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Measuring Systemic Risk:
A Single Aggregate Measure of Financial System Stability for Jamaica

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ABSTRACT

Systemic risk measurement lies at the very core of building financial system resilience to crisis. This paper presents a set of key systemic risk indexes (SRIs) used by the Bank of Jamaica to monitor financial stability and further consolidates them into a single, more informative, aggregate measure of systemic risk. These SRIs incorporate diverse variables which give emphasis to different components and dimensions of the financial system. Against the background of varying origins of financial stress in Jamaica, this paper evaluates the ability of the single aggregate measure (SAM) of systemic risk to foretell important macro-financial 'tail' events over a thirteen-year historical period. Review of the performance of this combined index in the capture of historical periods of financial system stress supports its use for macro-prudential policy purposes.

JEL classification numbers: E58; F30; G21
Keywords: Jamaica; Systemic Risk; Macro-prudential; Financial Crises

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1. Introduction

Central banks around the world have responded to the lessons from the global financial crisis through extensive financial stability policy reform. As a complement to micro-prudential supervision, these authorities are establishing an entirely new and separate macro-prudential policy channel with appropriate objectives, powers and dedicated tools capable of delivering policy response in limiting systemic, or system-wide, financial risk. As a central part of this reform, there has been a concerted effort of central banks to produce systemic risk indicators (SRIs) to measure and monitor the materialization of instability in their financial systems, and to mitigate the potential negative impact of shocks on the financial system components including damage to the economy. This modernized financial stability policy approach is designed to focus on the financial system as a whole – comprising financial institutions, financial markets and financial infrastructure – as opposed to just individual institutions or components, and the interconnection between households, firms, public sector and the financial system.

Systemic risk measurement lies at the very core of macro-prudential oversight. However, systemic risk is inherently difficult to measure so it is divided for operational purposes into two inter-related components or dimensions defined in the form of intermediate objectives – cyclical or time dimension and structural or cross-sectional dimension (see Borio, 2010 and Caruana, 2010). Both dimensions of risk require specific macro-prudential policy responses or regulations. The cyclical dimension deals with the evolution of aggregate risk in the financial system over the financial cycle, referred to as "procyclicality". This dimension concerns the collective tendency of financial agents to assume excessive risk in the financial upswing due to over-optimism ("risk illusion"), reflected in excessive leverage or maturity transformation and then to become overly risk averse resulting in illiquidity, higher correlations and loss of confidence in asset markets during the downswing (the "feast or famine" problem). The structural dimension is related to the distribution of risk across the financial system at a given point in time and is based on common exposures, systemic importance, misaligned incentives and the interconnectedness of financial institutions, as well as enhancing the system's capacity to weather shocks while continuing to provide essential financial services. Notwithstanding this categorisation of systemic risk, these two dimensions are not disconnected but may evolve jointly and accentuate each other over time.

In its conduct of macro-prudential surveillance, the Bank of Jamaica (BOJ) utilizes several analytic indicators which combine balance sheet positions, macro-prudential risk factors and macroeconomic data. These include: indicators based purely on balance sheet

data, such as FSIs; fundamentals-based models which rely on both macroeconomic data and balance sheet data to help assess macro-financial linkages, such as non-parametric signal-extraction approaches and regression-based approaches; market-based models help assess emerging risks from high-frequency market data and are thus suitable for tracking rapidly-changing market conditions, and; structural models that rely on balance sheet data and market data to estimate the impact of shocks on default probabilities. However, these SRIs incorporate diverse variables which give emphasis to different components and dimensions of the financial system. Hence may not be highly correlated during all historical periods of high instability due to narrow overlap of risk sub-dimensions. Against the background of alternative causes of financial stress in Jamaica, it is important to combine core SRIs in a single aggregate measure (SAM) of systemic risk in the conduct on macro-prudential surveillance.

Constructing a single composite indicator of financial stress based on the development of different segments of the financial system, highlights the importance of incorporating information on systemic risk emanating from various segments of the system to the overall financial stability assessment. As discussed earlier, the SRIs already encompass an aggregation of underlying variables by utilizing various statistical techniques. Importantly, the set of underlying variables for each SRI are affiliated with one of the two dimensions of systemic risk.

This paper presents a set of core SRIs used by the BOJ to monitor financial stability and further consolidates them into a single, more informative, proxy for systemic risk. The paper applies a higher level of systemic risk aggregation that synthesises information across times series and cross-sectional SRIs into a single proxy based on Principal Component Analysis (PCA).

Before aggregation, it is necessary to transform the SRIs to a common scale. The approach adopted in this paper is similar to Holló *et al*. (2012) in transforming each SRI to percentiles based on their sample cumulative distribution functions (CDFs) to make them comparable. Lower percentiles correspond to the smaller values, which are associated with lower levels of stress. After the SRIs are transformed to a common scale, this paper follows the recommendation by Hatzius *et al*. (2010) that indexes of financial stress should measure exogenous information in financial shocks and not reflect the endogenous component of past economic cycles captured by the feedback from current and lagged macroeconomic conditions. Specifically, the core SRIs are purged of fluctuations related to business cycle or monetary policy influences to make the SRIs more representative of the shocks to the

financial system. The primary factors from residuals acquired after the removal of the endogenous component from the SRI series are extracted by means of PCA. The percentage variation explained by these factors are then used to construct a single proxy for systemic risk represented as a weighted average of the primary factors. Section 2 of this paper presents the SRIs currently monitored by the BOJ. The empirical methodology for constructing the SAM is described in section 3. Discussions on the process of constructing the SAM and juxtaposing the SAM with historical stressful event periods for Jamaica is detailed in sections 4 and 5, respectively. Section 6 identifies the stressful event thresholds associate with the SAM and section 7 concludes.

2. Selection and Discussion of SRIs

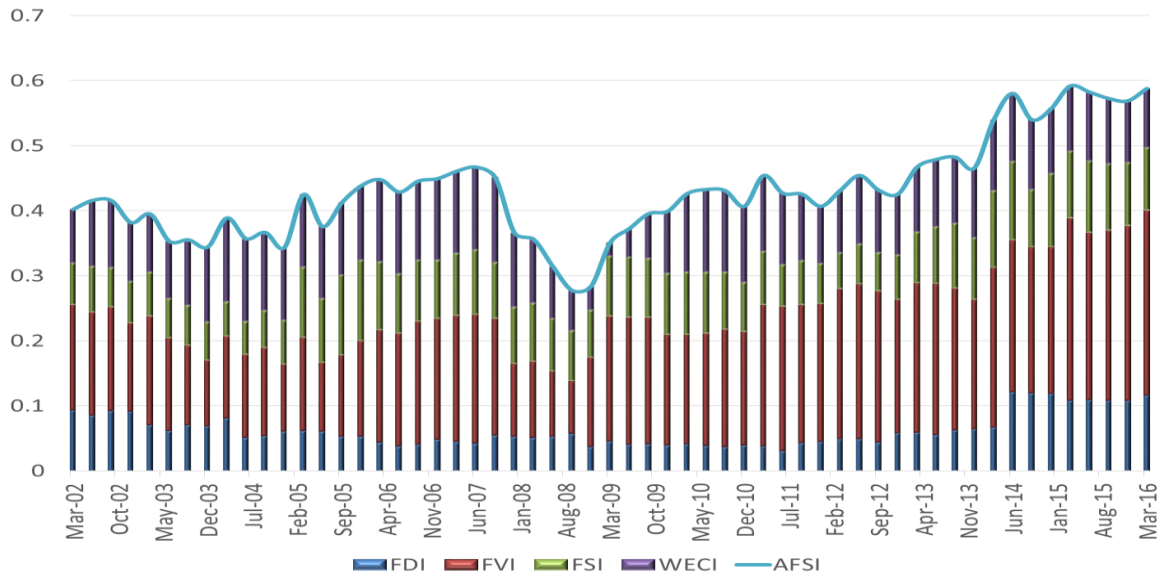
In order to construct a single composite indicator of financial stress, it is important to identify the underlying SRIs that capture important information across both time and cross-section dimensions of systemic risk. This section provides a synopsis of SRIs that are monitored by BOJ to assess both systemic risk dimensions for Jamaica's financial system. The SRIs used in the Bank's surveillance of the time dimension of systemic risk include: Aggregate Financial Stability Index (AFSI); Banking Stability Index (BSI); Credit-to-GDP 'Gap' Indicator and; Micro-Prudential and Macro-Financial 'Signal Extraction' Indices. Structural-type SRIs monitored by the Bank include: Composite Indicator of Systemic Risk (CISS), Contingent Claims Analysis (CCA), and; Absorption Ratio (AR). Information captured in the SRIs cover a broad set of vulnerabilities that have occurred across key local and global financial markets as well as major local financial institutions and financial sector participant groups. In the context of data availability, there are varied starting dates across the SRIs resulting in an unbalanced panel data set for estimation of the SAM.

2.1 Aggregate Financial Stability Index

The Aggregate Financial Stability Index (AFSI) monitored by the BOJ is computed as a weighted average of normalized balance sheet and macroeconomic partial indicators (including international factors) to indicate the level of stability of the financial system (see Albulescu (2010). The AFSI represents a single comprehensive measure of financial stability comprised of various variables reflective of different aspects of the macro-financial environment wherein an increase in value means an improvement in financial stability and a decrease means deterioration. These variables are grouped into four sub-indexes capturing financial development (FDI), financial vulnerability (FVI), financial soundness (FSI), as well

as the world's economic climate (WECI). Each variable is normalized using an empirical standardization technique in order to attain the same variance (ie variance-equal weighting scheme). Sub-indexes are calculated based on the equal weights approach by multiplying each variable by pre-determined weights. Arithmetic averages of the variables are taken to determine the values for the relevant sub-indexes. Lastly, the ASFI is computed by taking the sum of all the weighted variables using an econometric estimation approach to determine the weights.

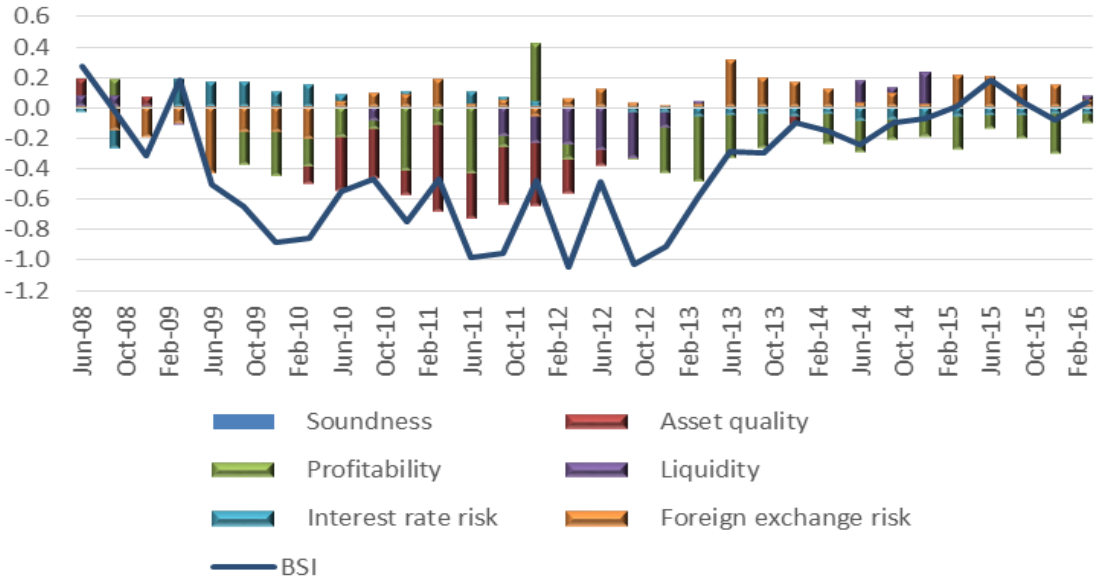
Figure 1. Aggregate Financial Stability Index for Jamaica



2.2 Banking Stability Index

Following Geršl A., and J. Hermánek (2008), the BOJ's Banking Stability Index (BSI) is a weighted average of normalized banking sector partial indicators of capital adequacy, profitability, asset quality, balance sheet liquidity, and sensitivity to market risk to indicate the level of stability of the banking sector. Each variable of the BSI is normalized using statistical standardization. Averages and standard deviations are computed for a 10-year period (or, with shorter samples, as far back as the data are available). Arithmetic averages of the relevant variables are taken to determine the values for the corresponding partial indicator. Lastly, the BSI is computed by taking equally weighted average of all the partial indicators. Similar to the AFSI, increases in the BSI correspond with improvements in financial stability and decreases mean deterioration.

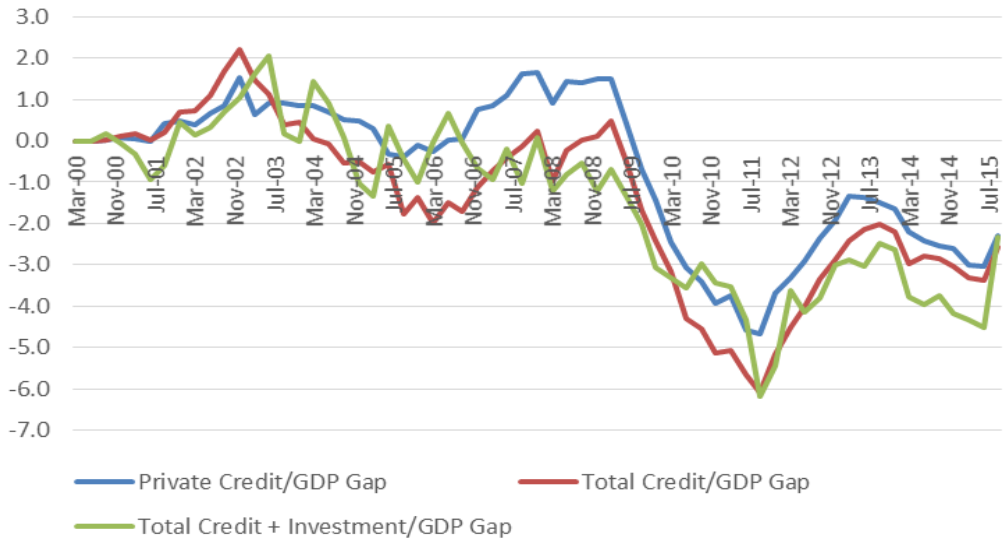
Figure 2. Banking Stability Index for Jamaica



2.3 Credit-to-GDP Gap Indicator

The BOJ monitors credit-to-GDP gap indicators as developed in Borio and Drehmann (2009) which measure credit-to-GDP variables relative to long-term trends to signal excessive credit risk accumulation in the financial system and capture the pro-cyclicality of systemic risk (sometimes 3 to 5 years before event). Trends are determined using only *ex-ante* information and are measured as deviations from one-sided Hodrick-Prescott filters, calculated recursively up to time *t.* Hodrick-Prescott filters with a lambda of 400,000 are employed which implies longer credit cycles relative to the business cycle consistent with significant financial contractions occurring about every 20 to 25 years. Thresholds are used to indicate when a positive gap might prompt policymakers to consider macro-prudential intervention such as activating countercyclical capital buffers. The Basel Committee of Bank Supervisors (2010) suggests a countercyclical capital buffer should be raised when a country's credit-to-GDP ratio exceeds its long-run trend by a critical threshold to be determined by national authorities depending on the country and policymaker's preference (i.e., representing "excessive credit growth").

Figure 3. Credit-to-GDP Gap Indicators for Jamaica



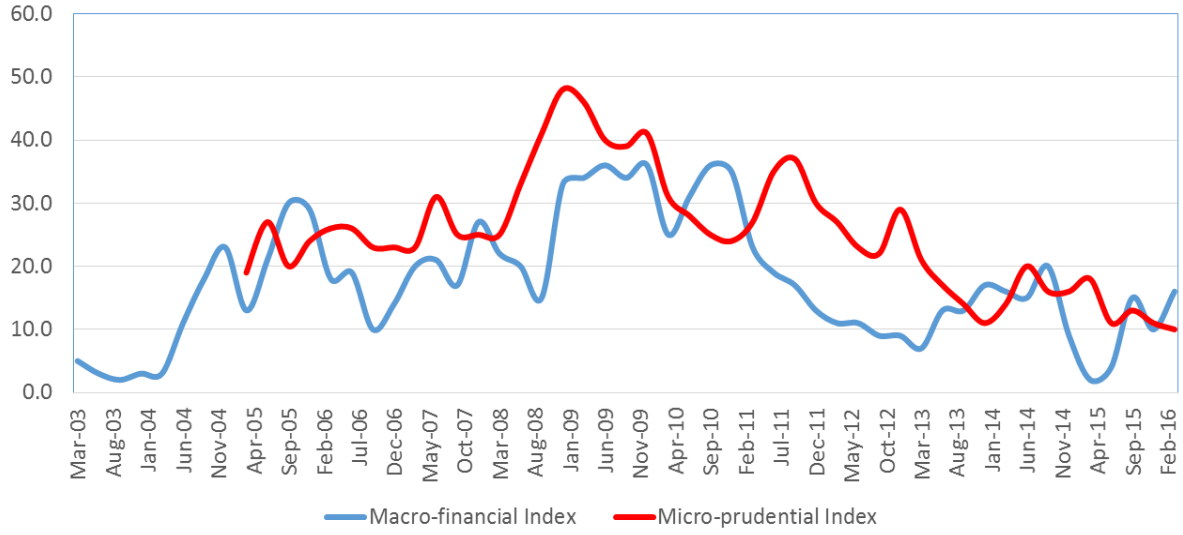
2.4 Micro-prudential and Macro-financial 'Signals-Based' Indices

The BOJ tracks two non-parametric composite indices of financial stability: a micro-prudential index and a macro-financial index which relies on the signals-based method of Kaminsky *et al.* (1998). The micro-prudential index is an asset-size weighted 'signals-based' composite indicator of core FSIs which points to the future state of vulnerability within the banking sector. Each weighted variable is monitored by determining whether its value deviates significantly from its normal behaviour during the tranquil period conditional on whether the applicable signal threshold falls in the upper tail or lower tail of the variable's statistical distribution. Similarly, the macro-financial index involves the monitoring of a selective set of macroeconomic indicators which typically influence the future state of macro-financial vulnerability. Aggregated macro-financial indicators are constructed and combined to reflect the influences from the financial sector, the real sector, the private sector, the public sector, and the external sector.

The BOJ's Micro-prudential Index and the Macro-financial Index both assess the position of each variable within the signalling window in terms of the number of 'tranquil period' standard deviations of that variable from its 'tranquil period' average. The tranquil period is defined as the eight-quarter rolling window that precedes the beginning of a signalling widow. The signalling window is defined as the eight-quarter rolling window that would immediately precede a potential banking crisis. If no systemic crisis materializes, then current the period of tranquillity as well as the signalling window "rolls ahead" one quarter. A potential for crisis is determined by: (a) aggregate severity of the signals and (b) number of

variables signalling. It is expected that on average, in the period leading up to a period of instability, the signals from the variables will increase in terms of both the number of variables signalling and the severity of the signals.

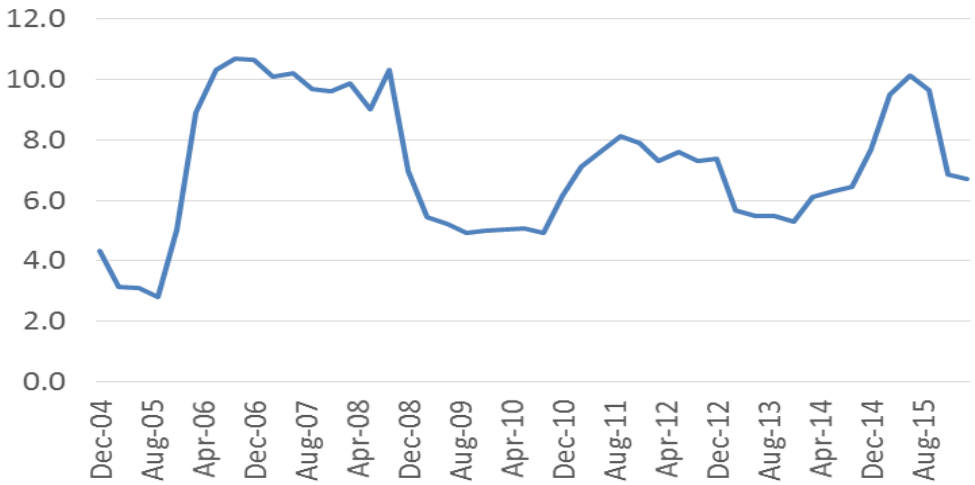
Figure 4. Micro-Prudential and Macro-Financial Indices for Jamaica



2.5 Distance-to-Default Measure

The BOJ uses a distance-to-default measure of the contingent claims approach (CCA) as an indicator of common exposure to systemic risk for the banking sector (see Crouhy, Galai and Mark (2000), Gapen *et al*. (2004) and Merton (1998). CCA relies on option pricing theory for computing banking sector probability of default based on Black-Scholes-Merton option pricing theory using historical balance sheet data couple with forward-looking equity price data. The model assesses the perception of the market of the likelihood that the market value of an entity's assets will fall below the value of its liabilities, where the value of an entity's equity is modelled as a call option on the value of its assets. The model assumes that if the market value of the firm's assets is less than its total liabilities at time T, then the firm declares bankruptcy and creditors receive the liquidated value of assets. The distance to default therefore measures the number of standard deviations from the mean before a firm's assets falls below a default barrier, where the default barrier DB is determined as a function of the short-term and long-term liabilities of the firm.

Figure 5. Distance-to-Default for Jamaica's Banking Sector

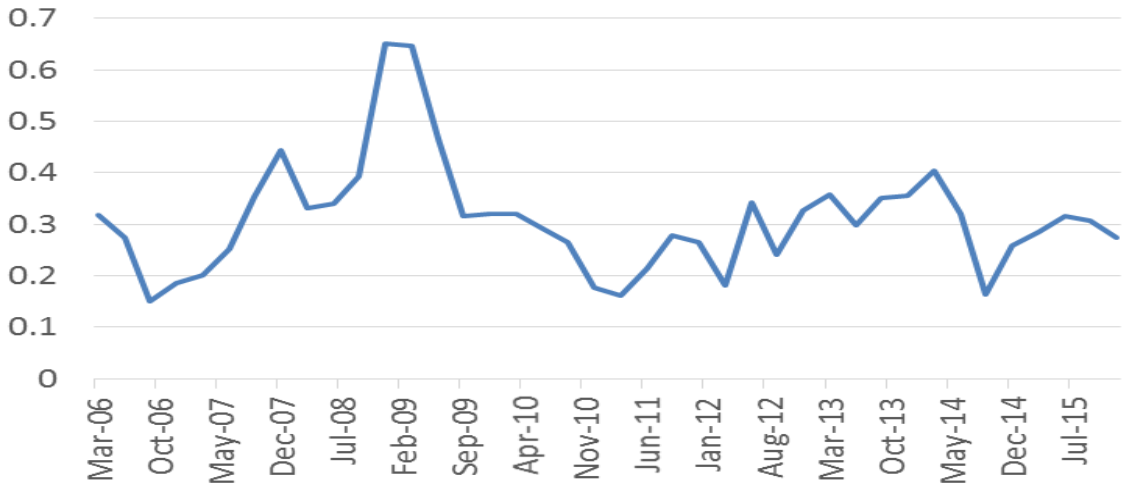


2.6 Composite Indicator of Systemic Stress

The Bank employs a Composite Indicator of Systemic Stress (CISS) to reflect the contagion impact across markets during times of stress. As presented in Holló *et al.* (2012), the CISS measures the joint impact of activity in financial markets using portfolio theory to determine contemporaneous stress in the most active financial markets. Relatively more weight is allocated on situations in which stress prevails in several market segments at the same time. This measure is computed by recursive transformation of the variables reflecting activity in government bond market, foreign exchange market, money market and equities market using the empirical cumulative distribution function (CDF) over an expanding sample period.

The recursive method for computing the CISS involves the step-by-step transformation of the raw indicators for each market with a new observation added at a time over the sample period. For each series in a market segment, the data is sorted by absolute value in ascending order. Next, the ranking number corresponding to the variable at a specific date is determined over the ordered sample of historical observations. Transformed variables of each market segment using the sample CDF are then aggregated into their respective sub-indexes by taking the arithmetic average. The final aggregation of the sub-indexes is based on portfolio theory which takes into account the cross-correlations between the aggregated transformed variables. An increase in the CISS indicates a high degree of correlation between markets which aggravates systemic risk. When the correlation between markets is low, the risk is reduced.

Figure 6. Composite Indicator of Systemic Stress for Jamaica

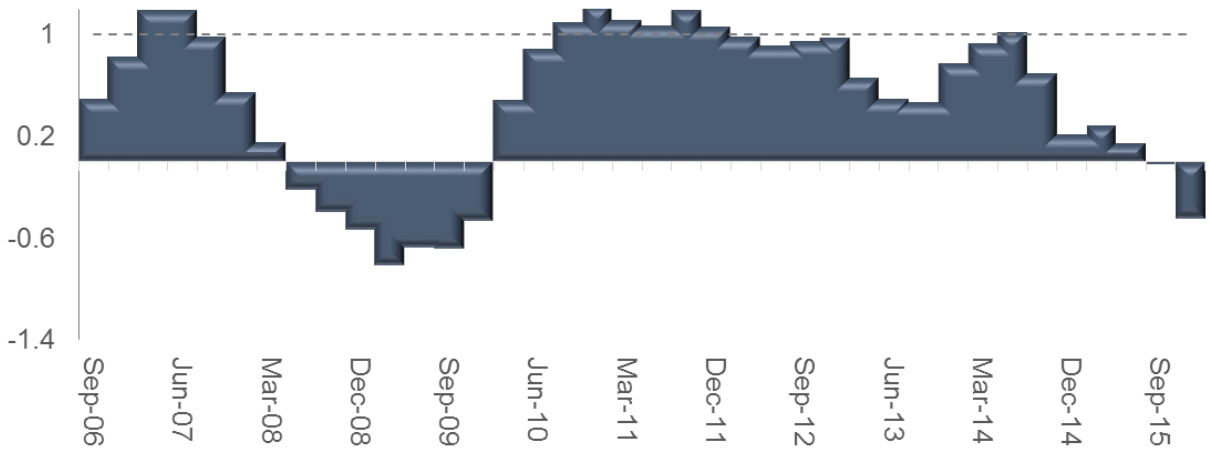


2.7 Absorption Ratio

The Absorption Ratio monitored by the BOJ is based on Kritzman *et al.* (2011) and represents a measure of potential contagion across markets accessed by banks. Specifically, the AR measures the extent to which markets are unified or tightly coupled, which implies higher vulnerability levels in the sense that negative shocks propagate more quickly and broadly when markets are closely linked.

The AR is computed as the fraction of the total variance of a set of time series explained or "absorbed" by a fixed number of eigenvectors from Principal Components Analysis (PCA). PCA is a statistical technique for examining the covariance structure between time series. In the absence of market price data, the AR methodology can be applied to bank performance indicators constructed from accounting data, which summarize the impact of balance sheet exposure to market risk. A high level of correlation of performance indicators, such as the return on assets (ROA), across banks is construed as being indicative of high exposure to common risks. The Standardized Shift of the Absorption Ratio (SAR) is defined as the difference between the 4-quarter moving average AR and the 12-quarter moving average, normalized by the standard deviation of the 12-quarter moving average. Values of SAR greater than one indicate strong tightening across markets or increasing commonality. On the other hand, values of SAR less than negative one indicate strong decoupling across markets.

Figure 7. Standardized Shift in Absorption Ratios using Banking Sector Return on Assets for Jamaica



3. Empirical Methodology for Constructing Single Aggregate Measure

The SRIs are constructed using quarterly data ranging from March 2000 to December 2015. Hence, as indicated in the previous section, an unbalanced panel is used to compute the SAM as the SRIs begin at different points in the sample. The first step in the aggregation of individual SRIs is to modify the signs on the SRI series such that higher values of the indicators reflect greater risk. This is important so that the direction of movement will have a consistent meaning across all indicators in terms of influence on systemic risk.

SRIs are then transformed into percentile scores based on their empirical Cumulative Density Functions (CDF).[1] The initial transformation of the SRIs using the empirical CDF is conducted by using a transitory pre-recursion sample and then the transformation is applied recursively over expanding samples as outlined in Holló *et al.* (2012). Consider the ordered sample for each SRI series, x_t, for $t = 1,2,\mathrm{K}\ n$, denoted as $x = (x_{[1]}, x_{[2]},.\mathrm{K}\ , x_{[n]})$, where $x_{[1]} \le x_{[2]} \le .\mathrm{K} \le x_{[n]}$ and the order statistic, $x_{[n]}$, is the pre-recursion sample maximum. Transformation of each SRI using the empirical CDF, $F_n(x_t)$, is computed as follows:

$$z_t = F_n(x_t) := \begin{cases} \dfrac{r}{n} \text{ for } x_{[r]} \le x_{[t]} \le x_{[r+1]}, & r = 1,2,,\mathrm{K}\ ,n-1 \\ 1 \text{ for } x_t \ge x_{[n]} \end{cases} \qquad [1]$$

[1] Note that the CISS is computed using the empirical CDF and hence is not transformed again.

The recursive transformation of each SRI series following the pre-recursion period is applied on the basis of the recalculation of ordered samples by adding the new observation for each quarter up to the end date, N, of the full sample as follows:

$$z_{n+T} = F_{n+T}\left(x_{n+T}\right) := \begin{cases} \dfrac{r}{n+T} \text{ for } x_{[r]} \le x_{[n+T]} \le x_{[r+1]}, & r = 1,2,,\text{K}\ ,n-1,\text{K}\ n+T-1 \\ 1 \text{ for } x_{n+T} \ge x_{[n+T]} \end{cases} \quad [2]$$

Following SRI transformations, the information contained in the transformed SRIs are synthesized following the approach of Hatzius *et al*. (2010). In this approach, the information in the transformed SRIs are synthesized using principal components analysis (PCA) whereby the feedback of macroeconomic conditions associated with the business cycle are first purged from the transformed SRIs. Specifically to capture pure financial shocks, the exogenous information associated with financial sector activity is proxied by the residuals obtained from the extracting of the endogenous embodiment in SRIs of historical economic activity by running regressions of each of transformed SRI against current and past values of real economic activity and inflation.

The regression equation for the i^{th} transformed SRI, Z_{it}, is represented as:

$$Z_{it} = A_i(L)Y_t + \omega_{it} \quad [3]$$

where $A(L)$ is the polynomial of L lags and ω_{it} is uncorrelated with vector of current and lagged values of the critical macroeconomic indicators denoted by Y_t. Consider that the residuals of interest, ω_{it}, can be decomposed as

$$\omega_{it} = \lambda_i' \Omega_t + \upsilon_{it} \quad [4]$$

where Ω_t represents a vector of unobserved financial factors and υ_{it} captures idiosyncratic variations in ω_{it} which are independent of Ω_t and Y_t. On the basis that υ_{it} are uncorrelated across the transformed SRIs, Ω_t, capture the covariation in the transformed SRIs. In the context of an unbalanced panel, iterative methods are employed to find the least squares solution, $\hat{\Omega}_t$, in the estimation of the principal components of estimated residuals, $\hat{\upsilon}_{it}$.

The final step in constructing the SAM follows the approach of Gómez *et al*. (2011). This approach computes the SAM starting at the beginning of the unbalanced portion of the full data set (i.e., unbalanced sample) even though the computation of the principal components is available only from the start of the balanced sample. The stages of the final step to compute the SAM are as follows:

i. Estimate the correlation matrix of SRI residuals for the full period of the unbalanced sample using the method of pairwise deletion of missing values.

ii. Use the correlation matrix to perform PCA and estimate the vector of unobserved financial factors for the balanced sample.

iii. The estimated factor loadings for the first set of components, which explain most of the variance of the balanced data set, are used to construct loadings for the unbalanced sample. This is done by assigning a factor loading of 0 at time t in the case of missing values and assigning the factor loading computed under the PCA when information is available. However, for the unbalanced sub-sample, the condition that the square of the factor loadings must sum to equal 1 at each t is not met unless the square factor loadings are rescaled. The rescaled square factor loadings are then used to compute new loadings with the assumption that they retain the same sign as the factor loadings computed under the PCA.

iv. The matrix of factor loadings (including rescaled loadings) for the full sample for each of the principal components is multiplied the by the transpose of the matrix of unobserved financial factors to obtain the principal components.

v. Finally, the marginal explanatory power of each component in the cumulative variance is used as weights of each component in the computation of the SAM.

4. Construction of the Single Aggregate Measure of Financial System Stability

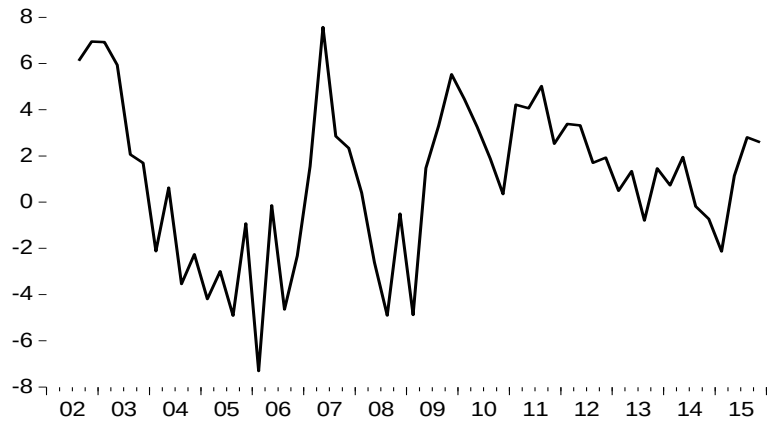
As outlined in the previous section, year-on-year percentage growth rate of real GDP and annual percentage point-to-point inflation rate together proxy macroeconomic conditions associated with the business cycle. Contemporaneous, one- and two-quarter-lagged values of these macroeconomic series were used to run equation (3) on each of the seven SRIs that were transformed using equations (1) and (2), respectively. The correlation matrix between the residual series of transformed SRIs for the full period of the unbalanced sample (September 2002 to December 2015) indicate highly correlated series (see Table 1). PCA is applied to extract the common financial factors from residual series, such that they are orthogonal to each other. Using the balanced sample (June 2008 to December 2015), three factors were extracted which explain 75 percent of the variance of the balanced data set. The SAM is constructed as weighted aggregation of the product of the matrix of residual series of transformed SRIs and the matrix of factor loadings (including rescaled loadings), where the weights are the respective proportion of variation explained (see Figure 1). The 4-quarter moving average of the SAM (SAM-MA) is used for macro-prudential surveillance in order to

smooth out short-term volatility as well as to highlight persistent deviations in the unobserved financial factors (see Figure 2).

Table 1: Correlation of Residual SRI Series over the Full Sample

	AFSI	SAR	BSI	CISS	CtoGDP	DtoD	MaFI	MiFI
AFSI	1.00							
SAR	-0.02	1.00						
BSI	0.44	0.34	1.00					
CISS	-0.08	0.56	0.09	1.00				
CtoGDP	0.49	0.35	-0.02	0.50	1.00			
DtoD	-0.42	0.25	0.02	0.46	-0.16	1.00		
MAFI	-0.24	0.07	0.00	0.11	-0.12	0.47	1.00	
MIFI	0.45	0.28	0.59	-0.03	-0.03	-0.07	0.18	1.00

Figure 1: Single Aggregate Measure of Financial System Stability



5. Juxtaposing the Single Aggregate Measure with Stressful Event Periods for the Financial System

The accuracy of the SAM-MA can be reflected in its ability to identify and measure stressful event periods for the financial system, which may be determined through the juxtaposition of the SAM-MA and a set of stressful events over the sample period as well as their relative impact. The list of stressful event periods was drawn from a review of Bank of Jamaica (BOJ) Annual Reports from 2002 to 2015 taking account of the extent of the impact on Jamaican financial system. Interestingly, all events were associated with vulnerabilities related to heavy concentration across financial institutions and markets in Government of Jamaica (GOJ) sovereign debt instruments. These events were manifested in the financial system mainly by episodes of significant exchange rate depreciation, volatility in money and

bond markets associated with interest rate increases by the central bank and material declines in the market value of sizeable GOJ bond portfolios held by financial institutions.

Table 2 lists the major stressful events and their approximate duration for the Jamaica financial system. High correlation between these events and the SAM-MA is evident from observing Figure 2.

Table 2. Stressful Events over Full Sample

Description of Stressful Event Period	**Quarters**
• Direct balance sheet impact influenced by sharply deteriorated GOJ fiscal position and subsequent downgrade of the outlook on Jamaica's sovereign debt by Standard and Poor's from 'stable' to 'negative' in December 2002 quarter • Increase in interest rates by 600 basis points and then by 1500 in December 2002 and March 2003 quarters, respectively • Excessive financial market volatility influenced by the GOJ's ability to refinance a maturing Eurobond in the capital markets and subsequent drawdown of NIR in March 2003 quarter • Excessive financial market volatility influenced by news of an impending war in Iraq in March 2003 quarter	December 2002 to June 2003
• Excessive financial market volatility and direct balance sheet impact influenced by deteriorating global conditions as a result of rising oil and agricultural commodity prices coupled with destruction of domestic agriculture sector, due to the passage of hurricane, during September 2007 and December 2007 quarters • Direct balance sheet impact arising from elimination of significant financial sectors' margin positions on GOJ Eurobonds held with international investment banks emanating from deteriorated credit conditions associated with intensification of sub-prime mortgage crisis in the USA during 2008.	September 2007 to December 2008
• Direct balance sheet impact influenced by downgrades by S&P, Moody's and Fitch of local and foreign currency GOJ bond ratings by 2 to 3 notches and maintained a negative outlook in December 2009 quarter. • Excessive financial market volatility and direct balance sheet impact influenced by impending implementation of the Jamaica Debt Exchange (JDX) in March 2010 quarter	December 2009 to March 2010
• Excessive financial market volatility during most of 2012 about the non-disbursement of foreign currency flows from multilaterals in the context of the delay in finalising an agreement between the GOJ and the IMF on Jamaica's medium-term economic programme • Excessive financial market volatility and direct balance sheet impact influenced by a second debt exchange in March 2013 quarter, named the National Debt Exchange (NDX), after failing to capitalize on the fiscal space created by the JDX.	March 2012 to March 2013

Figure 2: Single Aggregate Measure of Financial System Stability (Moving Average)

* Shaded areas correspond to stressful event periods

The first and highest peak in the SAM-MA occurred at the beginning of the sample between the December 202 and June 2003 quarters. This deterioration in the SAM coincided with the first stressful event period which was largely associated with uncertainty in financial markets and a direct impairment on financial institutions' balance sheets surrounding a large fiscal shock as indicated in Table 2.

Financial markets settled during the second half of 2003 due principally to the policy measures implemented by the BOJ which allowed for a series of reductions in the Bank's interest rate structure. Over years 2004 to 2006, there continued to be generally stable conditions and the restoration of strong foreign and local investor confidence in Jamaica's financial system.

The next major stressful event, which began in the September 2007 quarter, was due to severe adverse movements in key global commodity prices, widespread crop destruction in agriculture sector by the passage of a major hurricane as well as the onset of the subprime crisis in 2007 which intensified during 2008. During the December 2008 quarter, the Bank established a special loan facility to enable domestic financial institutions with US dollar liquidity needs to repay margin arrangements on GOJ global bonds that were being cancelled by overseas counterparts. An intermediation facility in both foreign and local currency was also established by the BOJ to counter a dysfunctional money market. The December 2008 quarter was the final quarter of this particular stressful period. Although the balance sheets of financial institutions were not immune to the developments in the international financial markets during 2008, there was no direct exposure of the system to sub-prime mortgages.

Accordingly, the level of stress during this period was not as high as high as during the 2002 to 2003 period.

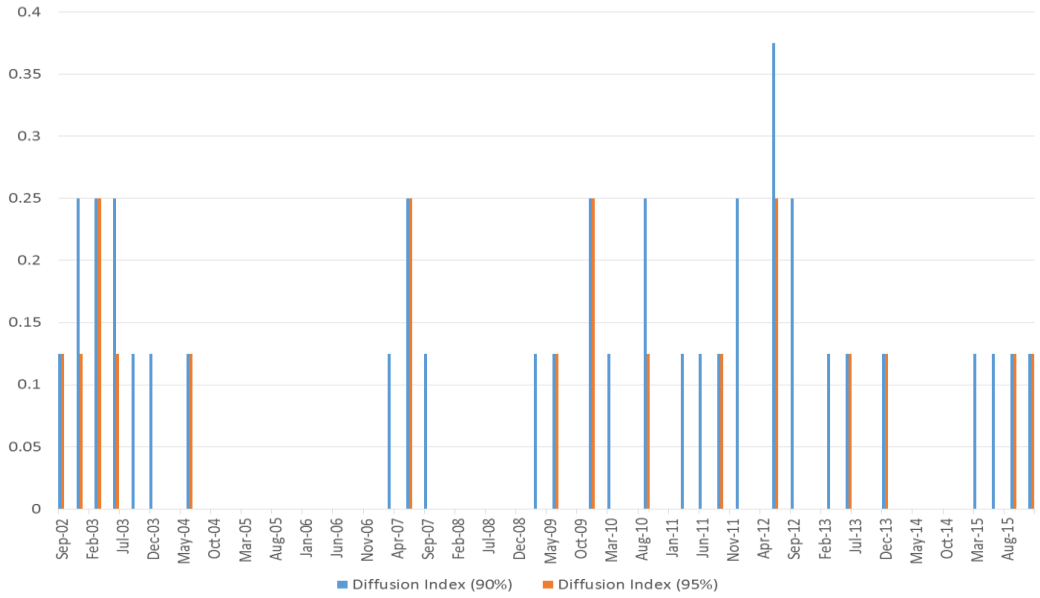
As mirrored in Figure 2, the next stressful event period began during the December 2009 quarter and arose from heightened uncertainty in the domestic market surrounding the terms and timing of the IMF agreement (negotiations started in June 2009 quarter) and market rumours of imminent non-market friendly GOJ debt management initiatives. During this quarter, there was a series of ratings downgrades on GOJ long-term foreign and domestic sovereign debt which would have had a significant adverse impact on financial institutions' balance sheets. Jamaica's first debt exchange, dubbed the Jamaica Debt Exchange or JDX, was launched by the GOJ in the March 2010 quarter as a prior action to a 27-month (IMF) Standby Arrangement to reverse an unsustainable level of public debt of 135 percent of GDP at the end of 2009. At this time, domestic debt accounted for over 75 percent of interest expense with 40 percent (27 percent of GDP) maturing within 2 years. This voluntary debt swap was 100 percent successful which led to improving domestic macroeconomic conditions in 2011 and general easing of monetary policy consistent with relative stability in the exchange rate during the year. This stressful episode concluded in the March 2010 quarter.

Most of 2012 was characterized by uncertainty in the financial markets surrounding the timing and content of an agreement with the International Monetary Fund (IMF) on a new medium-term economic programme following the non-disbursement of foreign currency flows from multilaterals due to the previous agreement with the IMF falling off track. This period concurs with a peak in the SAM during the March 2012 quarter. The end of the stressful period for financial markets came at the conclusion of a second debt exchange, named the National Debt Exchange (NDX), which was launched by the GOJ in the March 2013 quarter. Successful completion of the NDX was a prior action for a four-year Extended Fund Facility (EFF) agreement with the IMF as GOJ rose to almost 150 percent of GDP. The NDX was designed explicitly at achieving fiscal savings of 8.5 percent of GDP and thereby lowering the debt-to-GDP ratio to a near sustainable level of 95 per cent by 2020 in the context of a broad fiscal consolidation. Similar to the JDX, the NDX was 100 percent successful and entailed the voluntary rolling of GOJ securities by accepting new instruments with lower coupons and extended maturities.

6. Identification of Stressful Event Thresholds for the SAM-MA

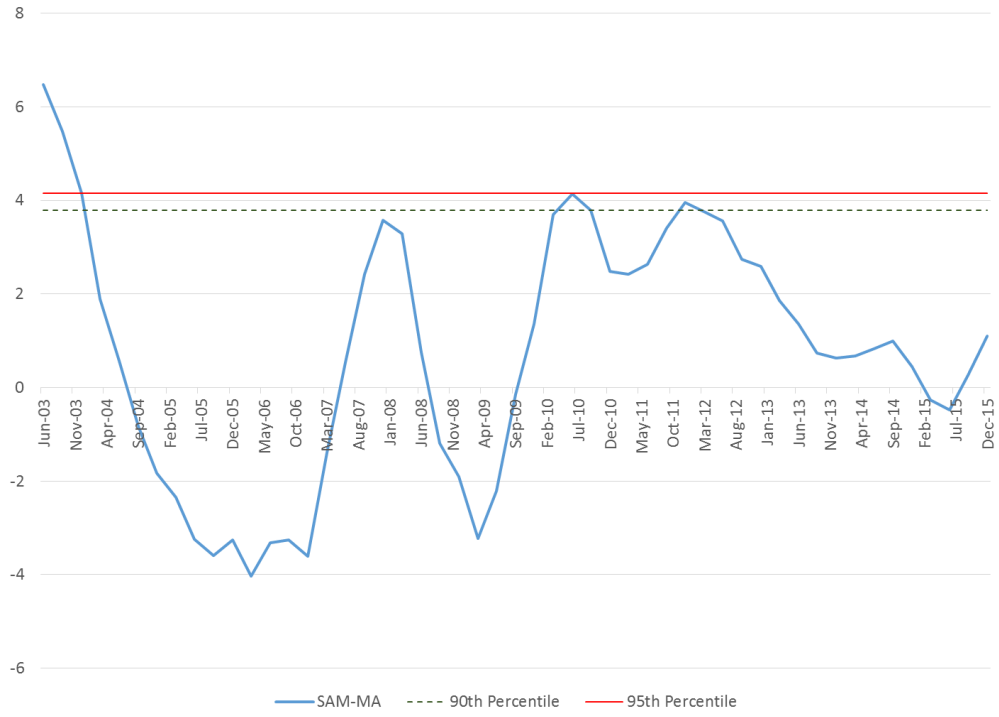
To enhance its usefulness as composite indicator of systemic risk, "stressful event thresholds" are established for the SAM-MA, based on the probability distribution of individual underlying SRIs, and a diffusion index (i.e. share of SRIs that exceed their threshold) constructed (see, for example, Roy *et al*., 2015).[2] In the case of both 90th and 95th percentile thresholds, 25 percent of all underlying SRIs signaled during the four stressful event periods in the sample, except for the second quarter of the March 2012 to March 2013 period when a third of all SRIs signaled at the 90th percentile threshold (see Figure 3 and Figure 4). At the 90th percentile threshold value of 3.8, the moving average SAM-MA signals all but the September 2007 to December 2008 stressful event period. While at the 95th percentile threshold value of 4.2, the December 2002 to June 2003 and December 2009 to March 2010 stressful event periods were captured by the SAM-MA. A visual assessment of the diffusion index and the SAM-MA series indicate that the SAM-MA successfully captures the buildup in systemic risk just prior to all four stressful event periods.

Figure 3: Diffusion Index of Underlying SRIs at 90th and 95th Percentile Levels



[2] Kernel density graphs of the underlying SRIs are illustrated in the Appendix.

Figure 4: Single Aggregate Measure of Financial System Stability (Moving Average) with Stressful Event Thresholds



7. Conclusion

Systemic risk must be measured, monitored and assessed as an explicit quantitative tool to be used as a basis for macro-prudential policymaking. This paper constructs a single aggregate measure of systemic risk in an effort to consolidate information from a core set of systemic risk indicators.

The first step in the aggregation of individual SRIs is to modify the signs on the SRI series such that higher values of the indicators reflect greater risk. SRIs are then transformed into percentile scores based on their empirical Cumulative Density Functions. Following SRI transformations, the information contained in the transformed SRIs are synthesized using principal components analysis following the approach of Hatzius et al. (2010) whereby the feedback of macroeconomic conditions associated with the business cycle are first purged from the transformed SRIs. Subsequently, the approach of Gómez *et al*. (2011) is used to calculate the single aggregate measure starting at the beginning of the unbalanced sample though the construction of loadings for the unbalanced sample from estimated factor loadings of the balanced sample.

Validation of the single aggregate measure was based on its ability to identify early and measure stressful event periods for the financial system, determined through the juxtaposition of the measure and a set of stressful events over the sample period as well as their relative impact. The measure was found to successfully capture of historical periods of financial system stress, supporting its use for macro-prudential policy purposes.

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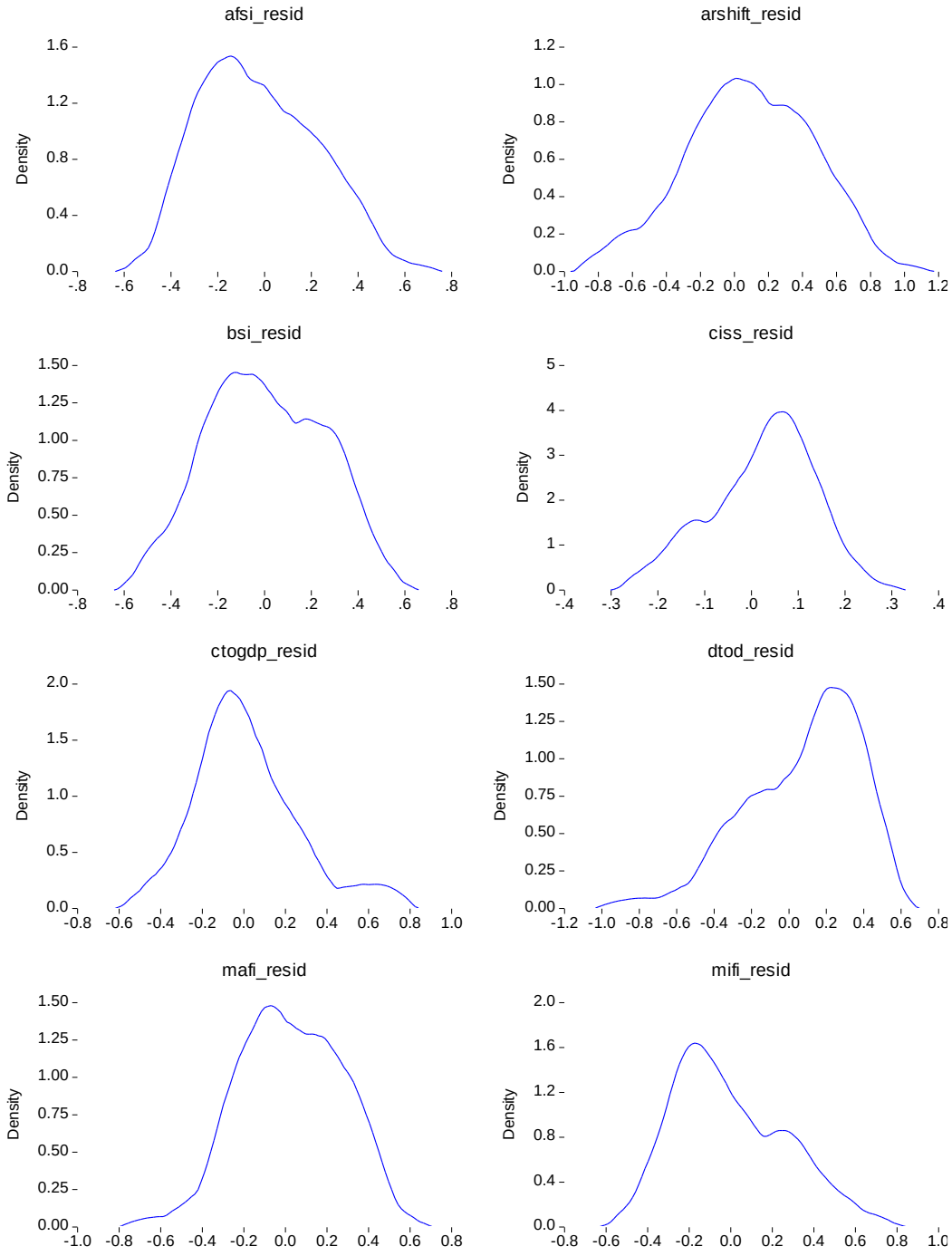
Appendix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0.4
0.2
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