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A Composite Indicator of Systemic Stress (CISS): The Case of Jamaica

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Abstract

This paper seeks to introduce a Composite Indicator of Systemic Stress (CISS) to enhance BOJ's existing toolkit for macro-prudential policy and to improve financial stability assessments going forward. Similar to Hollo, et al (2010, 2012), the development of the CISS involved the aggregation of sub-indices from the foreign exchange, equity, money and bond markets using portfolio theory to determine contemporaneous stress in the financial system. A VAR model was used to determine the impact of the CISS on economic activity in both a high stress and low stress regime. Results indicated that the shocks to the CISS had a sustained impact on economic activity in the high stress regime relative to the low stress regime. It was also found that shocks to the forecasted CISS values would also result in reduction in economic activity. The paper confirms that the CISS is an adequate policy tool that facilitates early identification of systemic stress within the Jamaican financial system. Hence, the generation of timely forecasts will allow for expedient action by the monetary authorities in ensuring financial stability.

Keywords: Systemic risk, financial stability, threshold vector autoregression (TVAR), financial crises

JEL Classification: C15, E52, G01

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1.0 Introduction

In the aftermath of the global financial crisis, authorities worldwide have focused their attention on the issue of systemic risk. Systemic risk is the risk that financial institution weaknesses becomes so widespread that it impairs the functioning of a financial system such that economic growth and welfare are eroded (ECB, 2009). This is an important issue for policy makers as the early detection of financial stress provides the opportunity for expedient remedial action to temper the effects of instability on the real sector. Early warning models in Jamaica have been used for surveillance and forecasting purposes in order to mitigate the effects of financial crises. These models include aggregated macro- and micro-prudential indicators such as Langrin (2002) as well as various stress testing frameworks. However, the use of a single measure of financial instability would provide information on the joint impact of several developments in the financial system. Morris (2010) sought to create a systemic risk index using indicators which aggregated microeconomic, macroeconomic and international factors together to capture and forecast stability in the banking system. However, the dynamics in the financial system can also be captured using market data which provides information on the response of market players to market developments. This paper creates an index which utilises financial market data to determine instability in the Jamaican financial system.

This paper develops a Composite Indicator of Systemic Stress (CISS) for Jamaica with a view to enhancing the BOJ's financial stability assessment by utilising this as an additional early warning, stress testing and forecasting tool. Similar to the methodology utilised by Hollo, et al (2010, 2012), the CISS involves the aggregation of sub-indices from the foreign exchange market, equity market, money market and bond market using basic portfolio theory to determine contemporaneous stress in the financial system. By taking into account the time-varying cross-correlations between sub-indices, the CISS will place a higher weighting on periods in which financial stress occurs simultaneously in the various market segments. It is expected that systemic risk is higher when the correlation between the stress indicators increases. This paper contributes to the existing literature by forecasting the impact of the CISS on economic activity. Economic activity is expected to be significantly lower when the CISS is at or above the estimated threshold level (high stress) than when it is below the threshold level (low stress).

The remainder of the paper is organised as follows. Section 2 presents an overview of the relevant literature while section 3 presents the methodology employed in this paper. Section 4 provides the econometric results while section 5 presents the conclusion and policy implications.

2.0 Literature Review

The existing literature on systemic risk includes several models that seek to measure risk and assess the impact of such risk. The development of composite measures for systemic risk has been a topical issue in the literature in recent years. Authors have utilised measures based on market data (Hollo, et al, 2010, 2012), balance sheet data, macroeconomic and microeconomic indicators (Morris, 2010) or a combination of the above (Louzis and Vouldis, 2011; Cevik et al, 2011) in the modeling of systemic risk. For the purpose of this paper, market data will be utilised to construct the CISS for Jamaica. The literature also varies in relation to the methods of aggregation utilised for the indexes. Illing and Lui (2006) provide a summary of common methods used in the literature such as factor analysis, credit weights, variance equal weights and transformations using sample cumulative distribution functions (CDFs). One of the more recent methods in the literature is the use of portfolio theory based schemes introduced by Hollo et al (2010, 2012) and Louzis and Vouldis (2011).

Hollo, et al (2010, 2012) measured systemic risk in the euro area using a single composite measure based on five market segments, namely the foreign exchange market, equity market, money market, bond market and financial intermediaries. The authors proposed the use of basic portfolio theory to aggregate the indicators for the market segments and also sought to determine the time-varying cross-correlations between sub-indices. They proposed the determination of critical levels for the CISS using the endogenous outcomes of two econometric regime switching models. Hollo et al (2010, 2012) modeled the dynamics of the CISS using an auto-regressive Markov switching model followed by its interaction with real economy by way of a bivariate threshold VAR model. The results indicated that real economic activity measured by industrial production, becomes impaired in response to a large positive CISS shock in high-stress regimes.

Cevik et al (2011) developed the Turkish Financial Stress Index (TFSI) for the period January 1997 to March 2010. In this research they utilised a unique combination of market data, macroeconomic data and balance sheet data to determine the sub-indices after which principal component analysis was used to weight each sub-index. Following the aggregation of the index, the TFSI was compared to a composite leading indicator (CLI) index developed by the Central Bank of Turkey where it was found that the TFSI tracked the CLI very well. The authors also assessed the empirical relationship between financial variables and the real sector by means of an unrestricted vector autoregression (VAR) model. Several measures of economic activity were incorporated and the results indicated that the TFSI was significant in affecting economic activity.

Louzis and Vouldis(2011) created a financial systemic stress index (FSSI) for Greece using market and balance sheet data and applied portfolio theory to aggregate the sub-indices. They estimated the time-varying cross-correlations between sub-indices using both the exponentially-weighted moving average (EWMA)and the Multivariate GARCH Baba, Engle, Kraft and Kroner(BEKK) technique. The results indicated that the FSSI was able to identify crises periods as well as the level of systemic stress in the Greek financial system based mainly on the use of the BEKK technique.

For Jamaica, Morris (2010) created an aggregate financial stability index (AFSI) using banking system data from March 1997 to March 2010. This was done by aggregating microeconomic, macroeconomic and international factors to form a single measure assuming equal weights for each sub-index. Morris (2010) noted that the index was successful in capturing key periods of financial instability during the sample period. She also indicated that the AFSI was sensitive to movements in key macroeconomic indicators. Of great importance is the ability of the AFSI to forecast the future level of financial stability. Using Monte Carlo simulations to provide a one-year ahead forecast of financial stability, Morris (2010) found that the AFSI would deteriorate in the second half of the calendar year 2010 due mainly to the impact of anticipated seasonal increased in the indicator, M2.

The CISS for Jamaica, developed in this paper, utilised market data as it captures the behavior of market participants in response to changes in the underlying economic and other factors. In order to facilitate real-time updating of the CISS, the cumulative distribution function (CDF) was used to transform the variables to provide the necessary robustness for the CISS. This is important as the non-recursive CISS would be subject to structural changes once new information is added. Additionally, the aggregation method utilised was based on portfolio theory since it uses time-varying cross-correlation between sub-indices to determine contemporaneous stress in the financial system. The advantage of this approach is that it allows for the analysis of the joint impact of stress in the market segments. Finally, a VAR model was used to determine the impact of the CISS on economic activity in high and low stress periods as it is important to assess this interaction from a policy perspective.

3.0 Methodology

3.1 *The Composite Indicator of Systemic Stress (CISS)*

3.1.1 Data

Similar to Hollo et al (2010, 2012) the indicators to be included in the market segments were narrowed down based on specific requirements with a few adjustments. First, the CISS is required to measure systemic stress in real time enabling it to be an appropriate short-term policy measure and as such monthly data was used in this paper. Second, the stress indicators represented market-wide developments. The third requirement is that the CISS should be computed using indicators that are comparable for a wide range of countries (both developed and developing). Finally, data for the CISS should be available for appropriate data samples in order to capture relevant episodes of financial stress and business cycles.¹

The stress indicators for each sub-index provide complementary information about the level of stress in the specific market segment. They capture one or more of the symptoms of financial stress. As a result, the indicators should be perfectly correlated only under severe stress levels while at lower levels there should be some differentiation across the components. Each sub-index was restricted to include two stress indicators as it ensured that the sub-index does not possess

¹ Due to data constraints, this paper focused on data following the Jamaican Financial Crisis of the 1990s.

different statistical properties that would arise from an unequal number of indicators. Realised asset return volatilities as well as risk spreads form the basis of the stress indicators for the CISS and are used to capture the main symptoms of financial stress in the various market segments. This is important as asset return volatilities highlight investor uncertainty about the future fundamentals of a particular instrument and about the behavior of other investors (Hollo et al, 2010, 2012).

The markets utilised in this paper are the money market, bond market, equity market and the foreign exchange market.^{2,3} Activity in the *money market* was captured by the volatility in the 30-day private money market rate as well as the interest rate spread. The money market is impacted by rate changes made by the Central Bank which acts as an indication of the authority's perception of the economy. Both indicators reflect liquidity and counterparty risk in the interbank market and as such captures flight-to-quality, flight-to-liquidity and the price impacts of adverse selection problems in heightened stress periods. Measures of *bond market* activity involve the yields on the one year and three year domestic benchmark investment notes (BMIs) offered by the Government of Jamaica. These indicators measure default and liquidity risk premia which also captures flight-to-quality and flight-to-liquidity. Yields increase once investors become more concerned about the Government default risk as well as uncertainty in the market fundamentals. Issues such as Government debt and fiscal sustainability as well as ratings announcements made by international ratings agencies also contribute to movements in BMI yields. Activity in the *equity market* was measured by the maximum cumulated loss over a one-year moving window (CMAX). According to Illing and Liu (2006), this measure is used to determine periods of crisis in international equity markets. Additionally, stress in the equity market is measured by realised volatility of the main Jamaica Stock Exchange (JSE) index which reflects investor uncertainties about microeconomic and macroeconomic issues. Activity in the *foreign exchange market* is measured by the realised volatility of the JMD/USD exchange rate as well as the bid-ask spread.

²Unlike Hollo et al (2012), the financial intermediaries are not isolated as a specific segment given that they are the major players of each of the market segments in Jamaica.

³See Table A.1 in the Appendix.

3.1.2 Transformation of raw indicators

The literature on the aggregation of stress indicators consists of several methodologies for transforming raw indicators into standardised measures. Among them are the empirical normalization utilised by Morris (2010), principal components analysis utilised by Louzis and Vouldis (2011) and the transformation based an empirical cumulative distribution function (CDF) utilised by Hollo, et al (2010, 2012). This paper utilised the empirical CDF based on ordered statistics to facilitate the real-time updating of the CISS. The data set of a raw stress indicators, x_t , can be arranged as $x = (x_1, x_2, \dots, x_n)$ with n the total number of observations in the sample. The ordered sample is denoted $(x_{[1]}, x_{[2]}, \dots, x_{[n]})$ where $(x_{[1]} \leq x_{[2]} \leq \dots \leq x_{[n]})$ and $[r]$ referred to as the ranking number assigned to a particular realization of x_t . The values in the original data set are arranged such that $x_{[n]}$ represents the sample maximum and $x_{[1]}$ represents the sample minimum. The transformed stress indicators $trans_t$ are then computed from the raw stress indicators x_t on the basis of the empirical CDF, $F_n(x_t)$ as follows:

$$trans_t = F_n(x_t) = \begin{cases} \frac{r}{n} & \text{for } x_{[r]} \leq x_t \leq x_{[r+1]}, \quad r = 1, 2, \dots, n-1 \\ 1 & \text{for } x_t \geq x_{[n]} \end{cases} \quad (1)$$

for $t = 1, 2, \dots, n$. The empirical CDF $F_n(x^*)$ measures the total number of observations x_t not exceeding a particular value of x^* (which equals the corresponding ranking number r^*) divided by the total number of observations in the sample (see Spanos 1999). If a value in x occurs more than once, the ranking number assigned to each of the observations is set to the average ranking. The empirical CDF is hence a function which is non-decreasing and piecewise constant with jumps being multiples $1/n$ at the observed points. This results in variables which are unit-free and measured on an ordinal scale with range $(0, 1]$. The quantile transformation of the raw indicators was applied recursively over expanding samples to facilitate the real-time characteristic of the CISS allowing for robustness to new information. This recursion occurs after the period January

2002 and December 2006 resulting in the recalculation of the ordered samples with one new observation added at a time⁴:

$$trans_{n+T} = F_{n+T}(x_{n+T}) = \begin{cases} \frac{r}{n+T} & \text{for } x_{[r]} \leq x_{n+T} \leq x_{[r+1]}, \quad r = 1, 2, \dots, n-1, \dots, n+T-1 \\ 1 & \text{for } x_{n+T} \geq x_{[n+T]} \end{cases} \quad (2)$$

for $T = 1, 2, \dots, N$ with N indicating the end of the full data sample. Once the raw indicators are transformed, the stress factors of each market category ($i = 1, 2, 3, 4$) are finally aggregated into

their respective sub-index by taking their arithmetic average $s_{i,t} = \frac{1}{2} \sum_{j=1}^2 trans_{i,j,t}$. This implies that each of the stress factors is given equal weight in the sub-index reiterating the point that the indicators in each sub-index provide complementary information. The difference between the recursive transformation of the raw stress indicators and the non-recursive transformation based on the full sample is generally small.⁵

3.1.3 Aggregation of sub-indices

Once the indicators have been transformed and each sub-index created, the aggregation of the four sub-indices is based on portfolio theory which takes into account the cross-correlations between individual asset returns (Hollo, et al, 2010, 2012 and Louzis and Vouldis, 2011). The aggregation of prices/returns on highly correlated risky assets results in an increase in the total portfolio risk as all asset prices tend to move in the same direction. In other words, a high degree of correlation aggravates systemic risk implying that the CISS puts more weight on situations in which high stress prevails in several market segments at the same time. On the other hand, when the correlation between asset prices is low the risk is reduced. The CISS is continuous, unit-free and bounded by the half-open interval (0,1] with all the properties of the individual stress factors and is computed as follows:

$$CISS_t = \sqrt{(w \circ s_t) C_t (w \circ s_t)'} \quad (3)$$

⁴The money market data begins at February 2002 while bond market data begins February 2005.

⁵See Figure A.1 in the Appendix

with $w = (w_1, w_2, w_3, w_4)$ representing the vector of sub-index weights, $s_t = (s_{1,t}, s_{2,t}, s_{3,t}, s_{4,t})$ represents the sub-indices, and $w \circ s_t$ represents the Hadamard-product (element by element multiplication of vector of sub-index weights and the vector of sub-index values in time t). C_t is the matrix of time varying cross-correlation coefficients $\rho_{ij,t}$ between sub-indices i and j :

$$C_t = \begin{pmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \rho_{14,t} \\ \rho_{12,t} & 1 & \rho_{23,t} & \rho_{24,t} \\ \rho_{13,t} & \rho_{23,t} & 1 & \rho_{34,t} \\ \rho_{14,t} & \rho_{24,t} & \rho_{34,t} & 1 \end{pmatrix} \quad (4)$$

The time-varying cross-correlations $\rho_{ij,t}$ are estimated recursively on the basis of exponentially-weighted moving average (EWMA) of respective covariance $\sigma_{ij,t}$ and volatilities $\sigma^2_{i,t}$ as approximated by the following formulas⁶:

$$\begin{aligned} \sigma_{ij,t} &= \lambda \sigma_{ij,t-1} + (1-\lambda) \tilde{s}_{i,t} \tilde{s}_{j,t} \\ \sigma^2_{i,t} &= \lambda \sigma^2_{i,t-1} + (1-\lambda) \tilde{s}^2_{i,t} \\ \rho_{ij,t} &= \sigma_{ij,t} / \sigma_{i,t} \sigma_{j,t} \end{aligned} \quad (5)$$

where $i = 1, \dots, 4$, $j = 1, \dots, 4$, $i \neq j$, $t = 1, \dots, T$ with $\tilde{s}_{i,t} = (s_{i,t} - \bar{s})$ representing the demeaned sub-indices obtained by subtracting the mean from each indicator. The decay factor or smoothing parameter λ is held constant through time at 0.93 while the covariances and volatilities are initialised for $t = 0$, i.e. January 2002. According to Hollo (2010, 2012), the cross-correlations indicate that the historical ranking of the stress level in two market segments is similar at a point in time. This is in contrast to the cross-correlations as used in Value-at-Risk (VaR) models which utilise them as economic predictions of correlation risk.

3.2 *Threshold vector autoregression (TVAR)*

An analysis was conducted to determine the impact of systemic stress on real GDP growth. The literature presents methodologies based on threshold levels for financial stress indexes which can be determined using two main methodologies, the historical benchmarking approach and by the

⁶See Figure A.2 in the Appendix.

use of statistical or econometric models. The historical benchmarking approach involves benchmarking the current level of stress against levels observed in history that caused significant disruptions to financial intermediation and economic activity (Hollo et al, 2010, 2012). With regard to the latter approach, some econometric models make the assumption of normality utilising the mean and standard deviations where a threshold is reached when the historical mean is exceeded. However, in practice, the normality assumption does not hold for the CISS and as such this paper employs an econometric model that tests the interactions with the real sector to endogenously determine periods of extreme stress.⁷ According to Hanson (2000), multiple equilibria may exist when modeling the financial system and the real sector which depend on whether the economy is in a state of high or low stress. This may reflect the interaction between externalities, asymmetry of information and certain special features of the financial sector such as illiquid assets and maturity mismatches. These factors can lead to powerful feedback and amplification mechanisms driving the system from a state of relative tranquility to a state of turmoil (Trichet 2011).

In light of the above, a threshold vector autoregression (TVAR) was developed to model the interactions of the CISS with the real economy. This method assumes regime switching where state transitions are triggered when an observed variable crosses a certain threshold. The threshold value was estimated from the data where the CISS was used as the threshold variable. Based on the model, economic activity is expected to be significantly lower when the CISS is at or above the estimated threshold (high-stress regime) than when it is below the threshold (low stress regime). The TVAR used in this paper utilised quarterly real GDP growth rate interpolated into monthly data by way of the quadratic matched average method in Eviews. The model is as follows:

$$\begin{aligned}
 X_t &= c^H + \sum_{i=1}^p \Psi_i^H X_{t-i} + e_t^H && \text{if } CISS_{t-d} \geq \delta \quad (\text{high-stress regime}) \\
 X_t &= c^L + \sum_{i=1}^p \Psi_i^L X_{t-i} + e_t^L && \text{if } CISS_{t-d} < \delta \quad (\text{low-stress regime})
 \end{aligned} \tag{6}$$

⁷See Hollo et al (2012) for disadvantages of the normality assumption.

where $X_t = (GDP_t, CISS_t)'$ represents the vector of endogenous variables real GDP growth and the CISS, respectively, c^s, Ψ_i^s the vector of intercepts and the two matrices of slope coefficients for states $s = H, L$ and lags $i = 1, \dots, p$. $CISS_{t-d}$ is the threshold variable with $d = d_0$ representing the maximum threshold lag or delay foreseen. The threshold parameter is δ and the vector e_t^s contains state-dependent regression errors with variance-covariance matrices $\sum_{s=H,L}$.

The first step involved testing for linearity in the VAR versus the alternative hypothesis that the VAR follows a threshold model. A generalization of the model in (6) is as follows:

$$X_t = c^s + \sum_{i=1}^p \Psi_i^s X_{t-i} + e_t^s \quad (7)$$

Tsay (1989, 1998, 2005) proposed the use of an arranged autoregression and recursive estimation to determine the alternative test for the threshold nonlinearity. The arranged autoregression transforms the model into a change-point problem and employs predictive residuals to construct test statistics that do not involve undefined parameters. The TVAR indicates two linear models depending on whether $CISS_{t-d} \geq \delta$ or $CISS_{t-d} < \delta$ (see **Equation 6**). For a realization $\{CISS_t\}_{t=1}^T$, $CISS_{t-d}$ can assume values $(CISS_1, CISS_2, \dots, CISS_{T-d})$. Let $(CISS_{[1]} \leq CISS_{[2]} \leq \dots \leq CISS_{[T-d]})$ be the ordered statistics of $\{CISS_t\}_{t=1}^{T-d}$ (i.e. arranging the observations in increasing order). The model can be written as:

$$X_{(j)+d} = \beta_0 + \sum_{i=1}^p \beta_i X_{(j)+d-i} + a_{(j)+d}, \quad j = 1, 2, \dots, T-d \quad (8)$$

where $\beta_i = \Psi_i^H$ if $CISS_{t-d} \geq \delta$ and $\beta_i = \Psi_i^L$ if $CISS_{t-d} < \delta$. The threshold is a change point for the linear regression which is referred to as an arranged autoregression in increasing order of the threshold variable, $CISS_{t-d}$ (see **Equation 8**). It is important to note that the dynamics of the series does not alter the dependence of X_t on X_{t-i} for $i = 1, \dots, p$ because $X_{(j)+d}$ still depends on

$X_{(j)+d-i}$. This ensures that the equation with the smaller $CISS_{t-d}$ appears before that with a larger $CISS_{t-d}$.

To detect changes in the model, the predictive residuals and the recursive least squares method are utilised (see **Equation 8**). If X_t is linear, then the recursive least square estimator of the arranged regression is consistent so that the predictive residuals approach white noise (see equation 8). In this case the predictive residuals are uncorrelated with the regressors. However, if X_t follows a threshold model, the predictive residuals would no longer be white noise because the least squares estimator is biased. This indicates that the predictive residuals would be correlated with the regressors.⁸ The predictive residuals and the standardised predictive residuals are derived from a recursive estimation of equation (8) followed by an estimation of the regression of the standardised residuals on $X_{(j)+d-i}$.

$$\hat{e}_{(m+j)+d} = \alpha_0 + \sum_{i=1}^p \alpha_i X_{(m+j)+d-i} + v_t \quad , j = 1, \dots, T-d-m \quad (9)$$

The $C(d)$ statistic was used to test $H_0: \alpha_i = 0$ in (9) for $i=0, \dots, p$. Under the null hypothesis that X_t follows a linear $AR(p)$ model, the $C(d)$ statistic is an asymptotically chi-square random variable with $(pk^2 + k)$ degrees of freedom. In other words, the null hypothesis specifies no model change in the arranged autoregression so that the standardised predictive residuals should be close to *iid* with mean zero and variance (see **Equation 8**). Based on a given p , the arranged regression is estimated for values of $d \leq p$ and the d which gives the most significant $C(d)$ is selected. Finally, to determine the threshold value the ordered VAR is divided into two regimes according to empirical percentiles of $CISS_{t-d}$ and two linear models estimated. The value of the CISS which minimizes the AIC is chosen as the threshold value.⁹

⁸For more information on the Threshold VAR see Tsay (1998, 2005).

⁹The starting point for the threshold values of the CISS, δ , was determined by fitting the ordered full CISS to the LogLogistic distribution using the @Risk software and taking the 95th percentile. This indicated a starting value of 0.585 for the threshold variable. See Figure A.3 in the Appendix.

3.3 Forecast Model

It is important to assess the future relationship between the recursive CISS and real economic activity as it allows for timely action by the authorities to counter the possible effects if needed. This was done by way of Monte Carlo simulations which first involved ordinary least squares analysis to determine the response of the CISS to select macroeconomic variables. The OLS regression included the fourth lag of the growth in $m2$ as measure of the level of liquidity in the financial system, the fourth lag of the inflation rate, inf , as price instability would lead to a deterioration of market confidence and hence the level of stress in the financial markets as well as the historical values of the CISS (see **Equation 10**).

$$CISS_t = c + \alpha * m2_{t-4} + \beta * inf_{t-4} + \gamma * CISS_{t-1} + \varepsilon_t \quad (10)$$

Once the regression is fitted, historical values of the *CISS*, *m2* and *inflation* were used to derive the forecast for the CISS from July 2012 to June 2013 using Monte Carlo simulations (10 000 iterations).

4.0 Results

4.1 The Composite Indicator of Systemic Stress (CISS)

The construction of the CISS was done both recursively and non-recursively over the sample period January 2002 to June 2012 using data from four financial markets. Although there was some variation in the empirical CDF for the recursive plot of the indicators compared to the non-recursive plot, both the recursive and non-recursive CISS were able to capture the heightened stress period in the Jamaican financial system. The CISS was also assessed with and without the bond market where it was found that the recursive CISS was marginally larger than the non-recursive CISS in both cases (see **Figures 1 and 2**).¹⁰The heightened financial market stress period between 2002 and 2003 was characterised by high interest rates, wide money market spreads, equity market volatility as well as significant depreciation in the exchange

¹⁰The bond market was excluded due mainly to the unavailability of data for the period prior to February 2005.

rate.¹¹ Additionally, the CISS was able to reflect the stress in the financial system between 2008 and early 2010 reflecting the effects of the global financial crises. This was evidenced by a greater pace of depreciation in the exchange rate, high bid-ask spreads in the foreign exchange market as well as significant increases in the GOJ BMI bond yield relative to the period 2002 to 2003.

Figure 1: Recursive and non-recursive CISS

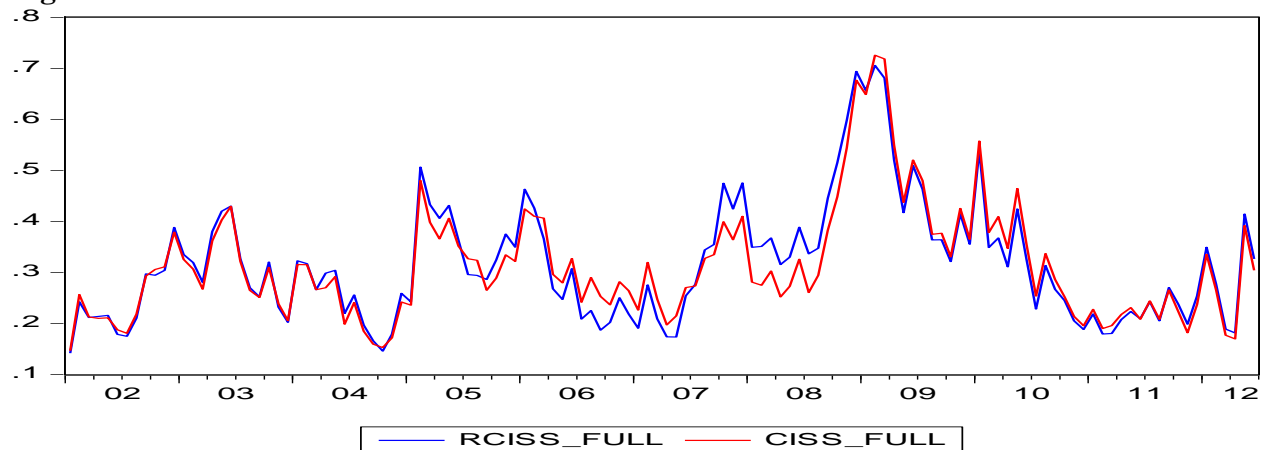
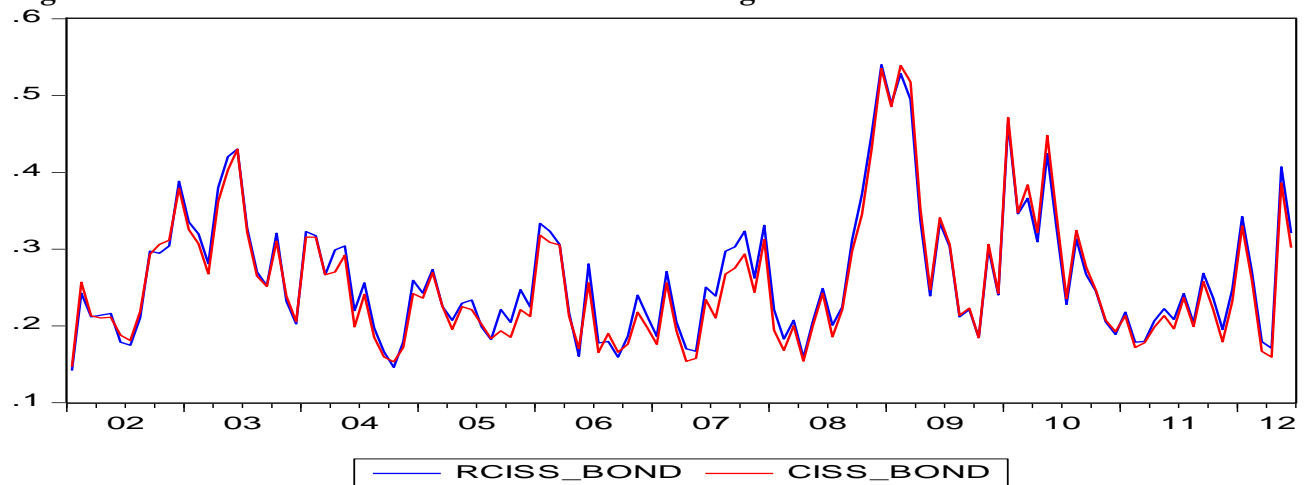


Figure 2: Recursive and non-recursive CISS excluding the bond market



4.2 Threshold vector autoregression (TVAR)

¹¹See Figures A.4 and A.5 in the Appendix.

For the purpose of this paper, the recursive full CISS was utilised based on the impact of the bond market on the overall financial system which is reflected in the heavy exposure to GOJ issued debt by market players. As stated in Section 4.1, the recursive CISS (referred hereafter as the CISS) performed well in highlighting the periods of financial stress in the Jamaican financial system. Unit root tests were conducted for both real GDP growth and the CISS to determine the order of integration. The results from each test revealed both variables to be stationary (see **Table 1**). Additionally, scatter plots of the CISS and real GDP growth reveal that lower growth rates were associated with higher values of the CISS.¹²

Table 1: ADF Unit Root tests

	RGDP	CISS
t-Statistic	-2.58605	-3.725410
P-Value	0.0990*	0.0242**

*Notes: *, **, *** indicates significance at the 10%, 5% and 1% level of significance, respectively.*

The TVAR model was unable to determine the threshold value for the CISS due to the limited number of observations above the 95th percentile. To overcome this drawback of the dataset, an alternative TVAR was employed to separate the data into two regimes. Regime 1 represented the period between January 2002 and December 2006 with an average CISS value of 0.29 and volatility of 0.09. This captured the period following the financial crisis of the 1990s in Jamaica which was characterised by the exchange rate and interest rate volatility as well as equity market losses in the earlier part of the period. On the other hand, regime 2 represented the period January 2007 to June 2012 with an average CISS value of 0.34 and volatility of 0.14. This was characterised by the global financial crisis and the second-round impact on the Jamaican economy which included interest rate volatility, significant exchange rate shocks relative to regime 1, as well as significant increases in bond yields. The CISS and real economic activity were positively correlated with a coefficient of 0.12 in regime 1 and negatively correlated with a coefficient of -0.71 in regime 2.¹³

¹²See Figure A.6 in the Appendix.

¹³See Figure A.7 in the Appendix.

A VAR model was estimated for both regimes and the granger causality tests, impulse response functions and variance decomposition analysed.¹⁴Granger causality tests for regime 1 revealed no granger causality between the CISS and real GDP growth, however, for regime 2 the CISS was found to Granger cause real GDP growth (see **Table 2**). The results indicate that for regime 2, past periods of systemic stress are better able to predict past periods of economic activity than past periods of economic activity alone.

Table 2: Granger Causality Test Results

	Low		High	
	Chi-sq	p-value	Chi-sq	p-value
CISS →RGDP	0.420229	0.8105	41.78108	0.0000*
RGDP→ CISS	1.191723	0.5511	5.942491	0.2035

*Notes : *, **, *** indicates significance at the 10%, 5% and 1% level of significance, respectively.*

Impulse response functions(IRF) trace out the effects of any shocks to the CISS variable on real GDP growth during both regimes.¹⁵ From the IRFs of regime 1, the effect of a one standard deviation (s.d) shock to the lagged CISS in regime 1 increases real GDP after 3 months then dies out after approximately 17 months.From the IRFs of regime 2, a one s.d. shock to the lagged CISS reduces GDP significantly relative to regime 1, where the same shock increased GDP. This impact in regime 2 gradually dies out after approximately 40 periods highlighting the significant impact of financial stress in the Jamaican financial system on economic activity in regime 2, the second round effect of the global crisis. The results indicate a distinct difference in the Jamaican economy between the two regimes with higher periods of financial stress persisting for a longer period. It also highlights the correlations observed in both regimes for the variables.

The variance decomposition, which captures the relative importance of each innovation towards explaining the behavior of endogenous variables, confirms the results of the IRFs as well as the graph of both variables. For regime 1, on average 97.0 per cent of the innovations for GDP were explained by itself while an average of 96.0 per cent of the innovations in the CISS were explained by itself. The results for regime 2 were markedly different as on average 71.0 per cent

¹⁴Lag length specification tests based on the Schwartz criterion indicated lag length of 2 for regime 1 and 4 for regime 2.

¹⁵See Figures A.8 to A.9 in the Appendix.

of the innovations in GDP were explained by the CISS compared to 93.0 per cent of the innovations of the CISS being explained by itself. Overall, in periods of high stress (regime 2), economic activity is significantly impacted by the stress in the financial system.

4.3 Forecast Model

Given the impact of financial stress on real GDP growth in Jamaica, this paper sought to forecast the CISS as well as its impact on growth. After running the OLS regression, the historical values of the independent variables, M2 growth and inflation series, were fitted with a distribution function.¹⁶ These fitted distributions as well as the correlation between both series were inputs in the Monte Carlo simulation (10 000 iterations) to provide a one-year forecast for the CISS to June 2013. This was used alongside interpolated values of quarterly forecasted real GDP growth.¹⁷ The forecasts revealed that the CISS would generally improve over the forecast period (see **Figure3**). A VAR model was then utilised to assess the relationship of the forecasted CISS and the forecasted GDP growth to determine the impact of the future CISS on future GDP growth.¹⁸ The results from the IRFs indicate that a one standard deviation shock to the CISS would reduce GDP after approximately 5 periods before dying out after 23 periods.¹⁹

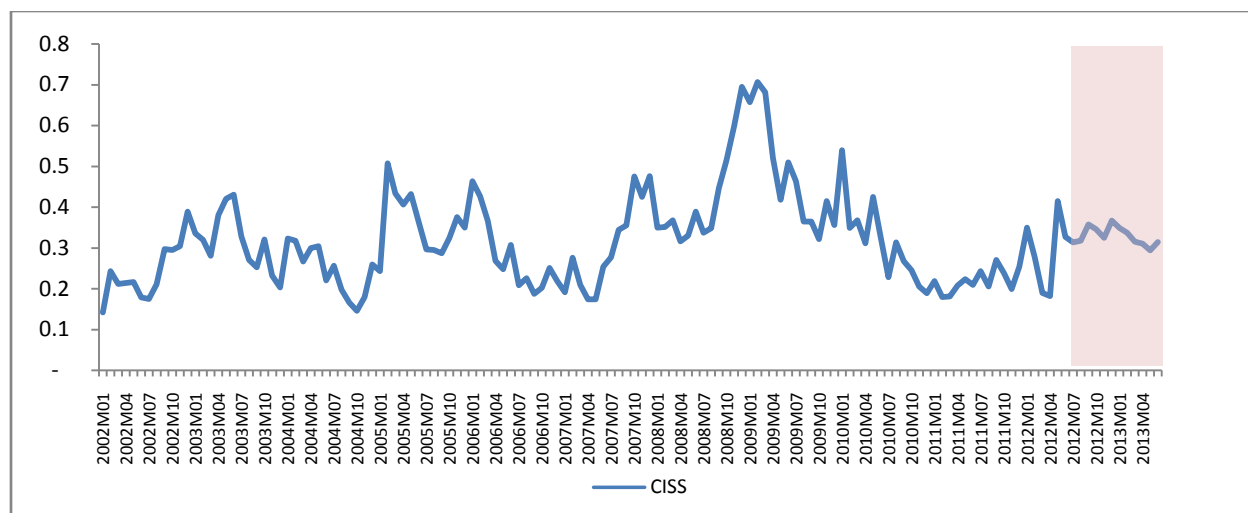
Figure3:One-Year AheadMonte Carlo Forecast of the CISS

¹⁶See Appendix Table A.2 for the results from the OLS estimation.

¹⁷Quarterly real GDP growth forecasts were as at October 9, 2012 and reflected the period September 2012 to June 2013.

¹⁸ The VAR model utilised data from January 2010 to June 2014 reflecting the most recent past. Lag length specification tests based on the Schwartz criterion indicated lag length of 1.

¹⁹See Figure A.10 in the Appendix.



5.0 Conclusion and Policy Implications

This paper introduced a Composite Indicator of Systemic Stress (CISS) to assess systemic risk for the financial markets in Jamaica using the methodology similar to Hollo, et al (2010, 2012). It involved the aggregation of sub-indices from the foreign exchange market, equity market, money market and bond market from January 2002 to June 2012. Basic portfolio theory was used to determine contemporaneous stress in the financial system by taking into account the time-varying cross-correlation between sub-indices. Both the recursive and non-recursive CISS indexes were able to identify known periods of stress in the Jamaican financial system. The recursive characteristic of the CISS facilitates real-time updates which allows for expedient actions by the authorities in response to signals from the financial markets. As a macro-prudential policy instrument of the Bank of Jamaica, the CISS would also enable the Bank to adequately identify the specific factors influencing systemic stress.

Of equal importance is the impact of systemic stress on real economic activity. Separating the data into two distinct regimes indicated a greater impact of the CISS on real GDP growth in regime 2 relative to regime 1. Notably, the shock to the CISS persists in the economy until about 40 periods, the equivalent of three years, before dying out. Additionally, Granger causality was found between the CISS and real GDP growth in regime 2 indicating that the CISS could be used

as a leading indicator for economic growth. In light of this, forecasts were derived for the CISS and the impact on future values of GDP was determined. The results from this estimation revealed that the pro-cyclical relationship between systemic stress and GDP would continue over a one-year period.

Although the CISS incorporates equal weighting for each market, further work could be done to explore the impact of various market weights on the CISS. Additionally, alternative methods of recursively estimating the variances and covariances could be utilised to construct the time-varying correlation matrix.

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APPENDIX

Appendix A

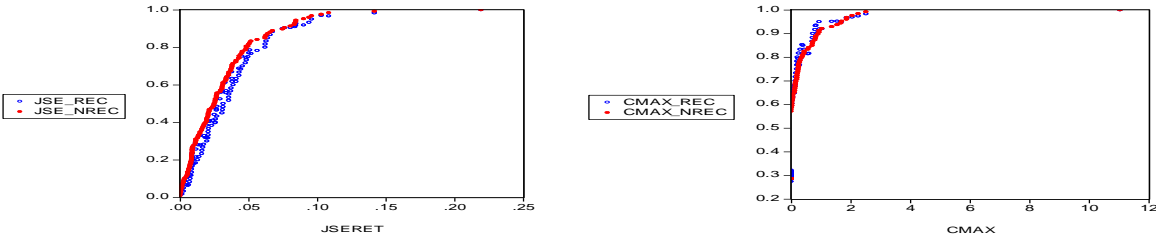
Table A.1: Market Indicators

Market Segment	Indicator
Money Market	<ul style="list-style-type: none">❖ Realised volatility of the 30 day private market rate (weekly average of daily rate changes)❖ Interest rate spread between the equivalent 180-day private money market rate (based on 30-day private money market rate) and the 180-day treasury bill rate
Bond Market	<ul style="list-style-type: none">❖ Realised volatility of domestic GOJ bond with one year to maturity (monthly average of absolute daily yields)❖ Realised volatility of domestic GOJ bond with three years to maturity (monthly average of absolute daily yields)

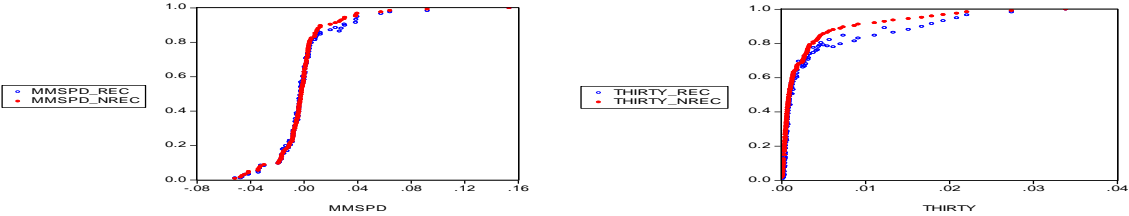
<p>Equity Market</p>	<ul style="list-style-type: none"> ❖ Realised volatility of the main JSE index (absolute monthly log index returns) ❖ CMAX of the main JSE index (maximum cumulated index losses over a moving 1-year window)
<p>Foreign Exchange Market</p>	<ul style="list-style-type: none"> ❖ Realised Volatility of JMD/USD (absolute monthly log of foreign exchange returns) ❖ Bid-Ask Spread (monthly foreign exchange bid-ask spread)

Figure A.1 Transformation of raw stress indicators – recursively and non-recursively

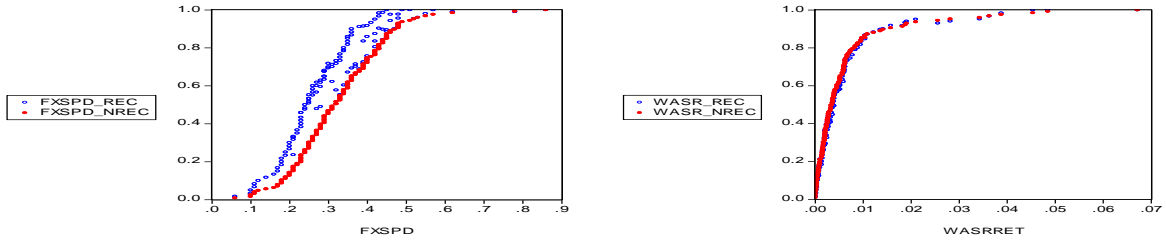
Equity Market



Money Market



Foreign Exchange Market



Bond Market

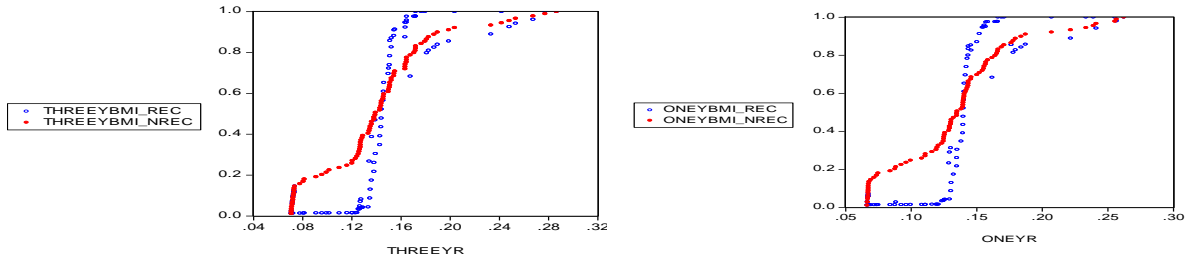


Figure A.2: Time-varying Cross-Correlations of each financial market pair

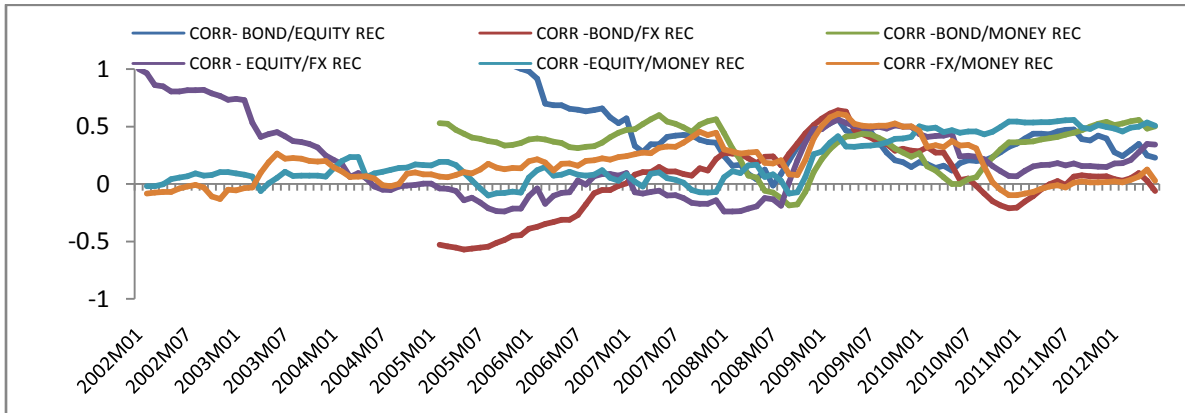


Figure A.3 LogLogistic distribution fit for the CISS

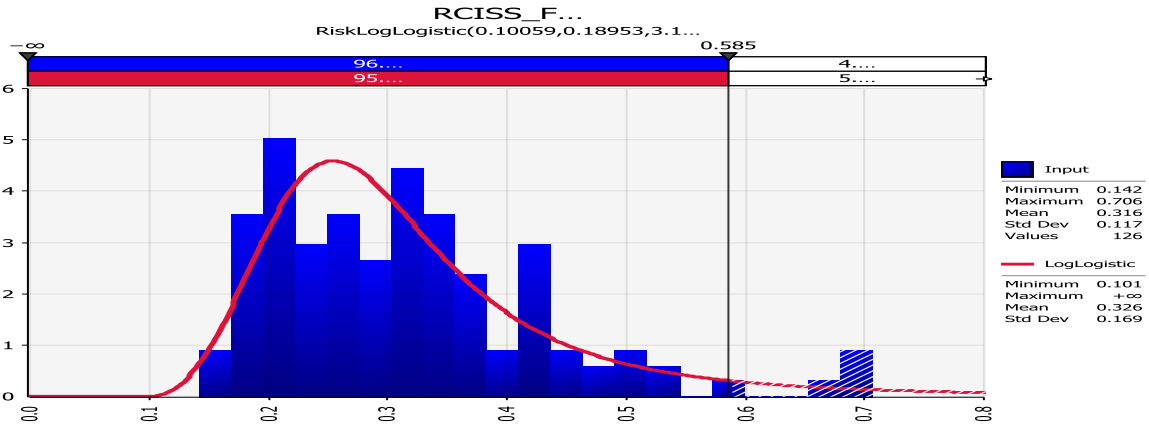


Figure A.4: Financial Markets and full recursive CISS

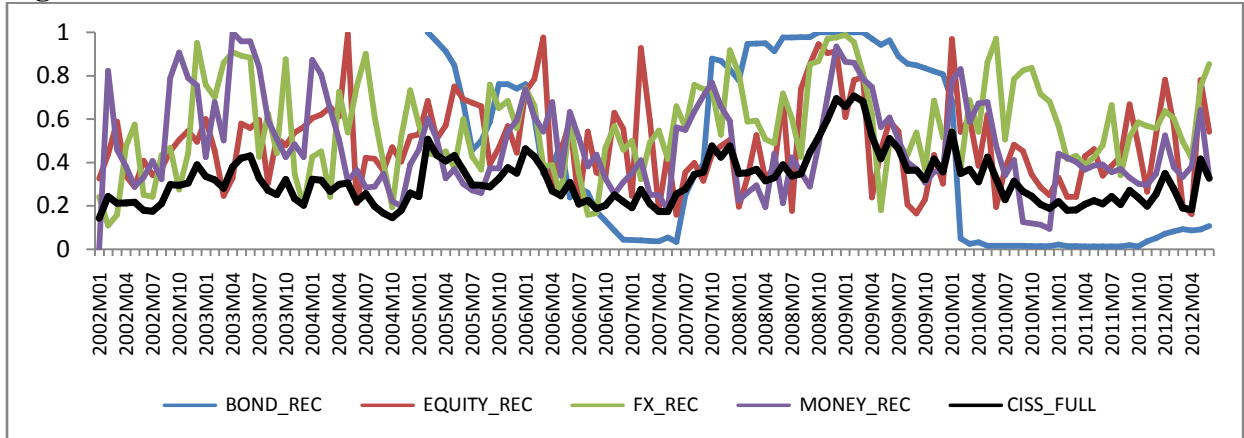


Figure A.5: Financial Markets and full recursive CISS without bond market

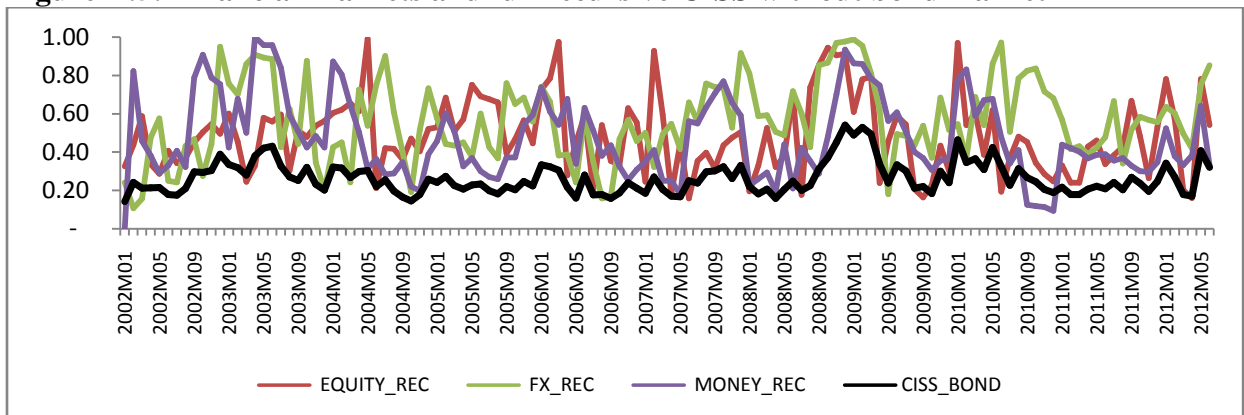


Figure A.6 Scatter plot of the CISS and real GDP growth

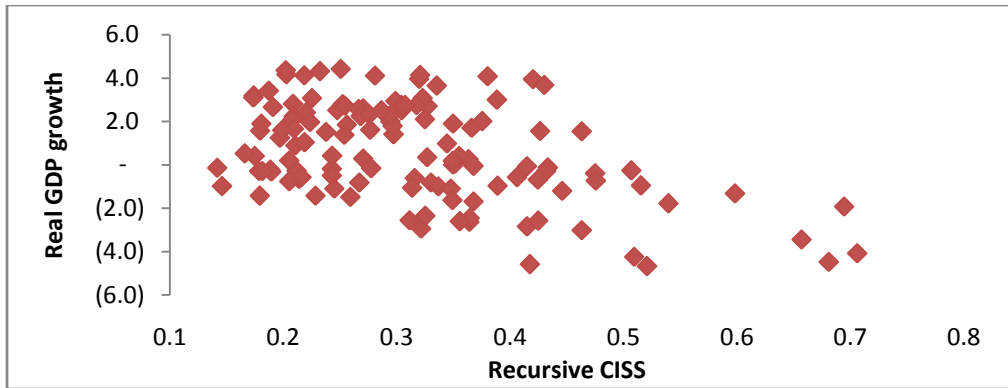
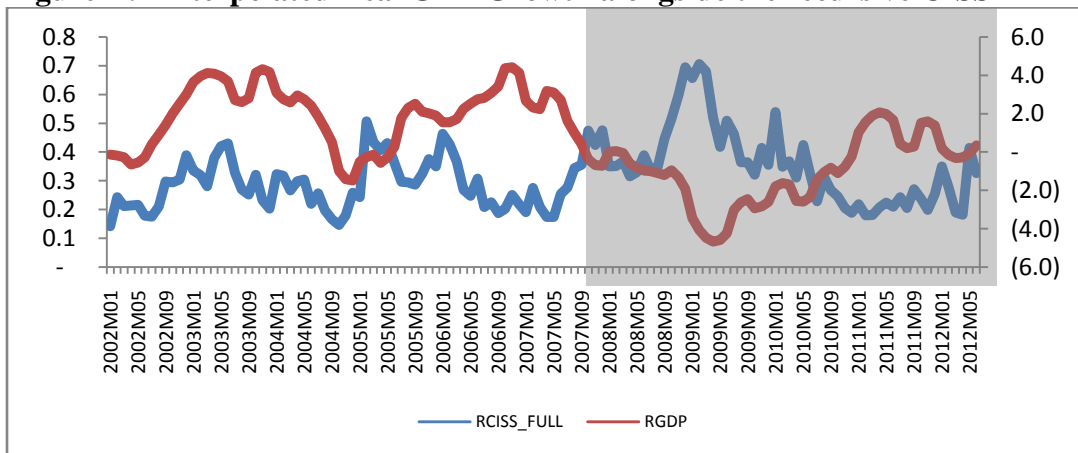


Figure A.7 Interpolated Real GDP Growth alongside the recursive CISS



Notes: The white region represents regime 1 while the shaded region represents regime 2.

Figure A.8 Impulse Response of lagged GDP to a one s.d. shock to the CISS under regime 1

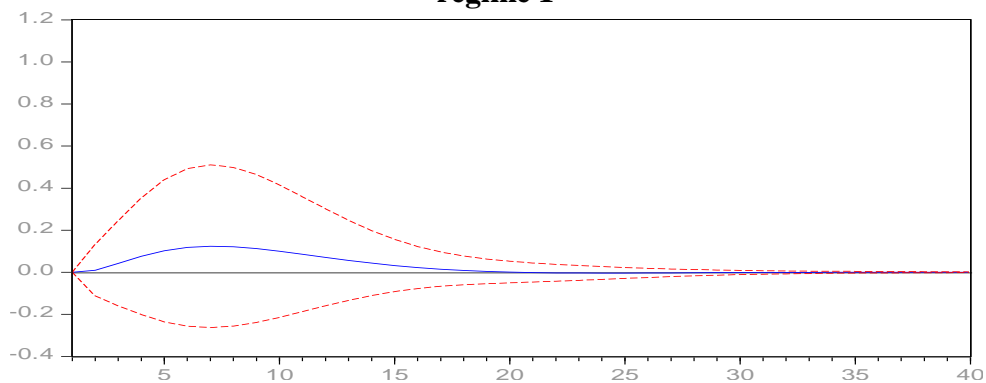


Figure A.9 Impulse Response of lagged GDP to a one s.d. shock to the CISS under regime 2

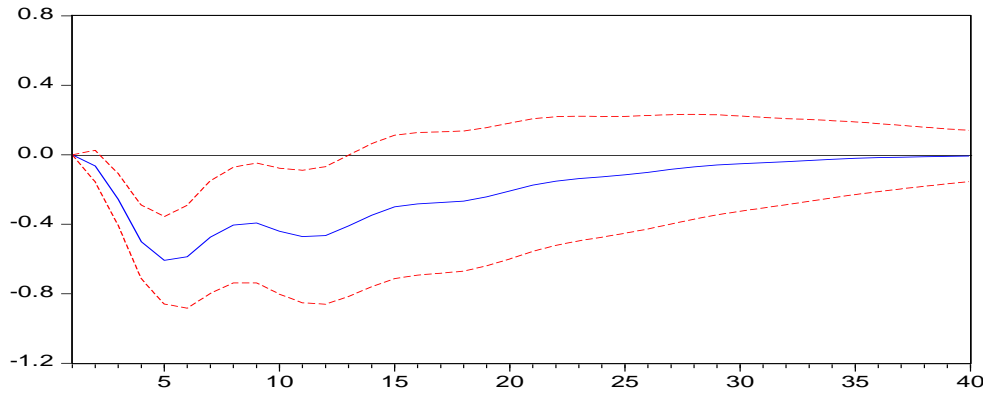


Figure A.10 Impulse Response of lagged GDP to a one s.d. shock to the CISS with forecasted data

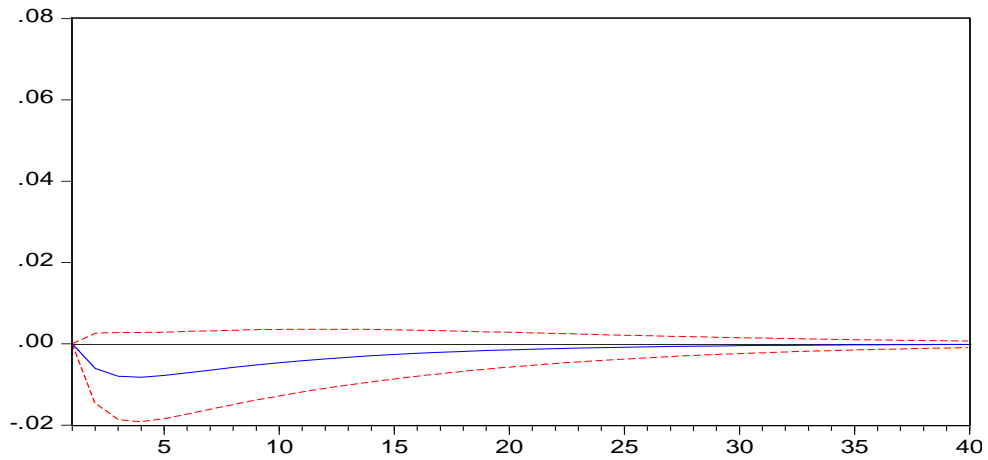


Table A.2 OLS Regression Results

$$CISS_t = c + \alpha * m2_{t-4} + \beta * inf_{t-4} + \gamma * CISS_{t-1} + \varepsilon_t$$

Variables	Constant	$CISS_{t-1}$	$m2_{t-4}$	inf_{t-4}
Coefficients	0.043758	0.734449	-0.006941	0.004023
P-Value	0.0326**	0.0000***	0.0639*	0.0102**

Notes: *, **,*** indicates significance at the 10%,5% and 1% level of significance, respectively.