An Early Warning System for Economic and Financial Risks in Jamaica

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Abstract

This paper develops composite indices that can be used to identify and analyze vulnerabilities within key sectors of the Jamaican economy using data over the period March 2001 to December 2015. In particular, interactions between a leading and composite indicator for the real economy as well as the interrelationship between composites for the international environment, financial sector and deposit-taking institutions' (DTIs) exposure to the household and corporate sectors were examined against known periods of fragility in Jamaica's financial system. Additionally, a vector error correction model (VEC) was utilized to analyze the response of fragility measures, in particular, the Z-score and the loan quality ratio to shocks from the household, corporate and coincident composite indicators over a twelve-quarter period. The results demonstrated that increased exposure of the banking sector to household and corporate sector loans led to improvements in the loan quality ratio. However, banks' increased exposure to the household sector led to increased performance in the Z-score, this was not the case as it relates to higher exposure to the corporate sector. The results determined that there is pro-cyclicality as evidenced by the response of the Z-score and NPL ratio to a shock in the leading indicator. Against this background, macro-prudential tools such as loan to value and debt to income limits can be used to mitigate the impact of systemic vulnerabilities emanating from deterioration in these composite indexes.

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[1] The views expressed in this paper are solely of the author and do not necessarily reflect those of the Bank of Jamaica.

1.0 Introduction

Over the past three decades, several countries have experienced periods of financial distress which have destabilized their domestic economies (IMF, 2011). According to Wolken (2013) a period of financial instability is sometimes preceded by periods of excessive credit growth and inflated asset prices. This can result in balance sheet imbalances such as maturity mismatches, large exchange rate and interest rate exposures which often leads to an increase in credit and liquidity risks within the financial system.

Against this background domestic policymakers should seek to calibrate and implement sound macro-prudential policies in an effort to reduce the likelihood of a reoccurrence of a financial crisis such as the one Jamaica experienced in the mid-1990s. The coordinated monitoring of all sectors within the Jamaican economy is of great importance given the strong likelihood that spillover effects from one sector to another can pose systemic risks to financial and economic stability.

Langrin (2002) established an early warning system (EWS) composite for the Jamaican financial system which involved the bivariate monitoring of a comprehensive set of macroeconomic and microeconomic variables which was used to forecast vulnerability in the banking sector. Similarly, a study by Lewis (2006) developed an Early-Warning Bank Failure Model for the Jamaican banking sector. The model which was employed captured the dynamics that caused banks' transition to fragility by employing a probability matrix.

Similar to the previous studies for Jamaica, this paper establishes composite indexes that can be used to identify and monitor systemic vulnerabilities. The paper utilizes the methodology employed by Bhattacharyay *et al*. (2009) for developing composite indicators which were examined against known period of stress or fragility in the Jamaica financial system[2]. These composite indices were established for the real economy, the international economic environment, and DTIs' exposure to the household and corporate sectors. In addition, a vector error correction model (VEC) was utilized to determine the response of key financial stability measures, in particular, the Z-score and the non-performing loans to total loans (NPL) ratio to shocks from the household, corporate and coincident composite indices[3]. This assessment is crucial in order to aid policymakers in determining

[2] Bhattacharyay *et al*. (2009) method was motivated by the Conference Board (2008), which has outlined three indicators which are used as a tool to track and forecast economic cycles. These three indicators is comprised of the leading, coincident and lagging which can provide macro prudential policymakers with the insights needed as to when to deploy specific macro prudential tools as they seek to reduce systemic events.

[3] The Z-score (insolvency risk) index is used as a measure of financial soundness. It captures the likelihood of a bank's earnings in a given year becoming low enough to eliminate the bank's capital base and thus the

appropriate measures to address the impact of the buildup of vulnerabilities in the aforementioned sectors.

The remainder of the paper is organized as follows: Section 2 presents an overview of the literature on composite indices. Sections 3 to 6 outline the indicators and methodology employed in the development of the indices and discuss the interrelationships between the indices. The empirical methodology and the results of the VEC analysis are discussed in Section 7 and 8. The conclusions and policy implications are presented in Section 9.

2.0 Literature Review on Composite Indices as an Early Warning Tool

Several techniques exists in the literature regarding the macro-prudential metrics used to assess economic and financial vulnerabilities. The most widely used methods include conventional trend analysis, econometric techniques and early warning systems. Firstly, trend analysis entails identifying periods for fragility when there exist major fluctuations in key economic variables. Secondly, econometric techniques include stress testing which assesses the impact on a particular variable to a hypothetic but plausible shocks. Finally, early warning systems are used which tracks and predicts the possibility of a crisis occurring.

The method utilized in this paper is based on an early warning system which was first introduced by Burns and Mitchell in the 1930s. Burns and Mitchell (1946) contributed to the development of sectoral composite indices and to the creation of a forecasting and coincident indicators of the real economy. By employing a recursive formula these composite indicators seeks to forecast the movement or similar formulas as to detect banking distress.

There have been a variety of approaches undertaken throughout the literature to construct composite indicators. Moore et al. (1967) designed a method which involves the seasonal adjustment of the original series. In addition, all nominal variables were deflated to ensure that the index would measure real variables. Subsequently, the month to month symmetric percentage changes for each component was established. The components were then standardized by using the absolute standard deviation of the changes. Finally, the index was computed as the average of the components standard

likelihood of the bank becoming insolvent. A higher Z-score implies a lower probability of insolvency. NPLs are defined as loans on which no payments of principal or interest that is due has been made for a period equal to or exceeding three months.

changes and the level of the index calculated. This index was also rebased by 100 in a chosen base year.

McGuckin (2001) established a methodology which is comprised of four (4) steps. Firstly, month-to-month changes in the variables were conducted by taking the arithmetic differences in the form of a percentage. Conversely, if the data was not in percentage form a symmetric method was used. Secondly, the month to month changes were adjusted for volatility. In addition, the measures of volatility were inverted and their sum computed. This was done as to make the index component's standardization factor equal one when summed. Thirdly, this was calculated using a symmetric percentage formula with the index being rebased to an average of 100 for a chosen year for the final step.

Bhattacharyay *et al*. (2009) designed composite indicators for the real economy, the money and capital markets, the banking sector and the international economy for Kazakhstan. The study assessed the interaction between these indicators in order to monitor vulnerabilities and crises periods. Moreover, all series were seasonally adjusted and transformed into stationary series. Furthermore, the series were standardized as to give a more effective estimate. Using monthly data, the study revealed that the system of composite indicators were effective in detecting vulnerabilities in the economy and the banking sector.

Using monthly data, Opolot (2011) constructed a composite indicator which encompassed two features of economic fluctuations; the co-movement among individual variables and asymmetric behavior in busts and booms. The method used decomposed individual indices, using a Henderson Moving Average Procedure. More specifically, to validate the model's effectiveness, the quarterly GDP data was used as a benchmark. The findings revealed that the composite indices significantly tracks this reference data.

Galaso *et al*. (2014) estimated a composite leading business cycle indicator for the Uruguayan economy which is based on the analysis of multiple series that have a leading relationship to the Industrial Production index. These variables were aggregated into a single composite indicator which spanned a 20 year period. The composite was used to predict the two turning points which occurred in Uruguay between 1994 and 2013.

3.0 Development of Composite Indices for Jamaica

Composite indicators have been designed to capture six sectors within the Jamaican economy, which include the real economy, household and corporate sectors, financial institutions, financial markets and the international economic environment. Based on the international literature, there exists a complex interrelationship between these sectors which can contribute to a significant amount of risk. This paper includes an additional composite to track movements in the real economy (see Table 1).

Table 1. Composite indicators
1. Real Economy CLI
2. Real Economy CCI
3. Household Sector CHS
4. Corporate Sector CCS
5. Financial Institutions CFI
6. Financial Markets CFM
7. International Economic Environment CIEE

4.0 Data and Methodology for establishing composite indices

The method employed to transform the series into the composite indicators closely follows the approaches proposed by Bhattacharyay *et al*. (2009) and Galaso *et al*. (2014). Against this background, each composite indicator was constructed using two steps which have been outlined below.

(1) All variables selected were adjusted for seasonality using the X12-ARIMA method along with the removal of trends by employing a one-sided Hodrick-Prescott Filter technique[4]. Furthermore, the data was transformed into a stationary series by finding the first difference. In addition, the series not expressed in percentage form were differenced using a symmetric percentage formula (p_i) which is outlined in equation 1:

$$p_i = 200 * \frac{x_{i,t} - x_{i,t-1}}{x_{i,t} + xi_{t-1}}. \qquad [1]$$

Where $x_{i,t}$ is the variable in time period t.

[4] The HP filter smoothing parameter is employed to remove the cyclical component. A lamda of 1600 was used for the CLI, CCI and the CIEE as business cycles are generally shorter financial cycles (IMF, 2013). However, a lamda of 400,000 was used for the CHS, CCS, CFI and the CMI.

(2) Each series was also standardized by dividing the sum of standard deviations for each period into one. This was done to attain the smallest variance, as more stable indicators have better signaling capabilities.

4.1Weighting and aggregation of series

Composite indicators were weighted by employing a standardization factor that measures it volatility (w_i) which gives more weights to those components that are less volatile. Moreover, the standardization factor is computed for each variable by finding the inverse of the standard error (sd_i) of its quarterly variations as shown in [2].

$$w_i = \frac{\frac{1}{sd_i}}{\sum_i sd_i} \quad [2]$$

Secondly, the quarterly contributions of each component of the composite indicator $(c_{i,t})$ was obtained. These quarterly contributions were calculated by finding the product of the quarterly variations $(v_{i,t})$ and the weights.

$$c_{i,t} = v_{i,t} \,.\, w_i \quad [3]$$

Thirdly, s_t was derived which represents the aggregation of the adjusted contributions computed in [3]:

$$s_t = \sum_i c_{i,t} \quad [4]$$

Finally, the composite is computed using a recursive formula which has an initial value of I_0= 100. Succeeding values are derived by:

$$I_t = I_{t-1} * \frac{200+s_t}{200-s_t} \quad [5]$$

5.0 Components of the composite indicators

The approach outlined in this study is grounded on the establishment of composite indicators for the real economy (leading and coincident composite indicators), the household sector (composite household sector indicator), the corporate sector (composite corporate sector indicator), financial institutions (composite financial institutions indicator), financial markets (composite financial markets indicator) and the international economic environment (composite international economic environment indicator). Indicators used were chosen based Jamaica's country-specific characteristics and span periods based on data availability (see appendix 1).

5.1 Leading Composite Indicator for the Real Economy (CLI)[5]

The CLI for the real economy was developed using quarterly data for the period March 2006 to December 2015 and includes five variables which capture consumer confidence, growth in oil prices as well as stock market performance. The specific variables utilized in constructing the composite are:

(1) Inverse of the growth in West Texas Intermediate (WTI) average oil price[6]: This variable is an important external factor which affects production within the Jamaican economy. [7] The prices of oil is one of the most important external factors of the Jamaican economy as it is linked to production within the domestic economy. Additionally, a protracted period of high oil prices can influence and signal a potential economic downturn.

(2) Growth in US Consumer Confidence Index: The degree of optimism of US consumers concerning the state of their economy is of significance to the Jamaican economy, given that the US is a major trading partner.

(3) Growth in Consumer Expectations on Business Conditions Index: This is a key measure of Jamaican consumers' expectations regarding Jamaican businesses and serves as a good indication of domestic business cycle conditions.

(4) Growth in Consumer Income Expectations Index: This indicator assesses the expectations of Jamaican consumers regarding their expected change in income. This indicator gauges consumers' expectation regarding income performance as well as general investor confidence in the economy.

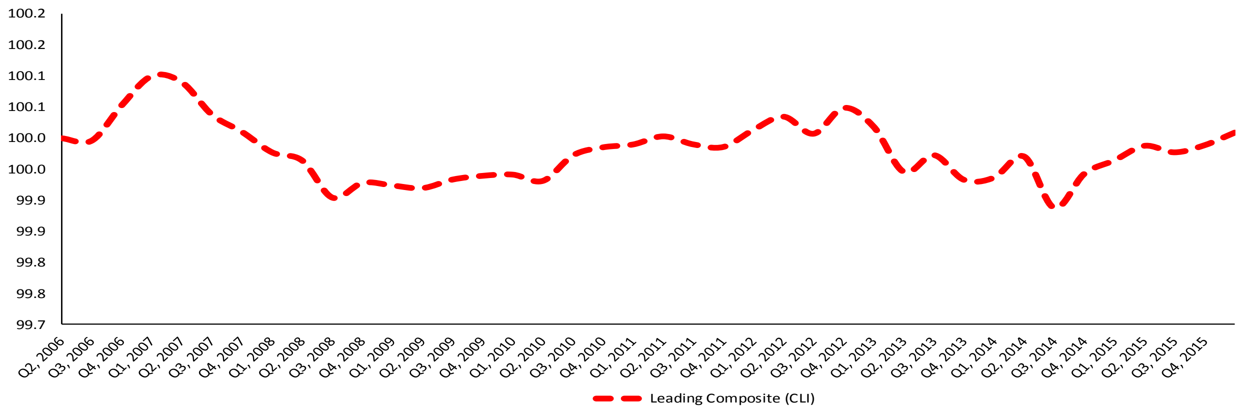
(5) Growth in Jamaica Stock Exchange (JSE) Main Index: This measure is utilized to capture investors' expectations regarding the performance of Jamaican firms and by extension economic growth.

[5] The CLI changes prior to reference cycle and the movement in economic activity

[6] The inverse is computed by multiplying the variable by -1.

[7] WTI is a specific grade of crude oil made in the United States of America, which is used as a benchmark in oil pricing.

Figure 1: The composite leading indicator for the real economy



5.2 Coincident Composite Indicator for the Real Economy (CCI)

This composite reflects the current changes in economic activity and includes five components:

(1) Real wages: This is an indicator of economic well-being, and increases either through scarce labor supply or through increased labor productivity.

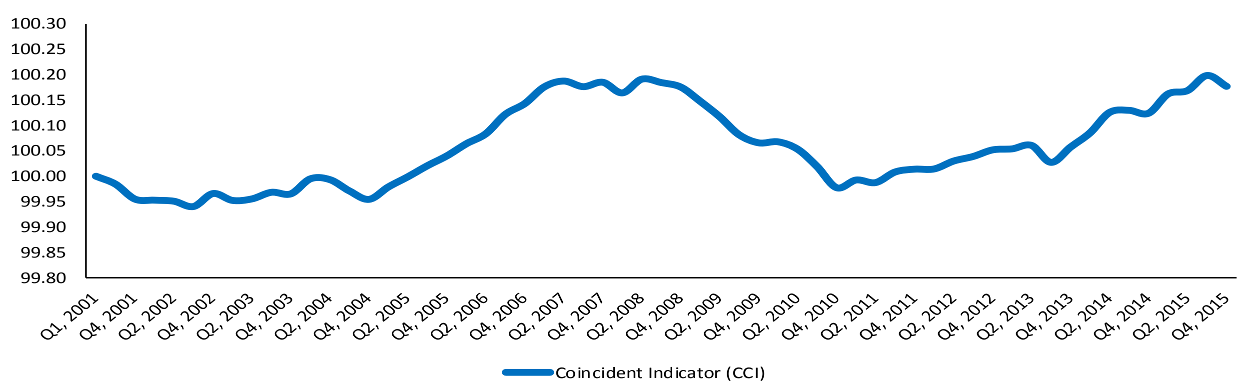
(2) Total production of goods: The assumption is that as more goods are produced and traded, there is an expected uptick in sales. Hence, this indicator is a good indicator for economic activity.

(3) Inverse of unemployment rate: A reduction in unemployment is generally synonymous with economic growth and therefore serves as a good indicator of the current state of the economy.

(4) Bauxite exports: An increase in this indicator may signal improved economic activity, as bauxite exports represent one of the country's highest earners of foreign exchange.

(5) Real GDP: This is the value of final goods and services produced in Jamaica and also serves as an indicator of the health of the economy.

Figure 2: The Coincident Composite for the Real Economy



5.3 Composite Indicator for the Household Sector (CHS)

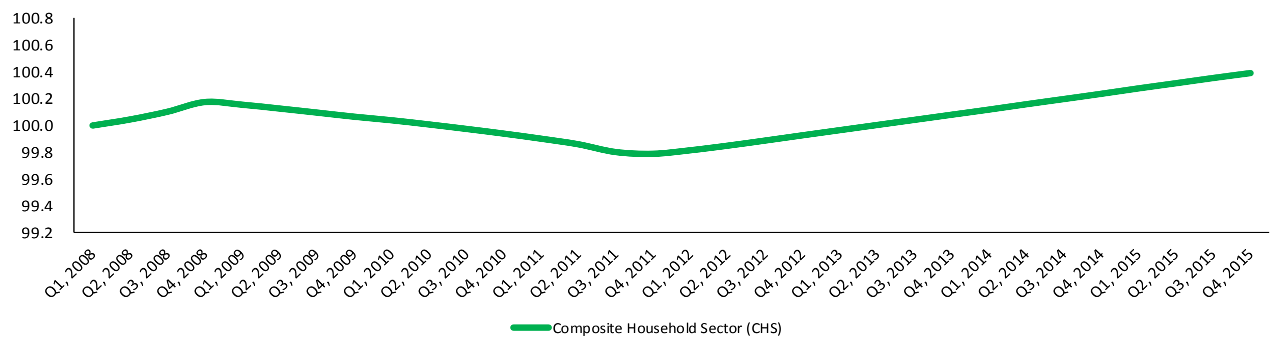
The CHS measures the vulnerability arising from excessive credit to the household sector. This is important as a shock to the household sector may lead to restriction of credit as well as NPL write-offs which can weaken financial institutions' balance sheets. There are three variables included in the CHS which are self-explanatory:

(1) NPLs to total DTI household sector loans.

(2) Households' debt to total loans.

(3) Household's debt to nominal GDP.

Figure 3: The Composite for the Household Sector



5.4 Composite Indicator for the Corporate Sector (CCS)

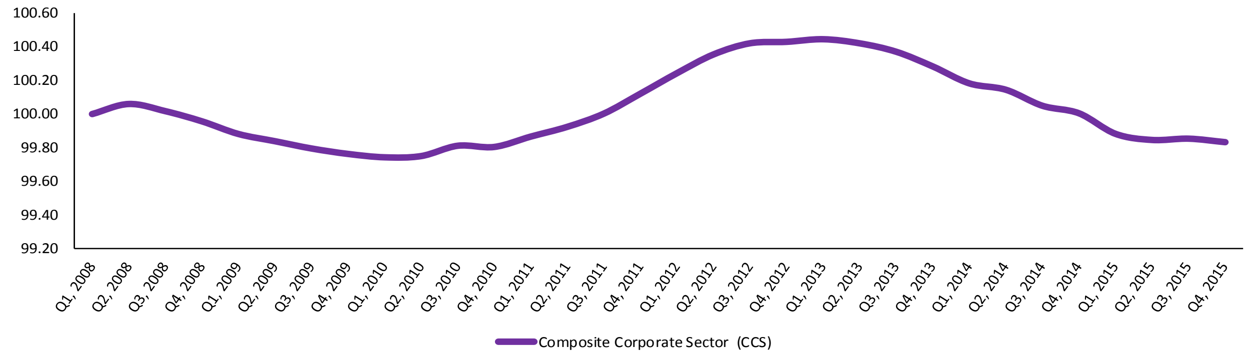
The CCS measures the significance of DTIs' exposure to corporate sector debt to the financial system. This composite is a coincident indicator for the corporate sector and a leading indicator for the household sector and is captured by 3 indicators, which are self-explanatory and outlined below:

(1) Real growth in corporate sector debt.

(2) NPLs to total loans for the corporate sector.

(3) Corporate sector debt to DTI assets.

Figure 4: The Composite for the Corporate Sector



5.5 Composite Indicator for Financial Institutions (CFI)

The CFI is a comprehensive indicator that is used to monitor financial system health. This composite is comprised of the following indicators:

(1) Total DTI loan growth: This measures the extent to which deposit taking institutions extend credit to the economy. The extension of credit to the economy is used as a proxy of the level of financial intermediation.

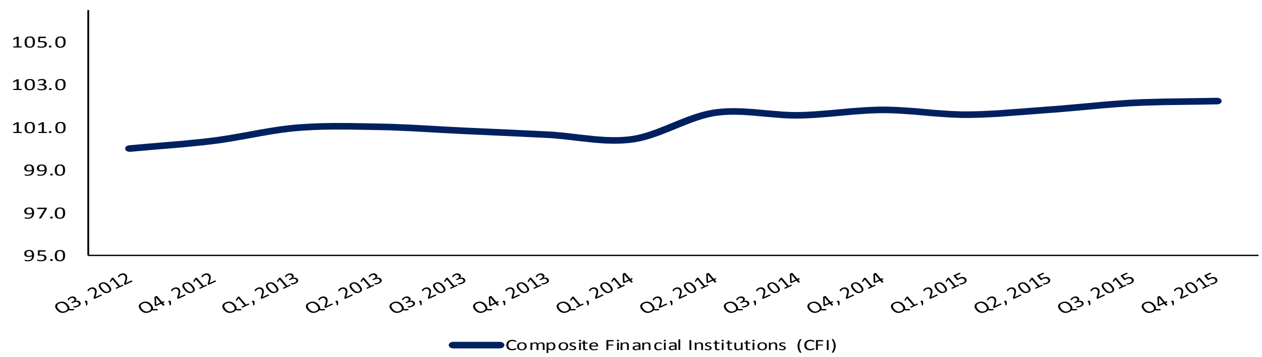
(2) Inverse of the weighted average lending and deposit rates spread: This is an earnings and profitability indicator for the deposit taking sector. It is used to gauge competitiveness and risk-taking within the sector. For instance, high spreads could indicate excessive risk taking and could lead to low credit demand and investment.

(3) Financial Institutions Stability Index: The index represents an overall stability index for the financial sector and is comprised of indicators for both deposit taking institutions and non-deposit taking institutions.[8] More specifically, it is a weighted average of the Banking Stability Index (BSI), Securities Dealers Index (SDI) and the Insurance Companies Index (ICI).[9]

[8] Non-deposit taking financial institutions include securities dealers as well as insurance companies.

[9] Indicators used to measure the stability of banks and securities dealers include: capital adequacy, asset quality, liquidity, profitability and sensitivity to market risk. The indicators used for insurance companies includes the same indicators and two additional indicators that measure reinsurance and actuarial issues. DTIs have larger weights as they have a larger asset base relative to other financial institutions.

Figure 5: The Composite for Financial institutions



5.6 Composite Indicator for the Financial Markets (CFM)

This composite is useful in gauging the degree of risk in the domestic financial markets and includes four indicators which are shown below.

(1) M2 to Foreign International Reserves: This measures the share of broad money in relation to foreign reserves. It is generally assumed that in periods of financial instability, the ratio will increase in the context of increased capital outflows.

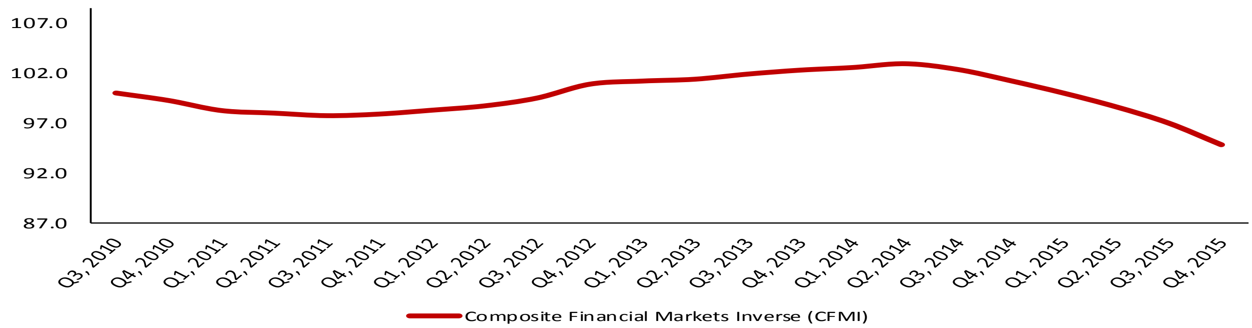
(2) TRE Spread: The TRE spread is the difference between 30-day Treasury bill rate and the average monthly value of daily 30-day private money market rate. Higher spreads means greater inefficiency in financial intermediation and allocation of resources and is indicative of increased counter party and liquidity risks in the money market.

(3) US interest rate differential: This is represented by the difference between interest rates on JMD 30 Treasury bill rates and US 30-day Treasury bill rates. A significant increase in this spread may signal the risk of significant capital flight inwards as investors seek greater return.[10]

(4) JGBI and EMBI Spread: This spread is the difference between the Jamaica Global Bond Index and the Emerging Market Bond Index. This indicator is a measure of investor confidence and measures the risk premium on Jamaican bonds. Higher spreads are suggestive of reduced investor confidence.

[10] These increases may indicate significant cash inflow from unstable sources. Capital flows can fuel credit booms, leading to the erosion of lending standards and exposure to macroeconomic shocks (IMF, 2013).

Figure 6: The Composite Indicator for Financial Markets



5.7 Composite Indicator for the International Economic Environment (CIEE)

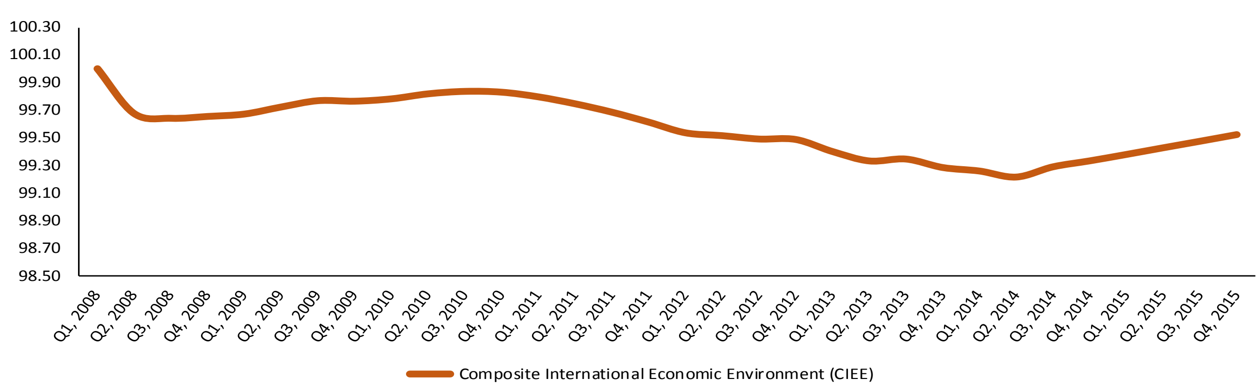
This composite captures potential vulnerabilities emanating from the international environment and is comprised of the following components:

(1) Growth in real effective exchange rate (REER): This indicator is used to measure competitiveness and is an indication of over (under) valuation of the domestic currency. If overvalued the REER is expected to produce a higher probability of a financial crisis.

(2) Terms of trade: An increases in terms of trade should strengthen Jamaica's balance of payments position therefore lowering the probability of crisis, while deterioration in the terms of trade may precede a currency crisis.

(3) External current account balance to GDP: This indicator signals the country's susceptibility to external shocks. A moderate increases in the current account are expected to signal a lower probability of a crisis occurring. However, a significant increase in this ratio is generally associated with large external capital inflows intermediated by the domestic financial system that may contribute to asset price and credit booms, which may precipitate a crisis.

Figure 7: The Composite Indicator for the International Economic Environment



6.0 Analyzing the signaling capabilities and the interrelationship between composite indicators

The composites were monitored over the period Q1 2006 to Q4 2015 in order to examine their signaling capabilities during known periods of vulnerability in Jamaica's financial system.

In reference to the Composite Financial Markets Index (Inverse), an increase in this indicator indicates a reduction in financial market risk[11]. The CFMI declined after a period of volatility in the financial markets consequent to the global financial crises of 2009 (see Figure 8). This decline in the CMFI was due to speculative attacks on the domestic currency, inefficiencies in the money market, widening in interest rate differentials and higher risk premiums on government securities.

In a similar manner, an increase in the composite indicator for financial institutions (CFI) signals an improvement in the conditions of financial institutions. Subsequent to the National Debt Exchange (NDX) in February of 2013, the CFI declined as there was initial deterioration in key profitability indicators for financial institutions. However the index showed improvement by the second quarter of 2014 as financial institutions actively restructured their asset portfolios (see Figure 9)[12,13]. Notably, the CMFI has a lead of 12 months between peak periods when compared to the CFI, where these two indicators reach the highest degree of correlation at 0.73 (see Table 2).

[11] The CFM is multiplied by minus 1 as to make it consistent with the movements in the direction of exposure of the CFI. Furthermore, the CFM can be used at a leading indicator for the CMFI.
[12] The NDX was an exchange of debt instruments between the Jamaican government and its domestic citizens in February 2013. This was done at restructure the composition and reduce Jamaica's debt stock.
[13] In contrast, a decline in the CFI may be due to short term wholesale funding reversals, liquidity restrictions, reduced profitability of financial institutions as well as increased exposure to foreign exchange risks.

Figure 8: The relationship between the Composite Financial Institutions and the Composite for the Financial Markets

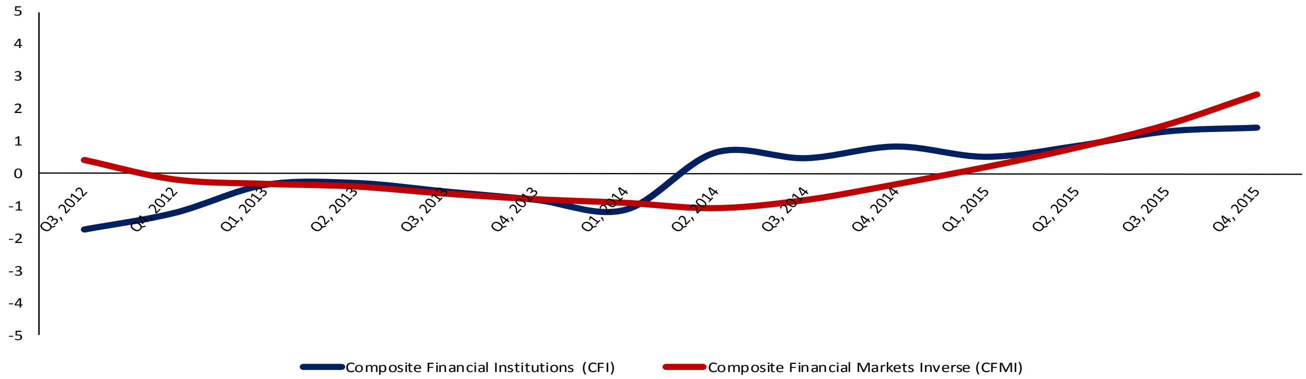


Figure 9: Deviation of the CFI from its long-term trend

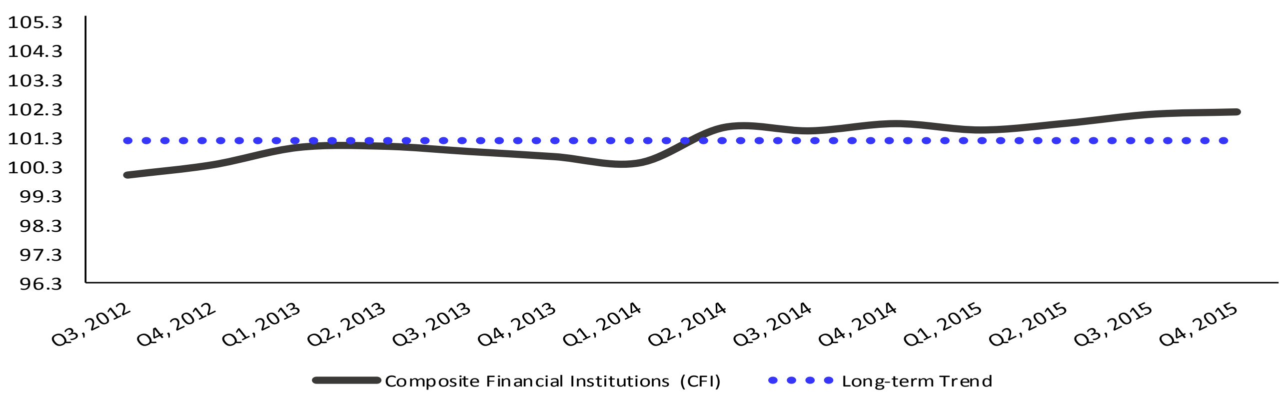


Table 2.

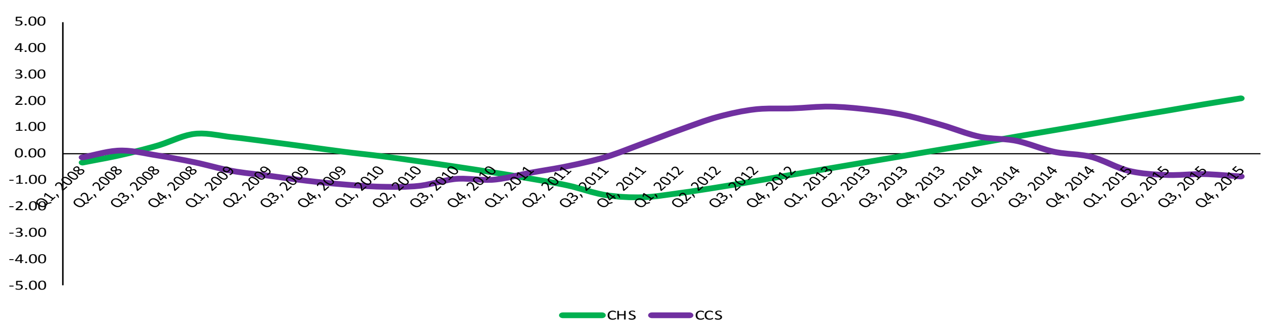
Number of lags (months)	Correlation coefficient between CFI and CFMI
3	0.65
6	0.67
9	0.69
12	**0.73**
15	0.64

An increase in the CHS indicates an increasing risk exposure of DTIs to household debt. The CHS peaked during the fourth quarter of 2008 without a strong reaction of the CCS (see Figure 10). This may be a result of the CHS lagged effect on the CCS. More specifically, increased credit to the household sector may improve the balance sheets of the corporate sector. In turn, this could result in more credit being extended to the corporate sector in subsequent periods.

Of note is that sharp increases of these two composites can indicate excessive lending by banks which can pose a systemic threat to financial system stability.[14] In this case, contractionary macro prudential tools such as, caps on credit and debt to income (DTI) and loan to value (LTV) ratios can be used mitigate inflated asset prices in the housing and stock markets.

Additionally, the CHS has a clear lead of the CCS. Although the reaction time of the CCS to the growing exposure in the CHS varied between 39 and 48 months, there is a lag of 45 months between the first peaks. Similarly, the slowing down of the CHS and the CCS in March 2012 and December 2015 respectively, also showed a lag of 45 months (see Table 3). Therefore it can be stated, that increased exposure to the household sector will eventually be followed by increased exposure to the corporate sector.

Figure 10: Comparison of the Composite Household Sector and the Composite Corporate Sector (both Standardized)



[14] Excessive credit results from the credit to GDP gap being above 2 percent.

Table 3.	
Number of lags (months)	**Correlation coefficient between CHS and CCS**
39	0.73
42	0.91
45	**0.98**
48	0.96

As it regards to the leading composite index for real economic activity (CLI), an increase in this composite signals an uptick in the real economy. Furthermore, the analysis of the relationship between the CLI and the CCI reveals a lead of the leading indicator of about 2 ½ years (see Figure 11). This is the estimated number of months that it takes for the peaks to reach their highest degree of correlation which is 0.54 when assessing different lag lengths. The correlation results of different lag lengths are shown in Table 2.

Figure 11: Comparison of the Composite Leading indicator and the Composite Coincident Indicator (both Standardized)

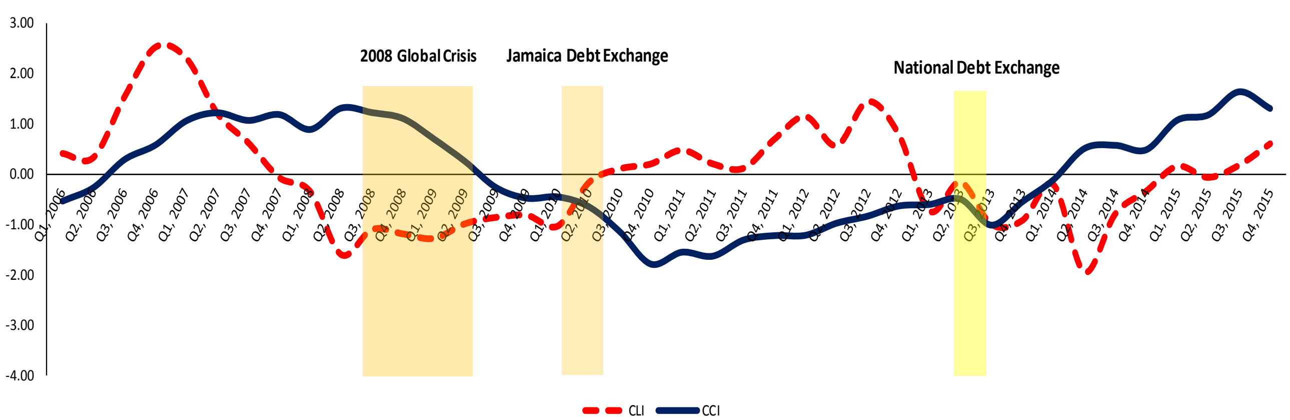
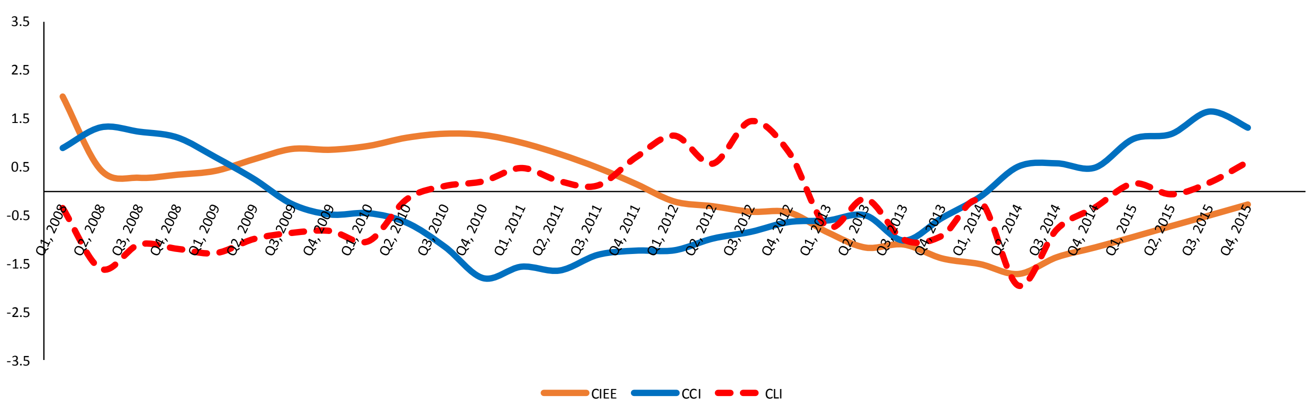


Table 4.	
Number of lags (months)	**Correlation coefficient between CLI and CCI**
27	0.52
30	**0.54**
33	0.50
36	0.51

The composite indicator for the international economic environment measures Jamaica's performance relative to its international trading partners. A comparison of the CIEE, CCI and the CLI between the period 2008 and 2015 showed that starting from Q3 2008 the world economy accelerated faster than Jamaica's economy (see Figure 12). Conversely, while the CIEE declined rapidly during the Q3 of 2010, the leading composite for the Jamaican economy increased significantly until the second quarter of 2013. This indicated that as the world economy contracted during this period, the CLI forecasted economic improvement approximately two and a half years after. As, such the CIEE has a clear lag on the CCI.

Figure 12: The relationship between the Composite Coincident Indicator and the Composite for the International Economic Environment both Standardized)



7.0 Estimation

7.1 Model

In order to measure the impact of the CCI, CHS and CCS on the non-performing loans to total loans ratio (NPLs) for the banking sector and the Z-Score, the VEC estimation method was employed. The type of VEC employed in this analysis was nonstructural as all variables were treated as endogenous and as a lagged function of itself in a linear system of equations as set out in [6].

$$\begin{bmatrix} 1 & r_{12} & \cdots & r_{1n} \\ r_{21} & 1 & \dots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & 1 \end{bmatrix} \begin{bmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{nt} \end{bmatrix} = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} + \begin{bmatrix} \Pi_{11}(L) & \Pi_{12}(L) & \cdots & \Pi_{1n}(L) \\ \Pi_{21}(L) & \Pi_{22}(L) & \dots & \Pi_{2n}(L) \\ \vdots & \vdots & \ddots & \vdots \\ \Pi_{n1}(L) & \Pi_{n2}(L) & \cdots & \Pi_{nn}(L) \end{bmatrix} \begin{bmatrix} y_{1t-1} \\ y_{2t-1} \\ \vdots \\ y_{nt-1} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \\ \vdots \\ e_{nt} \end{bmatrix} \qquad [6]$$

Or

$$Ry_t = A + \Pi(\mathrm{L})\mathrm{y}_{t-1} + e_t \qquad [7]$$

where $R\ is\ \ nxn$ matrix of contemporaneous coefficient of n endogenous variables in y_t vector space. Further, A is $nx1$ vector of constant, $\Pi(\mathrm{L}) is\ a\ n \times n$ matrix of lag operator polynomials and e_t is the $n \times 1$ vector of structural disturbances (serially uncorrelated), that is, $e_t \sim N(0, \Omega)$. The study estimated the reduced form VEC outlined in [8]:

$$y_t = D_0 + D_1(L)y_{t-1} + \varepsilon_t \qquad [8]$$

$$where\ D_0 = R^{-1}A,\ D_1(L) = \mathrm{R}^{-1}\Pi(\mathrm{L})\ and\ \varepsilon_t = R^{-1}e_t.$$

where vector y consists of the composite indices developed in this paper, which are the CCI, CHS and CCS.

The AIC, SBIC and HQC were utilized to specify the optimal lag length of the model.[15] Of importance, the VEC model was used to generate impulse response functions in order to illustrate and verify how shocks to the composite indicators would affect the level of the banking sector's loan quality ratio and the Z-score index. The impulse response functions were estimated for 12 quarters. An examination of the inverse roots of the autoregressive characteristic polynomial of the VEC model showed that the system was stable and satisfied stationarity conditions.[16] The Phillips Perron (PP) test was used to test for unit roots and the appropriateness of the VEC specification. The PP demonstrated that all variables were non stationary in levels. The results of the test showed that all variables were I (1).

[15] See appendix 1b, Table 5
[16] See appendix 1b, Table 6

8.0 Diagnostic Tests

8.1 Serial Correlation

The Lagrange Multiplier (LM) test for autocorrelation was applied in order to ensure that the model was correctly specified. The results indicated that the model had no autocorrelation in the residuals using 12 lags, with the exception of lag 2.[17,18]

8.2 Generalized Impulse response function

The Generalized Impulse Response Function (GIRF) was used as it is invariant to the ordering of the variables in the VEC, this allows a unique solution to be achieved. Impulse response functions were estimated for 12 quarters.

8.3 Co-integration results

The Johansen co-integration tests, more specifically the trace statistic and the maximum eigenvalue, were used to assess if the variables were co-integrated. In instances where both tests show conflicting results, the maximum eigenvalue test was relied on as recommended.[19] The co-integration results showed that at least one co-integrating equation existed at the 5.0% level of significance for both equations and therefore there is a long run relationship among the variables (see **Table 9**).

8.4 Results

8.4.1. NPL model

The VEC model was first used to capture the interaction between the NPL ratio for the banking sector, the composite for the household sector (CHS), the composite for the corporate sector (CCS) and the composite coincident indicator CCI. The results of this model showed that there was a general improvement in the banking sector's NPL ratio in response to a one standard deviation shock in the CCS in the context of continued strong credit screening and risk management of corporate customers by the banking sector. A similar shock to the CHS also resulted in a decline in the NPL ratio. This finding was consistent with *a priori* expectations, which also underscores the generally cautious credit practices of the banking sector. In addition, the NPL ratio showed a general decline in response to the shock to the CCI. As expected, this highlights the pro-cyclical response between the CCI and

[17] The null hypothesis for this test is that no serial correlation exists at lag order h.
[18] See Appendix 1b: table 5
[19] Banerjee et al. (1986) notes that this method is more reliable for smaller samples.

asset quality. Furthermore, the evidence suggests that as the business cycle improves, banks will continue to practice sound credit risk management.

Concerning the variance decomposition, the NPL ratio is predominantly explained by the CCI, which accounted for 58.6 per cent of the variation in the indicator followed by the NPL ratio itself which explained 24.4 per cent of the variation (see **Appendix 1b: Table 8**).

8.4.2 Z-Score model (Base model)

The second VEC model was used to examine the impact of the composite indicators on the Z-Score. The impulse response functions showed a general improvement of the Z-Score in response to a shock to the CHS. The performance in the Z-Score index was largely driven by the improved profitability to the banking sector as a result of the high interest earnings from loans extended to the household sector, partially due to higher interest rates on personal loans. This improved performance in earnings and profitability more than offset the potential declines in the capital to asset ratio which impacts the Z-score.

The results showed that a shock to the CCS resulted in a deterioration of the Z-Score. This finding suggests that though increased credit exposure to the corporate sector would lead to increased interest earnings and profitability, this was more than offset by potential declines in the capital to asset ratio, largely due to lower interest rates on corporate sector loans. In response to a shock to the CCI, the Z-Score showed a strong initial improvement and substantiates that there is evidence of pro-cyclicality for the banking sector.

Regarding the variance decomposition of the z-score, the results demonstrated that the z-score predominantly explained itself which accounted for 82.9 per cent of the variation, followed by the CCI which explained 14.6 per cent of the variation (see **Appendix 1b: table 8**).

9.0 Conclusion & Policy Recommendation

Seven composite indices were developed to analyze potential vulnerabilities within the Jamaican economy. For the period spanning the first quarter of 2008 to the last quarter of 2015, correlation results revealed that the CHS was a leading indicator for the CCS for known periods of vulnerability such as the global crisis, JDX and NDX periods. In addition, the FMI was a leading indicator for the CFI for the JDX and NDX periods.

The VEC approach determined that there is pro-cyclicality as evidenced by the response of the Z-score and NPL ratio to a shock in the CCI. Furthermore, the CCI accounted for the most variation in the NPL ratio and accounted for the second most variation for the Z-Score.

Against this background, it may be useful for policymakers to employ tools such as debt to income (DTI) ratios and loan to value (LTV) ratios to limit the impact of the buildup of DTI's exposure to the household and corporate sectors, in order to mitigate systemic events.

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Appendix 1a

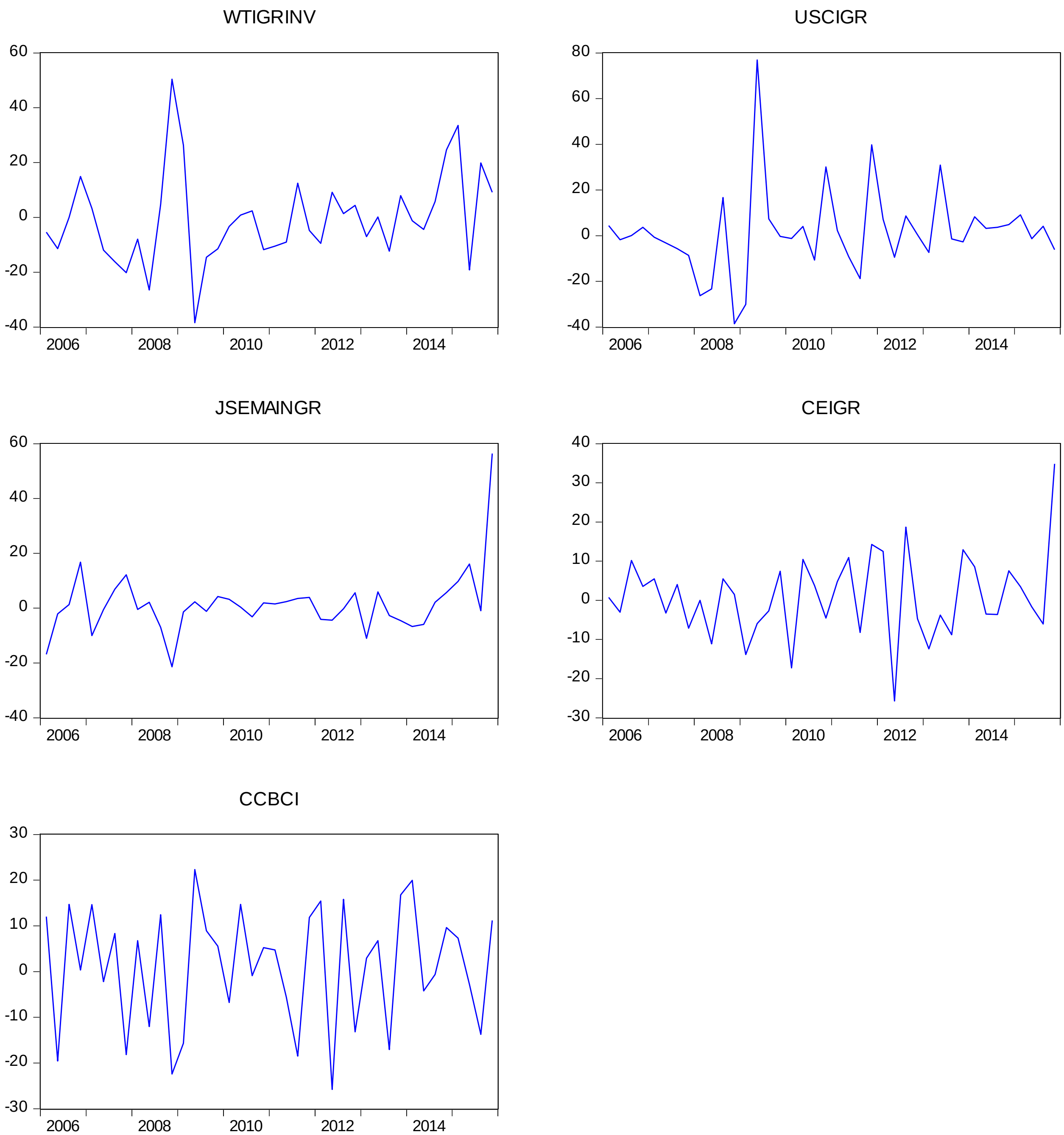
Table 1: Descriptions of Data

Indicators	Percentage/ Nominal amount	Range of the figures of the respective source
CLI		
1. West Texas Intermediate Average	Percentage	Q1 2006 - Q4 2015
2. US Consumer Confidence Index	Percentage	Q1 2006 - Q4 2015
3. Consumer Expectation on business condition Index	Percentage	Q1 2006 - Q4 2015
4. Consumer Income Expectation Index	Percentage	Q1 2006 - Q4 2015
5. JSE Main Index (growth)	Percentage	Q1 2006 - Q4 2015
CCI		
1. Real Wages	Nominal	Q1 2006 - Q4 2015
2. Total Production	Nominal	Q1 2006 - Q4 2015
3. Unemployment Rate	Percentage	Q1 2006 - Q4 2015
4. Bauxite Exports	Nominal	Q1 2006 - Q4 2015
5. Real GDP	Nominal	Q1 2006 - Q4 2015
CHS		
1. NPLs to DTI Loans to the HH Sector	Percentage	Q2 2008 - Q4 2015
2. Household debt to Total Loans	Percentage	Q2 2008 - Q4 2015
3. Household debt to nominal GDP	Percentage	Q2 2008 - Q4 2015
CIEE		
1. REER (growth)	Percentage	Q1 2008 - Q4 2015
2. Terms of Trade	Percentage	Q1 2008 - Q4 2015
3. Current Account Balance to GDP	Percentage	Q1 2008 - Q4 2015
CCS		
1. Corporate Sector Debt (Growth)	Percentage	Q2 2008 - Q4 2015
2. NPLs to Total Loans for the Corporate Sector	Percentage	Q2 2008 - Q4 2015
3. Corporate Sector Debt to DTIs Assets	Percentage	Q2 2008 - Q4 2015
CFI		
1. Total DTI loan growth	Percentage	Q1 2012 - Q4 2015
2. WALD Spread	Percentage	Q1 2012 - Q4 2015

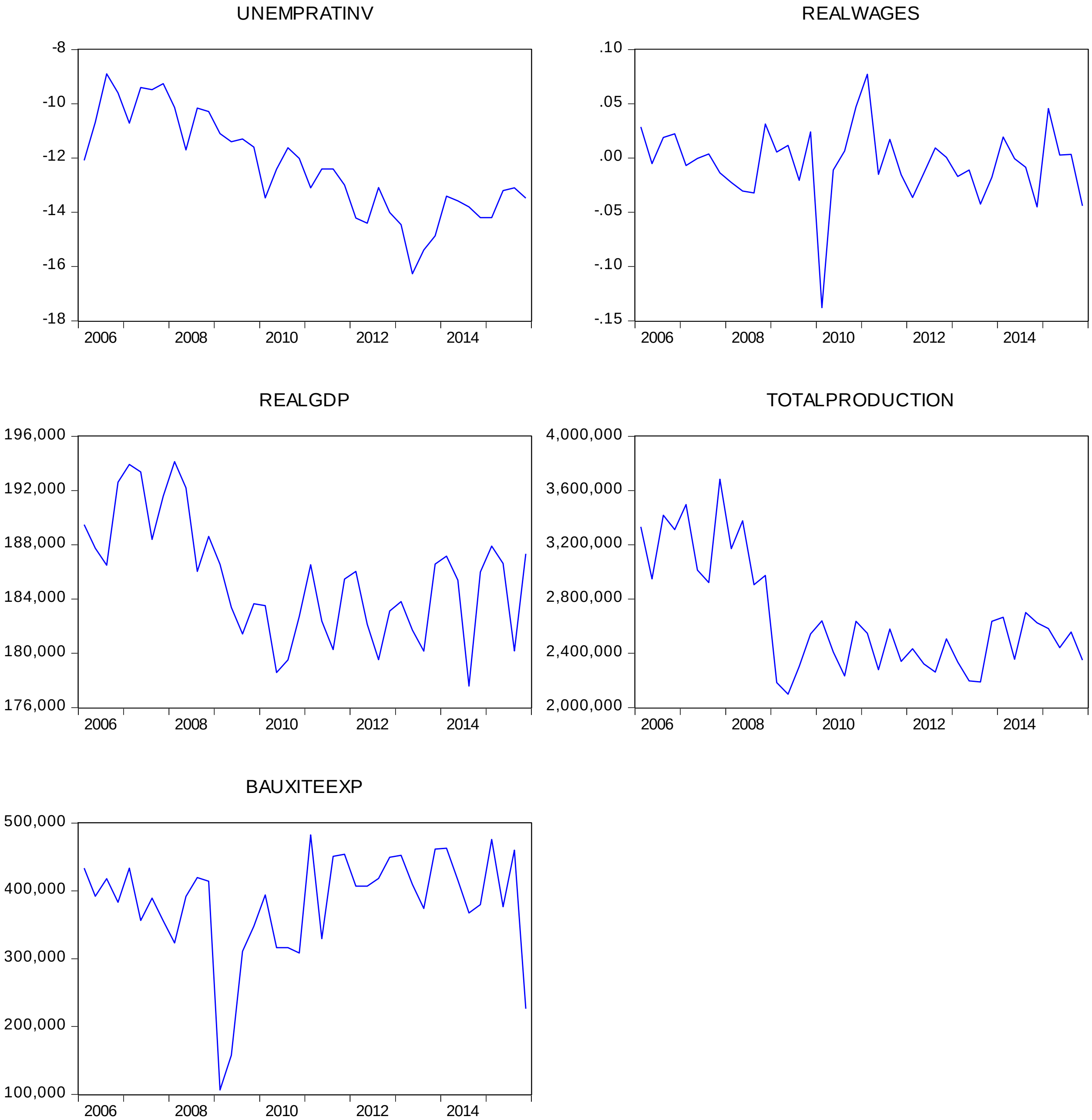
3. Financial Institutions Stability Index	Percentage	Q1 2012 - Q4 2015
CFM		
1. M2 to Foreign International Reserves	Percentage	Q1 2012 - Q4 2015
2. TRE Spread	Percentage	Q1 2012 - Q4 2015
3. US Interest rate Differential	Percentage	Q1 2012 - Q4 2015
4. JGBI and EMBI Spread	Percentage	Q1 2012 - Q4 2015
CIEE		
1. REER (growth)	Percentage	Q1 2008 - Q4 2015
2. Terms of Trade	Percentage	Q1 2008 - Q4 2015
3. Current Account Balance to GDP	Percentage	Q1 2008 - Q4 2015

Figure 13: Components of composite indicators

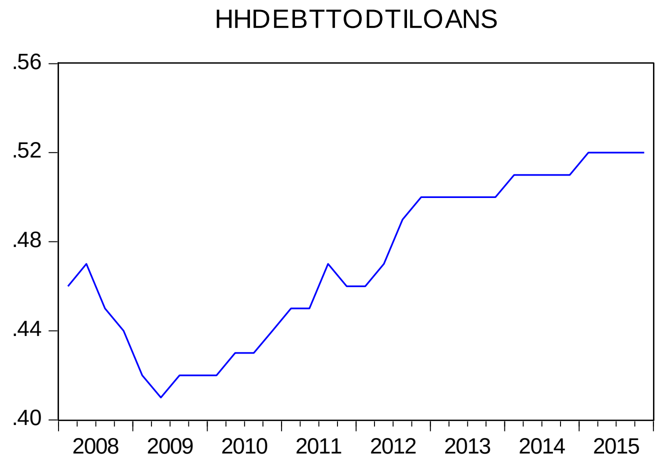
The Components of the Composite Leading Indicator (CLI)

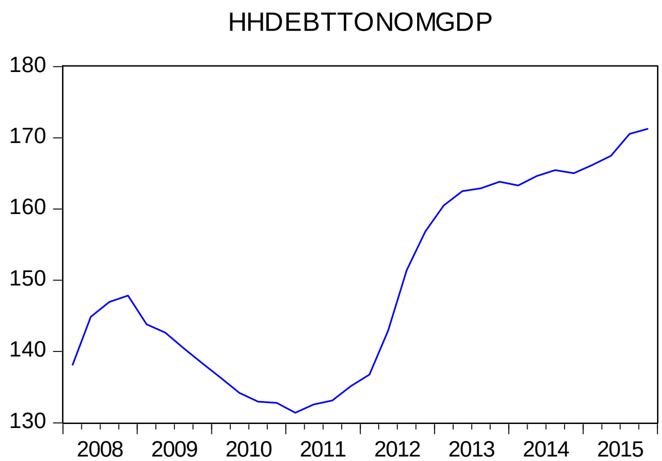


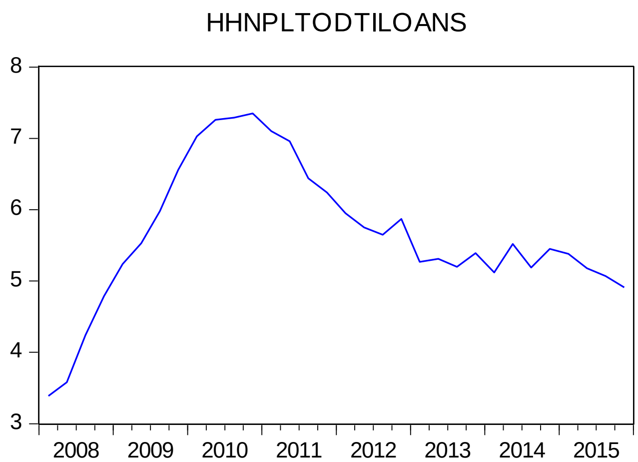
The Components of the Composite Coincident Indicator (CCI)



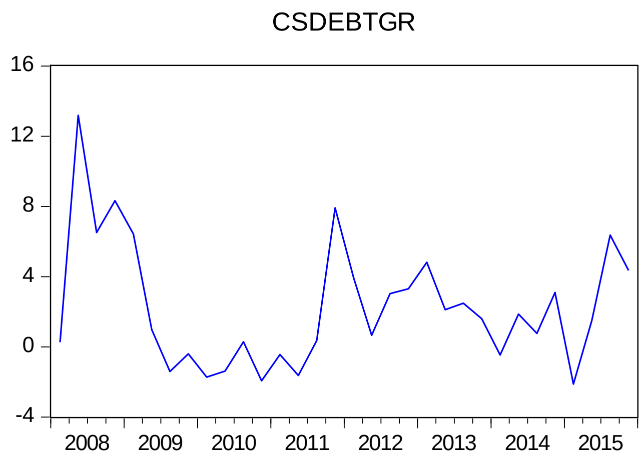
The Components of the Composite Household Sector (CHS)

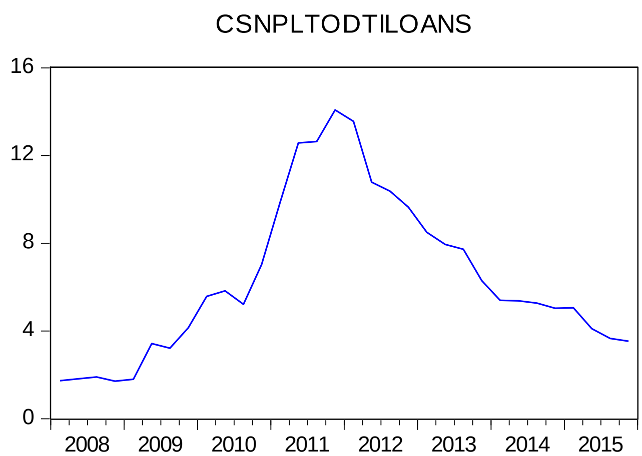


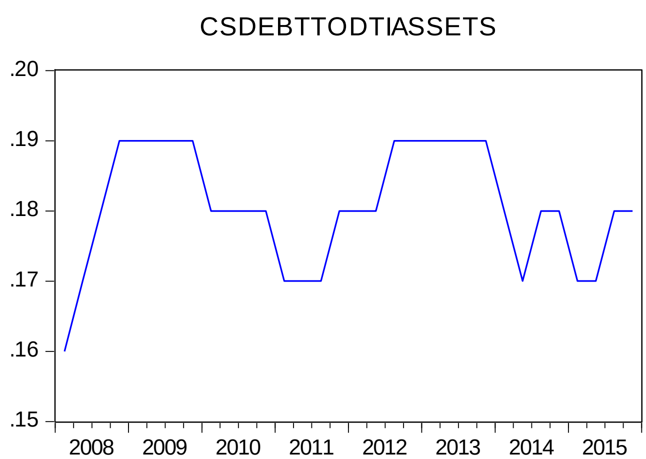




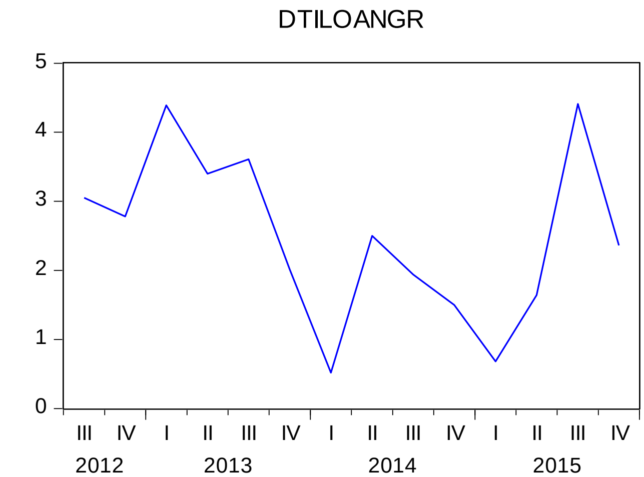
The Components of the Composite Corporate sector (CCS)

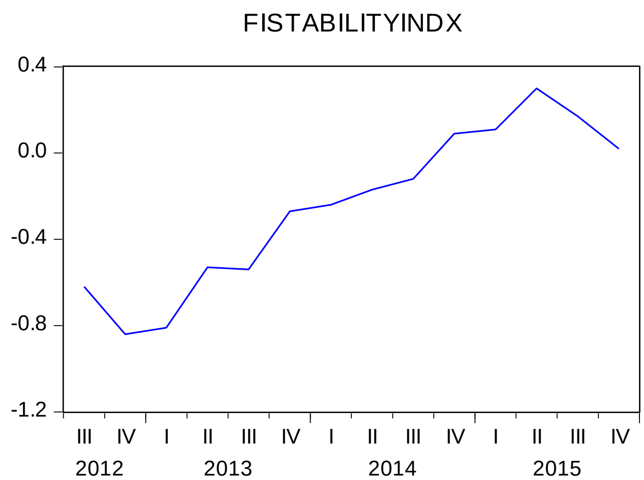


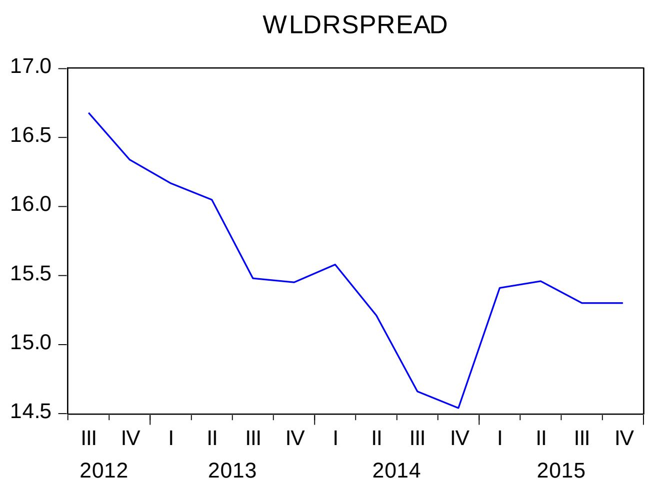




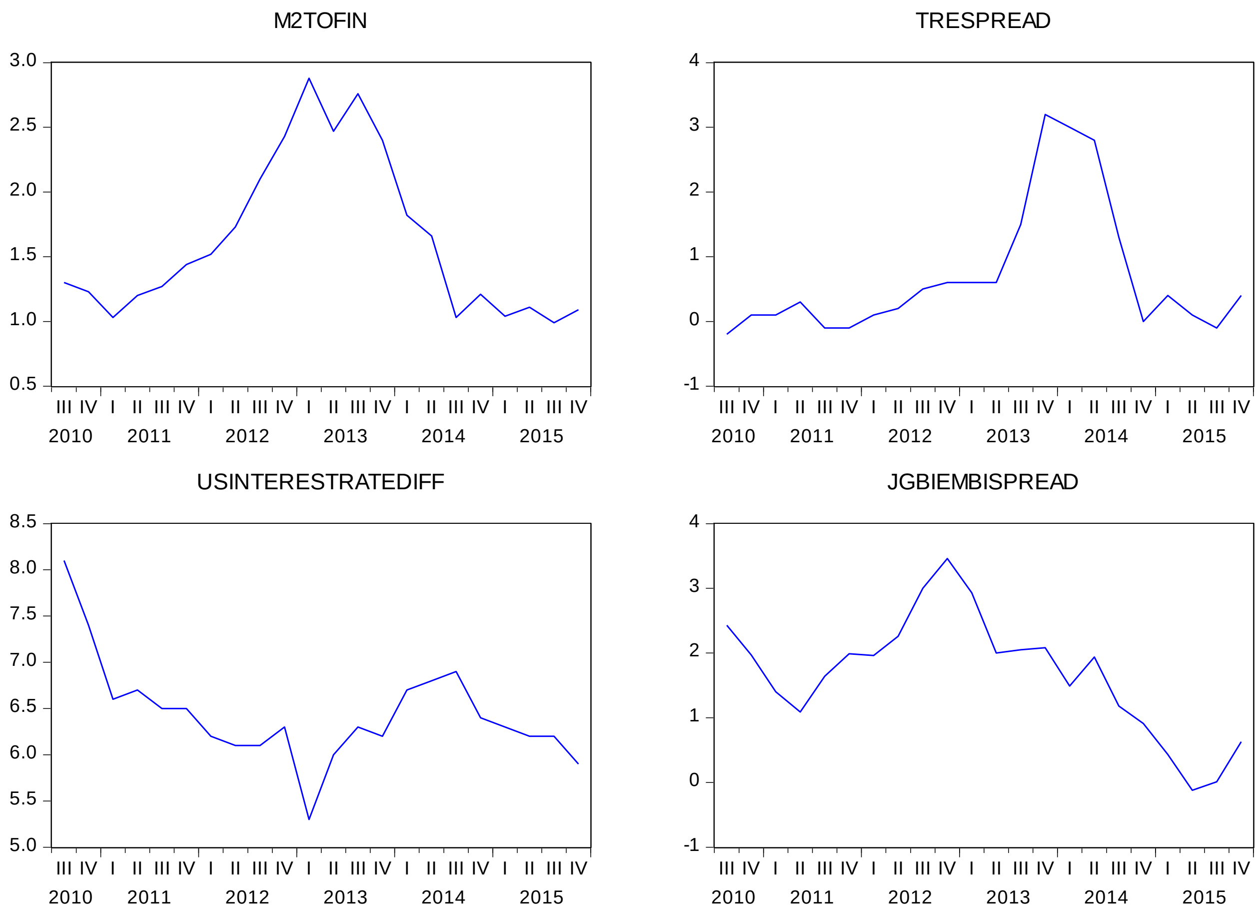
The Components of the Composite for Financial Institutions (CFI)



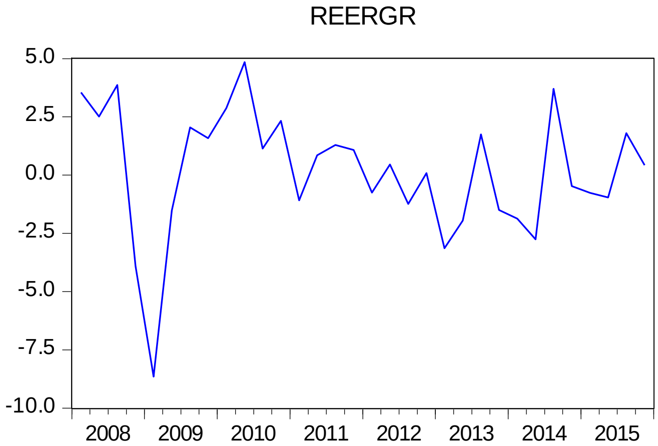


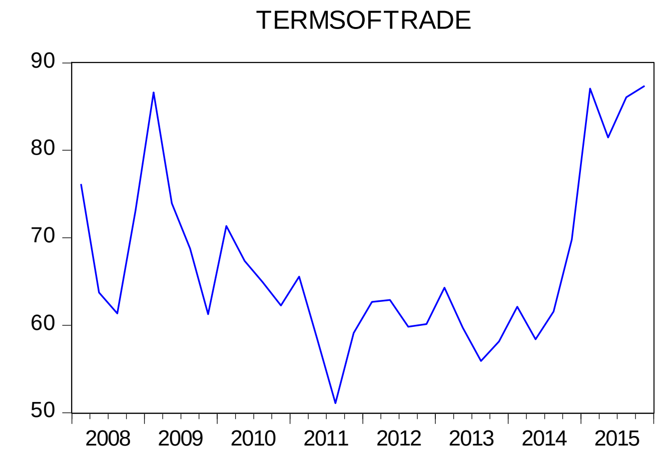


The Components of the Composite for Financial Markets (CFM)



<u>The Components of the Composite for the International Economic Environment (CIEE)</u>





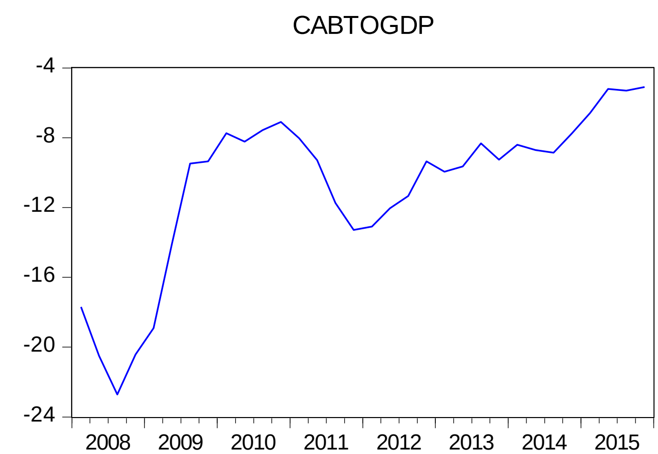


Table 2: Descriptive Statistics

	NPL ratio	Z_SCORE	CCI	CHS	CCS
Mean	5.43	27.58	100.09	100.05	100.03
Median	5.24	25.27	100.07	100.04	100.00
Maximum	8.88	50.15	100.20	100.39	100.44
Minimum	2.33	15.50	99.98	99.79	99.74
Std. Dev.	1.81	10.14	0.07	0.16	0.23
Skewness	0.20	0.85	0.18	0.26	0.55
Kurtosis	2.27	2.60	1.71	2.39	1.96
Jarque-Bera	0.91	4.04	2.39	0.86	3.04
Probability	0.63	0.13	0.30	0.65	0.22
Sum	173.76	882.53	3202.78	3201.71	3201.09
Sum Sq. Dev.	101.41	3190.31	0.15	0.81	1.61
Observations	32	32	32	32	32

Table 3: Unit root results

	Level	Difference
Variables	**PP**	**PP**
NPL ratio	0.410	0.319
CCI	0.690	0.505
CCS	0.580	0.198
CHS	0.922	0.428
Z-Score	0.248	0.000

Table 4: Correlation matrix

NPL ratio model				
	NPL ratio	**CHS**	**CCS**	**CCI**
NPL ratio	1.00	-0.73	0.34	-0.86
CHS	-0.73	1.00	-0.38	0.81
CCS	0.34	-0.38	1.00	-0.24
CCI	-0.86	0.81	-0.24	1.00

Z Score model				
	Z_SCORE	**CHS**	**CCS**	**CCI**
Z_SCORE	1.00	0.41	-0.10	0.72
CHS	0.41	1.00	-0.38	0.81
CCS	-0.10	-0.38	1.00	-0.24
CCI	0.72	0.81	-0.24	1.00

Appendix 1 b

Table 5: Lag length selection Criteria

NPL ratio model

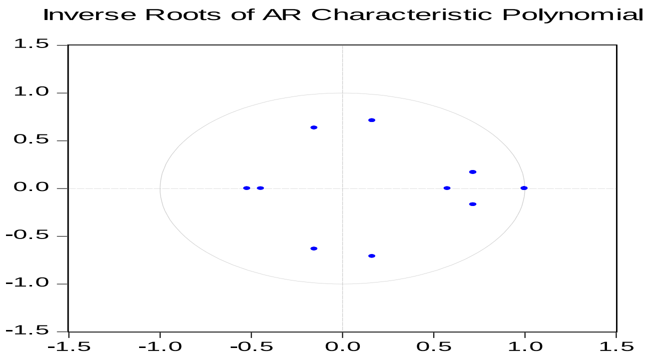
Lag	LogL	LR	FPE	AIC	SC	HQ
0	156.44	NA	0.00	-10.24	-9.86	-10.12
1	197.15	64.57347*	7.84e-11*	-11.94166*	-10.81010*	-11.58727*
2	211.37	18.63	0.00	-11.82	-9.93	-11.23

Z-Score model

Lag	LogL	LR	FPE	AIC	SC	HQ
0	80.64872	NA	7.84E-08	-5.010257	-4.633072	-4.892127
1	119.3026	61.31298*	1.68E-08	-6.57259	-5.441035*	-6.218201*
2	136.6842	22.77597	1.68e-08*	-6.667877*	-4.781952	-6.077229

Table 6: AR root table

NPL ratio model



Z-Score model

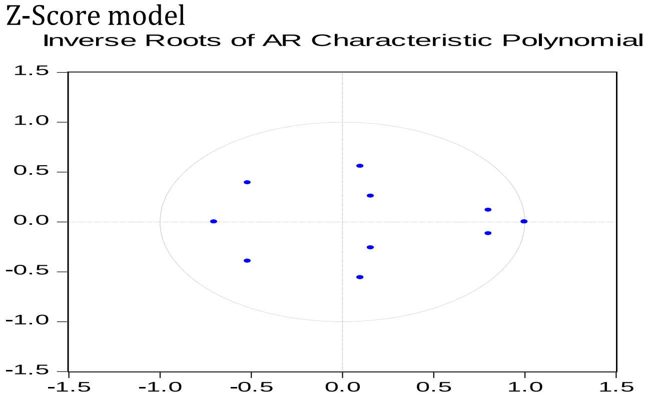


Table 7: Serial Correlation

NPL model

Lags	LM-Stat	Prob
1	14.85182	0.5355
2	27.4952	0.0363
3	15.07097	0.5194
4	10.81986	0.8205
5	6.23334	0.9854
6	18.29579	0.3069
7	15.63176	0.4789
8	16.39106	0.426
9	18.55021	0.2927
10	14.1225	0.5896
11	10.91945	0.8144
12	5.478829	0.9928
Probs from chi-square with 16 df.		

Z-Score model

Lags	LM-Stat	Prob
1	15.2707	0.5049
2	11.88963	0.7515
3	21.98332	0.1437
4	14.00086	0.5986
5	13.55083	0.6321
6	20.07237	0.217
7	8.787816	0.9219
8	17.13183	0.3771
9	16.4396	0.4227
10	10.77161	0.8234
11	21.89615	0.1466
12	12.56679	0.7041
Probs from chi-square with 16 df.		

Table 8: Variance Decomposition

NPL model

Period	S.E.	NPL ratio	CCI	CCS	CHS
1	0.022643	84.85424	3.902648	9.618262	1.624852
2	0.034246	65.5239	11.07019	20.66127	2.744631
3	0.046057	48.95429	24.07139	25.30982	1.664501
4	0.054806	38.26807	36.04441	24.70989	0.977633
5	0.06256	33.52683	43.66083	21.6467	1.165642
6	0.069926	30.09481	49.00939	19.07654	1.819267
7	0.07738	28.10826	52.27621	17.88188	1.733641
8	0.084666	26.82583	54.35269	17.26967	1.551816
9	0.091684	25.84669	55.98349	16.63327	1.53655
10	0.098505	25.15502	57.22394	16.03908	1.581961
11	0.105222	24.73589	58.04479	15.63642	1.5829
12	0.111799	24.44209	58.61082	15.38701	1.560088
Cholesky Ordering: NPL CCI CCS CHS					

Z-Score model

Period	S.E.	Z_SCORE	CCI	CCS	CHS
1	5.833081	100	0.000000	0.000000	0.000000
2	7.784003	98.00168	0.192809	1.056414	0.749096
3	9.785481	84.89332	11.53046	1.687818	1.888404
4	11.23488	80.21867	16.34181	1.986611	1.452913
5	12.0637	79.28349	17.12854	1.85494	1.733037
6	12.87608	79.6631	17.0547	1.70109	1.581107
7	13.829	80.28184	16.59354	1.6142	1.510413
8	14.7457	80.67135	16.26987	1.577	1.481783
9	15.52345	81.21167	15.90022	1.514815	1.373293
10	16.23931	81.83789	15.43731	1.443946	1.280852
11	16.95766	82.41151	14.95795	1.383095	1.247453
12	17.6708	82.85734	14.55473	1.338665	1.249265
Cholesky Ordering: Z_SCORE CCI CCS CHS					

Table 9: Co-integration results

NPL ratio model in levels

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.700577	62.9525	47.85613	0.0011
At most 1*	0.387751	26.77556	29.79707	0.1072
At most 2	0.319992	12.05706	15.49471	0.1542
At most 3	0.01612	0.487555	3.841466	0.485

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.700577	36.17695	27.58434	0.0031
At most 1*	0.387751	14.7185	21.13162	0.3091
At most 2	0.319992	11.56951	14.2646	0.1279
At most 3	0.01612	0.487555	3.841466	0.485

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level

Z-Score model

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.496876	42.89576	47.85613	0.1351
At most 1*	0.310953	22.28819	29.79707	0.2828
At most 2	0.25968	11.1148	15.49471	0.2045
At most 3	0.067439	2.094623	3.841466	0.1478

Trace test indicates 1 cointegration at the 0.05 level

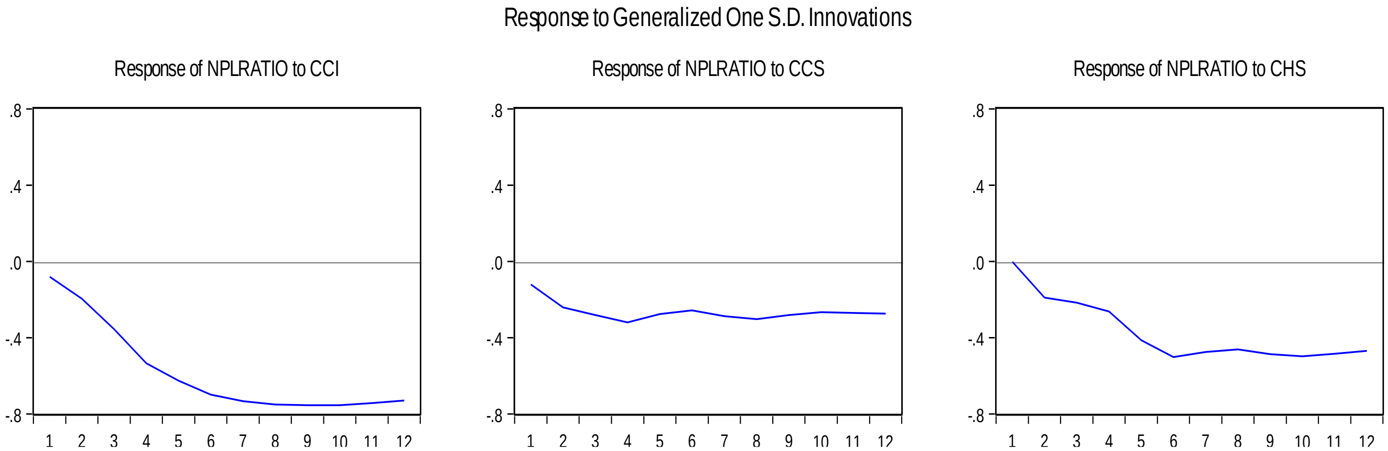
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None*	0.496876	20.60757	27.58434	0.3006
At most 1*	0.310953	11.17339	21.13162	0.63
At most 2	0.25968	9.020175	14.2646	0.2845
At most 3	0.067439	2.094623	3.841466	0.1478

Max-eigenvalue test indicates no cointegration at the 0.05 level

Graph 1: Impulse responses

NPL ratio model



Z-Score model