

'What-if' Scenario Analysis

Simulations of three scenarios were performed to check the robustness of the banking sector loans to macroeconomic shocks. **Scenario 1** recreates Jamaica's economic environment during pre-financial crisis period. Since financial crises are typically related to credit risk shocks which originates from poor loan quality, it is important to determine the robustness of banking institutions' loan book to similar combination of economic shocks in a post-crisis period.[34] Therefore, the combination of abnormal economic impulses being considered is an appreciating REER, higher prices (CPI), greater TOT and high interest rate

[34] The Jamaican financial crisis developed (i.e.pre-1996) in the context of a liberalized foreign exchange market, the removal of capital controls, a high inflation environment and tight monetary policy to manage import demand and inflationary tendencies.

(RI) (see Table 3). **Scenario 2** simulates an abnormal appreciation in the REER, coupled with a hike in RI to delineate the effects of tightening monetary conditions. **Scenario 3** simulates favourable extreme movements in the GDP growth rate (RM1) and inflation (CPI). The latter scenario is desirable by BOJ in terms of maintaining a climate of low stable prices necessary for sustained economic growth.

Table 3: Specified Innovations for Scenarios

Scenario 1		Scenario 2		Scenario 3	
Variables (% Growth rates)	Shock	Variables (% Growth rates)	Shock	Variables (% Growth rates)	Shock
REER	3.33	REER	3.33	RM1	15.54
CPI	2.83	RI	9.58	CPI	2.83
TOT	19.56				
RI	9.58				

The effects of scenario 1 are largely consistent, in terms of direction, across each set of institutions and on the system at large. That is, the economic conditions which prevailed in the lead up to the financial crisis are likely to have the same deteriorating effect on the NPL ratio. However, the magnitude of such level effects on the NPL ratio is a separate issue. Commercial banks' NPL ratio is expected to rise to a high of about 2.5 per cent from 2.2 per cent (see Figure 2.1). It is therefore clear that even under the combined effects of severe shocks, commercial banks are not likely to absorb losses comparable to those in the financial crisis period (of a high of 30.0 per cent). With regards to FIAs, there appears to be a multiple phased impact on loan quality. The NPL ratio slightly improves over an 8 months period from 4.4 per cent, and then rises steeply to 6.5 per cent in two years time before climbing to a peak of 7.0 per cent. This outcome is particularly owed to the susceptibility of FIAs to inflationary triggers as was alluded to earlier. The worsening of the NPL ratio for the building societies peaks at 4.0 per cent (from 3.5 per cent) which is marginal compared to the July 1998 figure of nearly 17.0 per cent. The ratio stabilizes just below 4.0 per cent at the end of the forecast horizon. Given these events, confirms that there is minimal concern of a systemic risk as the NPL ratio for the banking system remains slightly below the 3.0 per cent mark; however this should be taken *cum grano salis* (see Figure 2.1).

Figure 2.1: Response of NPL ratio to Scenario 1

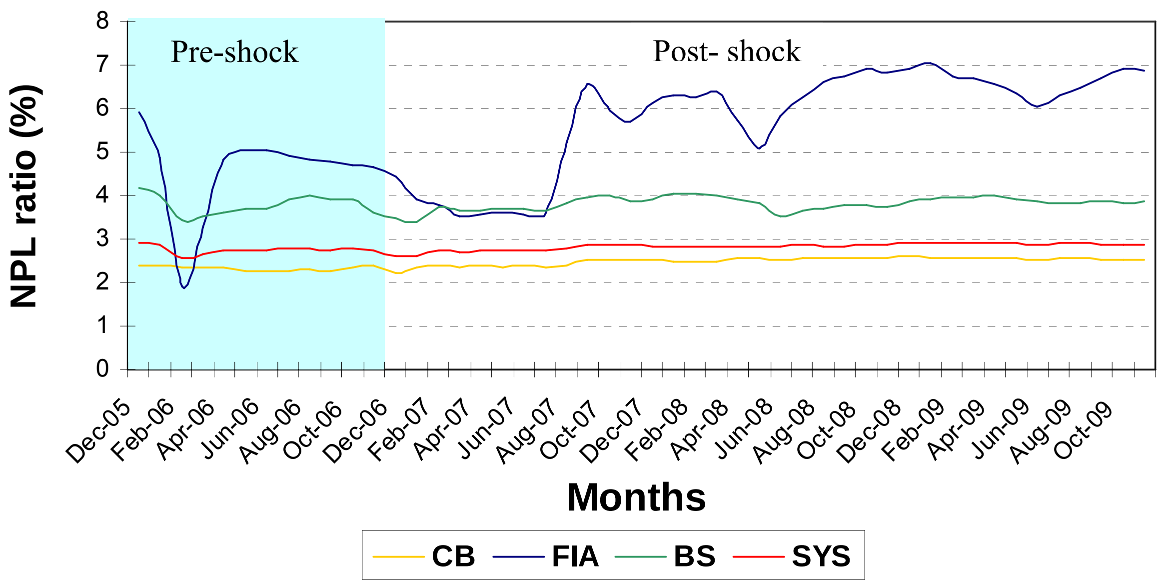


Figure 2.2: Response of NPL ratio to Scenario 2

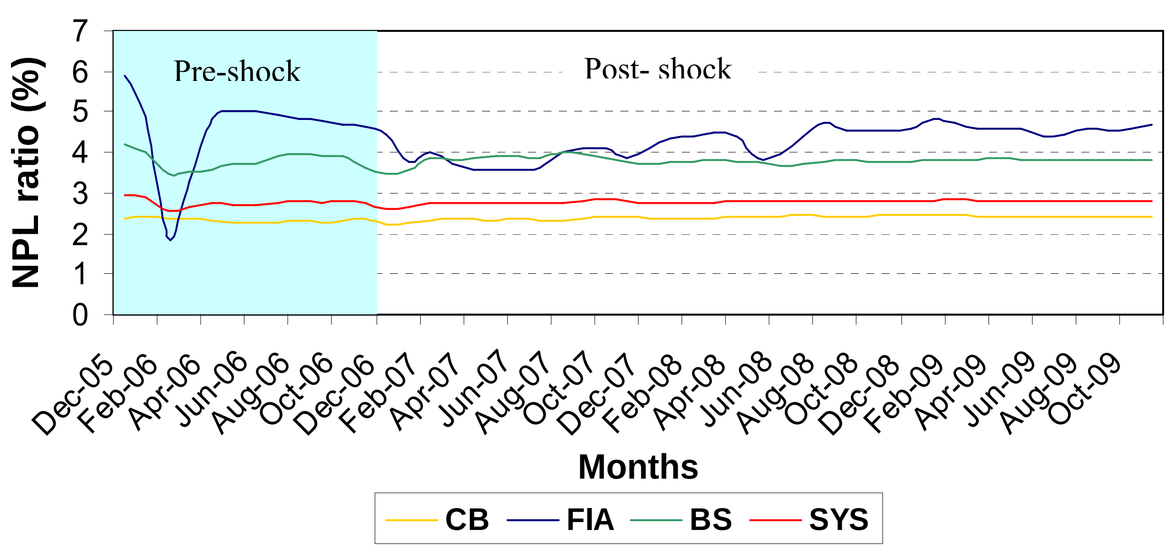
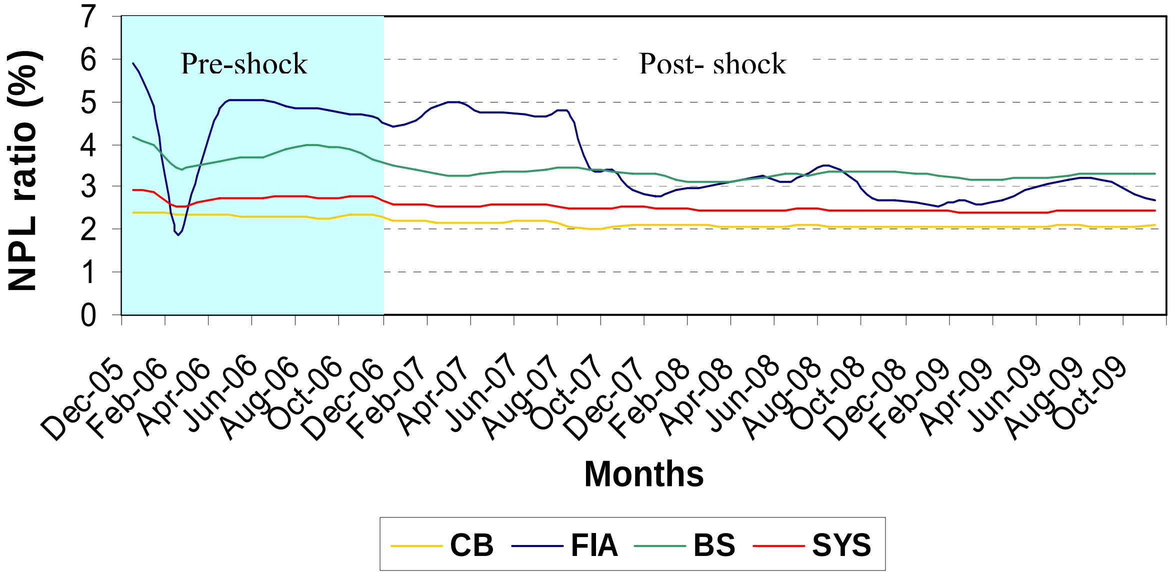


Figure 2.3: Response of NPL ratio to Scenario 3



According to the simulations of scenario 2, tight monetary conditions tend to stimulate marginal increases in the NPL ratio for each set of institutions over the three years period. However, once again the FIAs are more susceptible and experience relatively volatile movements in the NPL ratio. Taking this into account, the proxied banking system forecasts only a slight 0.3 percentage points deterioration in loan quality (see Figure 2.2). These results are consistent with the conclusion of Filosa (2007) that tight monetary conditions induce loan defaults.

Not surprisingly, scenario 3 spurs a positive swing in loan quality in the banking sector (see Figure 2.3). Although the responses of loan quality appear rather weak in terms of commercial banks and building societies, FIAs' loan quality improves by almost 2.0 per cent by the end of the three year period.

Since the financial crisis, banking institutions have maintained relatively tight credit risk management standards and have tended to diversify their asset portfolios resulting in relatively low NPL ratios. Further, although FIAs according to the simulations are the major risk factors, their asset base in comparison to the banking sector is relatively low, hence the marginal effects on the outcome of the system. To effect desired changes in the system policies should be primarily aimed at commercial banks.

V. CONCLUSION

The paper seeks to quantitatively ascertain the impacts of moderate and extreme macroeconomic shocks on credit quality for commercial banks, building societies and FIAs. The VAR methodology derives some useful conclusions. The results of forecasting would suggest that macroeconomic variables feature in loan quality determination. Also, the likely outlook for the NPL ratio is that there should be a continuation of its downward trend up to the end of 2008 across all set of institutions.

Monetary and structural influences are reflected through the use of cumulative impulse response functions. Monetary factors have been important contributors to the intensity of financial crises. From the results, aside from credit risk shocks, it is clear that inflation, interest rate and real exchange rate play relatively significant roles in shaping loan quality in the banking sector. The adverse effects of inflation are particularly prominent in the FIAs' loan portfolios. The cost of higher real interest rates shows up transparently for commercial banks and building societies but only in the long run for FIAs. Exchange rate shocks in terms of a depreciation are evident in procuring good credit quality for commercial banks but have undesirable implication for other institutions; although the overall effect on the proxied banking system is encouraging. Therefore, monetary authorities should take caution when using the exchange rate as a policy tool since its impact on credit risk exposure is not homogeneous across all institutions. Further, the role of structural factors such as economic growth and foreign trade is not without relevance in determining credit quality. There is evidence that economic upturns are related to favourable NPL ratio for commercial banks and FIAs (however in the longer run). Interestingly, the countercyclicality theory of loan quality marginally bears out for building societies. In terms of foreign trade, the FIAs are mainly susceptible to a "favourable" terms of trade although adversely. The results highlight the marginal effects of foreign trade on Jamaica's banking sector loan quality.

However, the simulations do not support *a priori* expectations that credit expansion is commensurate with poor loan quality for all institutions except building societies. Therefore, it can be implied that the provision of more credit actually improves loan quality provided they are being put to productive uses. The findings also fail to support the hypothesis that loan quality is adversely affected by public sector crowding out.

Under extreme but plausible conditions based on the system results from sensitivity analysis, rising interest rate and high inflation rate are relatively good early warning macroeconomic signals of worsening loan quality which is also largely autoregressive. Scenario analysis suggests that the Jamaican banking sector has attained considerable strength to mitigate the deleterious impacts of macroeconomic shocks. However, this result provides no inference about institutional specific behaviours (such as effective prudential risk management and asset concentration) in relation to credit quality. Also, the simulations confirm that the implications of expansionary monetary policy, robust economic growth and price stability are improvements in loan quality. The latter two confirm the conclusion of Baboucek and Jancar (2005). Note that economic growth and price stability are usually preconditions of banking crises (as in the Japanese financial crisis). These favourable conditions are typically matched by excessive credit expansion with less critical credit risk assessment. Therefore, as a caveat, government regulators and banks should maintain strict risk assessment under favourable economic conditions.

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VII. APPENDIX[35]

A1

This estimation is a variant of the Fisher's equation of exchange, that is, MV = PY. The idea is that demand for money is a function of an economy's wealth. On a decade of quarterly data, all regressors (except the constant) are significant at the 1% level of significance. Therefore, real GDP growth rate affects real money with a lag of three quarters. Also, the R-square of 70.6% seems satisfactory. Despite a fairly high DW statistic of 2.23, it should be noted that it is not valid in the presence of a lag dependent variable as a regressor. Hence, to attest to the correctness of the model specification and the efficiency of the parameters, the stronger LM serial correlation test detects no significant serial correlation. Then, it is satisfactory to use real M1 as a proxy for real growth rate. Note that other broader measures of real money were considered such as M2 and M3 but in terms of the goodness-of-fit diagnostics M1 had better results.

Dependent Variable: DLRM1

Sample (adjusted): 10 41

Included observations: 32 after adjustments

Convergence achieved after 13 iterations

MA Backcast: 5 9

	Coefficient	Std. Error	t-Statistic	Prob.
C	0.004214	0.008018	0.525597	0.6033
DLRGDP(-3)	1.641297	0.274399	5.981415	0.0000
AR(5)	-0.933649	0.073797	-12.65162	0.0000
MA(5)	0.915371	0.057437	15.93693	0.0000

R-squared	0.705614	Mean dependent var	0.010530
Adjusted R-squared	0.674072	S.D. dependent var	0.084040
S.E. of regression	0.047979	Akaike info criterion	-3.119658
Sum squared resid	0.064454	Schwarz criterion	-2.936441
Log likelihood	53.91453	Hannan-Quinn criter.	-3.058927
F-statistic	22.37102	Durbin-Watson stat	2.233128
Prob(F-statistic)	0.000000		

Inverted AR Roots	.80-.58i	.80+.58i	-.30+.94i	-.30-.94i
	-.99			
Inverted MA Roots	.79-.58i	.79+.58i	-.30+.93i	-.30-.93i
	-.98			

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.525888	Prob. F(2,26)	0.597184
Obs*R-squared	1.162153	Prob. Chi-Square(2)	0.559296

[35] The results of other output not presented here will be furnished upon request.

A2

Level Series

These are the graphs for the original data series. It is easy to see that all variables are non-stationary except TOT and RF.

A4

Figure 1: Commercial Banks' NPL ratio

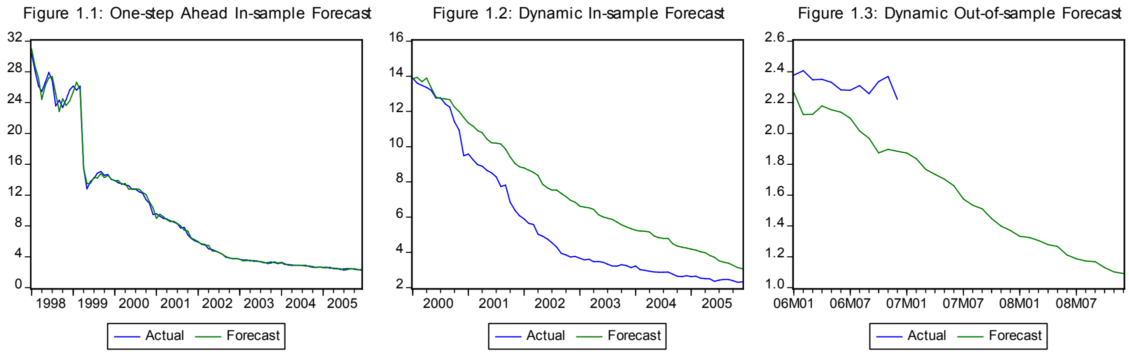


Figure 2: FIAs' NPL ratio

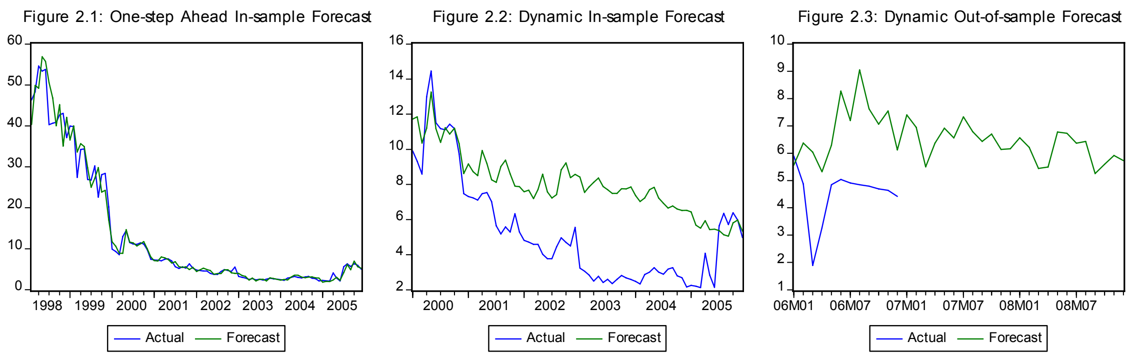


Figure 3: Building Societies' NPL ratio

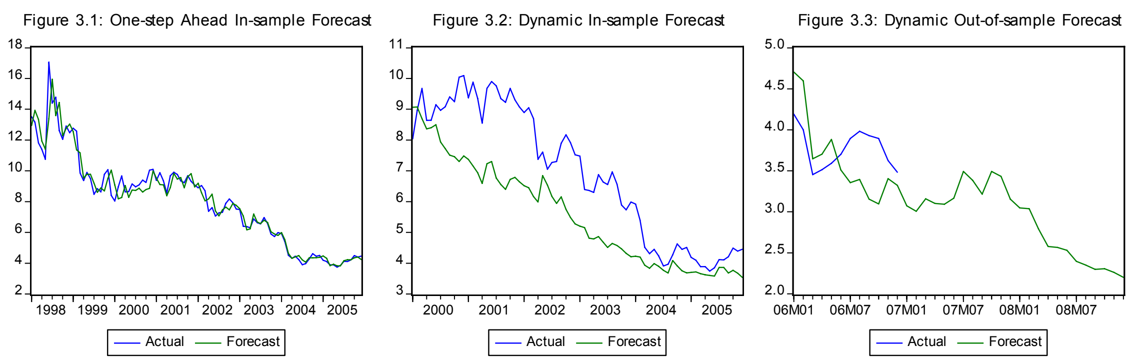
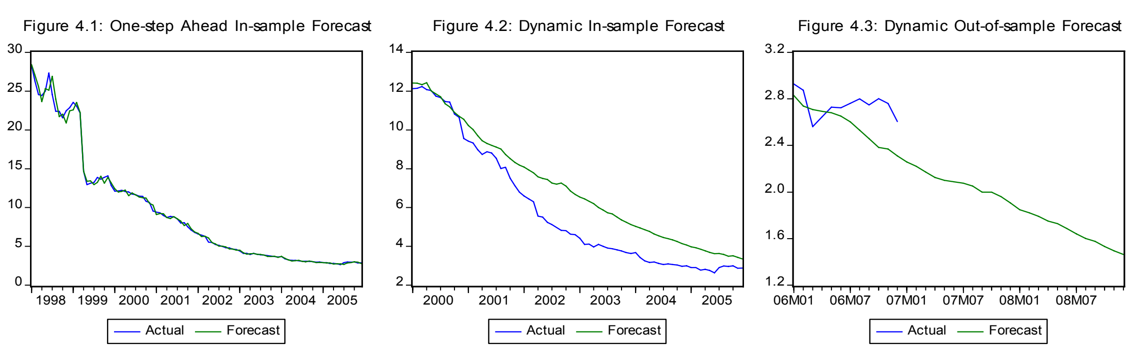


Figure 4: Banking System's NPL ratio



A5

* DL_NPL is the differenced log of the NPL ratio for the system. These are cumulative responses measured as percentage changes in the level of the NPL ratio for the given period.

Table 1: System – cumulative responses of the NPL growth rate (DL_NPL)*

	Impulses						
Months	DL_TOT	DL_RM1	DL_REER	DL_NPL	DL_LOAN	DL_CPI	D_RI
6	-0.16	-0.43	-0.80	3.85	-2.12	0.66	1.70
12	0.00	-0.21	-1.16	4.17	-2.70	0.93	2.29
18	-0.29	-0.51	-1.29	4.10	-2.56	1.16	2.09
24	-0.25	-0.50	-1.29	4.18	-2.52	1.28	2.24
30	-0.31	-0.67	-1.24	4.06	-2.53	1.37	2.26
36	-0.27	-0.62	-1.21	4.00	-2.41	1.41	2.24
40	-0.37	-0.67	-1.20	4.04	-2.41	1.59	2.32

Table 2: Commercial banks – cumulative responses of the NPL growth rate (DL_CNPL)*

	Impulses							
Months	DL_TOT	DL_RM1	DL_REER	DL_CPPL	DL_CPI	DL_CNPL	DL_CLOAN	D_RI
6	0.02	-1.12	-1.16	-0.11	0.32	4.28	-2.56	1.11
12	0.46	-0.82	-1.88	-0.51	0.40	4.85	-3.65	1.75
18	0.39	-1.44	-2.18	-1.01	0.27	4.77	-3.94	1.67
24	0.44	-1.30	-2.16	-0.94	-0.02	5.05	-3.84	1.86
30	0.41	-1.28	-2.14	-1.07	-0.17	4.90	-3.80	1.71
36	0.40	-1.09	-1.99	-0.97	-0.25	4.91	-3.66	1.67
40	0.33	-1.09	-1.92	-1.02	-0.08	4.97	-3.80	1.75

Table 3: FIAs – cumulative responses of the NPL growth rate (DL_FNPL)*

	Impulses						
Months	DL_TOT	DL_RM1	DL_REER	DL_FNPL	DL_FLOAN	DL_CPI	D_RI
6	1.11	2.76	3.24	11.66	0.41	4.25	-2.28
12	2.05	0.33	2.99	15.64	0.37	13.62	-1.63
18	4.20	-1.19	1.85	12.74	-1.39	9.96	-1.04
24	6.24	-1.85	1.64	13.08	0.34	14.35	1.81
30	5.76	-1.95	0.90	13.80	-0.08	10.53	1.22
36	6.66	-2.76	0.05	13.18	-0.73	13.33	2.08
40	5.80	-2.72	0.19	13.52	-0.45	11.83	1.76

Table 4: Building Societies – cumulative responses the NPL growth rate (DL_BNPL)*

	Impulses						
Months	DL_TOT	DL_RM1	DL_REER	DL_CPI	DL_BNPL	DL_BLOAN	D_RI
6	-1.45	0.82	0.78	0.59	5.69	1.07	2.37
12	1.60	0.10	1.35	1.60	4.55	2.30	2.24
18	0.43	0.51	1.56	2.29	4.44	0.84	1.61
24	0.27	0.62	1.34	1.44	4.64	0.98	1.70
30	0.12	0.41	1.39	2.41	4.59	1.21	2.01
36	0.47	0.53	1.33	1.85	4.60	0.79	1.73
40	0.27	0.43	1.28	2.23	4.44	0.67	1.77

A6

Specified Innovations

Variables	99.5^{th} Quantiles\shock	Std. Dev.	# of Std. Dev.
Inflation Rate (**DL_CPI**)	2.83	0.68	4.1946
Money growth (GDP proxy) (**DL_RM1**)	15.54	5.50	2.8265
Real Effective Exchange Rate (**DL_REER**)	3.33	1.36	2.4450
Real Interest Rate (**D_RI**)	9.58	1.91	5.0253
Terms of Trade Growth (**DL_TOT**)	19.56	6.02	3.2507
C. Bank Loan Growth (**DL_CLOAN**)	9.13	3.98	2.2951
FIAs Loan Growth (**DL_FLOAN**)	4.66	1.66	2.7996
Building soc. Loan Growth (**DL_BLOAN**)	48.61	13.29	3.6569
System Loan Growth (**DL_LOAN**)	10.77	4.36	2.4719
Public\Private Loan (**DL_CPPL**)	29.23	9.97	2.9306
C. Bank NPL Ratio (**DL_CNPL**)	21.66	7.18	3.0155
FIAs NPL Ratio **(DL_FNPL**)	78.12	21.78	3.5862
Building Soc. NPL Ratio (**DL_BNPL**)	45.02	11.78	3.8204
System NPL Ratio (**DL_NPL**)	18.00	6.29	2.8619

Note: All impulses are measured as differenced log (denoted with the prefix DL) except D_RI which was differenced. The differenced log impulses are multiplied by 100 to present the shocks in percentages and D_RI is in percentage points.

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Table 1: Commercial banks – cumulative stressed responses of the NPL growth rate (DL_CNPL)*

Months	Impulses							
	DL_TOT	DL_RM1	DL_REER	DL_CPPL	DL_CPI	DL_CNPL	DL_CLOAN	D_RI
6	-0.56	-1.77	-1.36	2.92	0.94	25.86	-5.29	3.79
12	1.40	0.43	-3.21	1.76	4.15	29.32	-8.11	6.46
18	0.71	-1.66	-3.98	-0.35	3.74	28.79	-8.35	5.94
24	1.17	-1.01	-3.78	0.16	2.19	30.53	-7.83	7.05
30	1.16	-1.13	-3.73	-0.46	1.31	29.63	-7.59	6.32
36	1.39	-0.64	-3.29	-0.06	0.48	29.70	-7.23	6.19
40	1.22	-0.52	-3.01	-0.22	1.05	30.03	-7.62	6.68

* DL_CNPL is the differenced log of the NPL ratio for the commercial banks. These are cumulative responses measured as percentage changes in the level of the NPL ratio for the given period.

Table 2: FIAs – cumulative stressed responses of the NPL growth rate (DL_FNPL)*

Months	Impulses						
	DL_TOT	DL_RM1	DL_REER	DL_FNPL	DL_FLOAN	DL_CPI	D_RI
6	10.58	3.83	8.34	53.41	2.82	-2.92	-7.46
12	6.65	-3.91	6.82	71.69	3.07	39.06	-3.42
18	13.04	-8.49	5.33	58.40	-4.51	24.95	-2.17
24	17.71	-4.95	2.81	59.92	2.67	51.55	13.32
30	17.08	-6.31	0.64	63.23	1.00	33.71	9.71
36	17.36	-7.62	-1.43	60.39	-1.75	50.79	13.36
40	15.09	-7.97	-1.29	61.97	-0.55	42.59	11.89

* DL_FNPL is the differenced log of the NPL ratio for the FIAs. These are cumulative responses measured as percentage changes in the level of the NPL ratio for the given period.

Table 3: Building Soc. – cumulative stressed responses of the NPL growth rate (DL_BNPL)*

Months	Impulses						
	DL_TOT	DL_RM1	DL_REER	DL_CPI	DL_BNPL	DL_BLOAN	D_RI
6	-7.85	0.26	-2.54	1.66	33.04	1.24	9.08
12	3.31	-1.22	1.28	2.78	26.44	6.33	9.03
18	-0.66	-0.55	1.56	5.23	25.77	0.99	7.55
24	-1.11	-0.20	0.59	2.28	26.95	1.41	7.30
30	-2.12	-0.57	0.93	6.91	26.65	2.29	8.95
36	-0.65	-0.52	0.51	4.32	26.70	0.72	7.67
40	-1.54	-0.72	0.47	6.38	25.77	0.35	8.08

* DL_BNPL is the differenced log of the NPL ratio for the building societies. These are cumulative responses measured as percentage changes in the level of the NPL ratio for the given period.

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Sensitivity Analysis – These are all cumulative responses measured as net acceleration or deceleration.

Figure 1: Commercial Banks' Pre and Post Stress Test Results

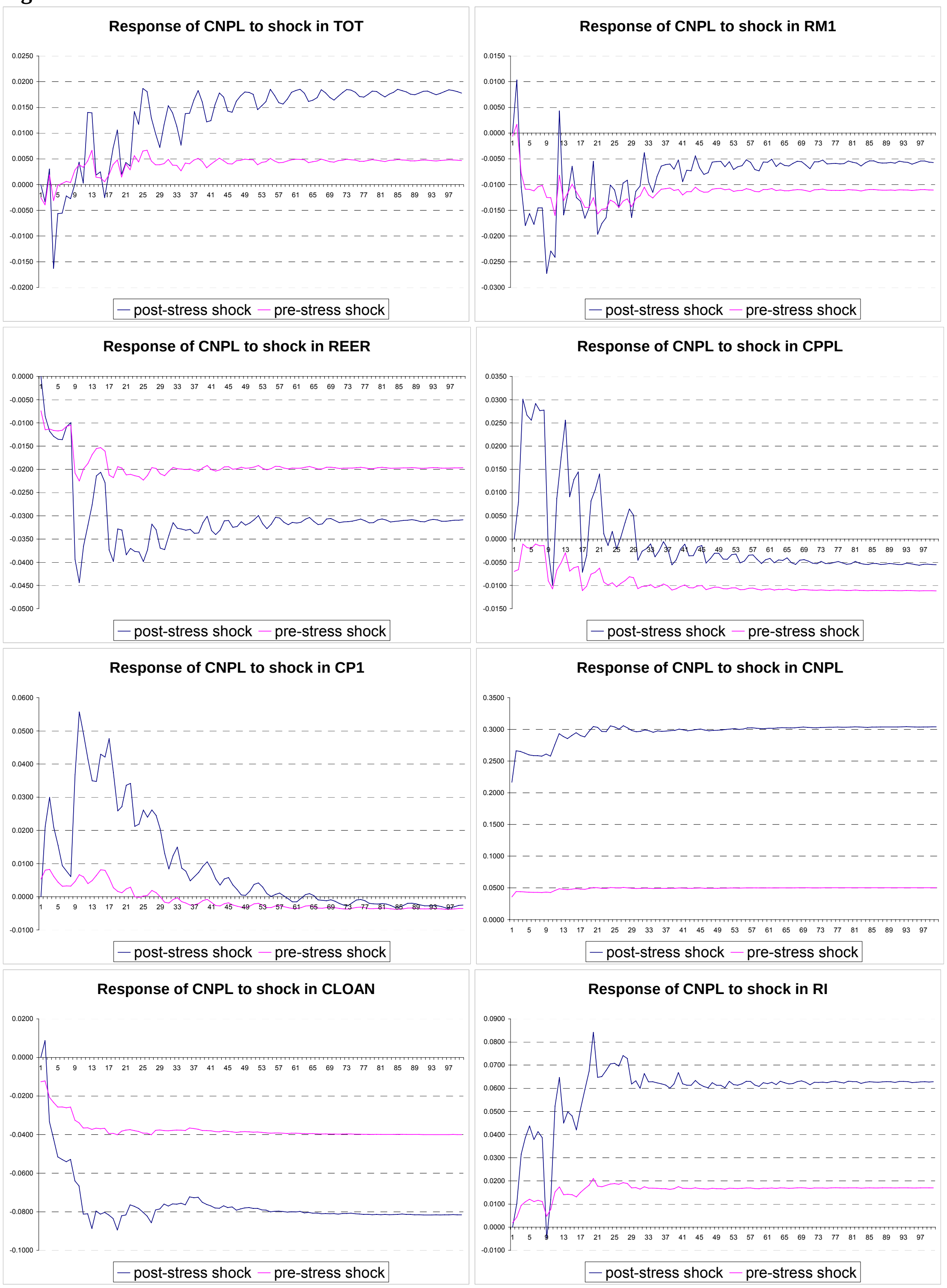

Figure 2: FIAs' Pre and Post Stress Test Results

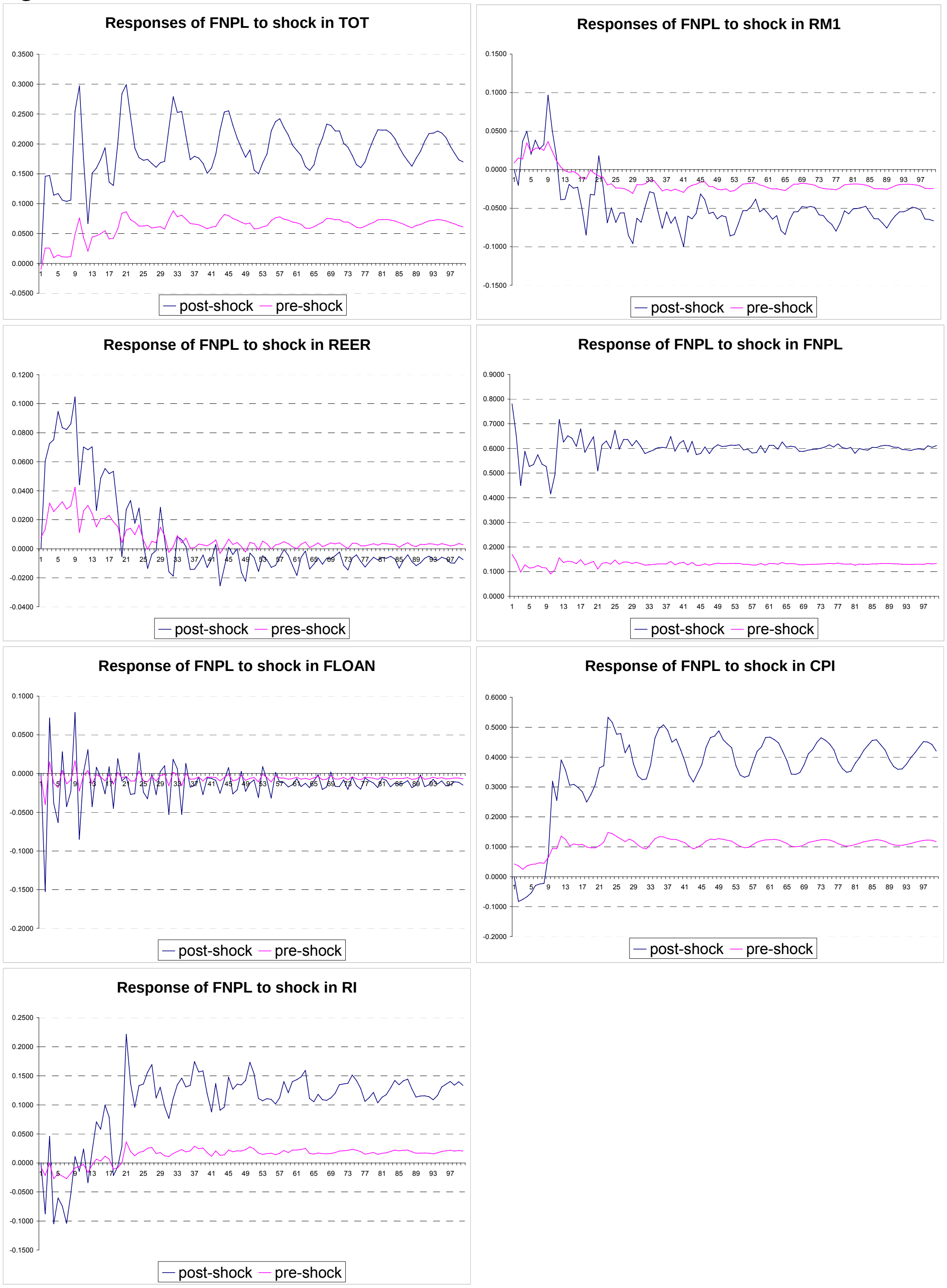

Figure 3: Building Societies' Pre and Post Stress Test Results