The Absorption Ratio as an Indicator for Macro-prudential Monitoring in Jamaica

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Abstract

The systemic monitoring of the financial system often utilizes indices created from the aggregation of various financial and economic variables. This paper uses the principal components technique as an alternative to variable aggregation when creating a stability indicator for the Jamaica banking system. Based on this principal components approach, the paper: i) measures changes in the extent of common risk exposure over time ii) identifies periods in which this common exposure became a systemic concern iii) identifies systemically important institutions and sectors. The results show that Jamaica's financial system has demonstrated multiple periods in which common exposure was a systemic concern. During these periods there was varying contributions to common exposure by institutions but the foreign exchange and equity markets were identified as key market drivers.

Keywords: Systemic Risk; Principal Components Analysis; Absorption Ratio

JEL Code: G1; G2

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Introduction

The U.S financial crisis of 2008 and subsequent international contagion exposed gaps in the effectiveness of financial oversight and the disastrous implications this could create for the real economy. A critical lesson from the crisis was that fact that micro-prudential supervision is a necessary but not sufficient condition for system-wide risk monitoring. Against this background, regulatory stakeholders have been developing macro-prudential approaches to financial oversight that should be utilized in conjunction with traditional micro-prudential supervision of individual institutions to minimize the potential of financial disruptions that could systemically impact financial markets and the broader economy (Bernanke, 2011).

The goal of macro-prudential surveillance is to identify potential systemic vulnerabilities with the ultimate aim of avoiding financial crisis. Critical for the task of recognizing worrisome levels of systemic risk and the potential for crisis is the understanding of the various means by which shocks could spread through the system. Two broad means of propagation of financial distress can be described. Firstly, financial fragility can spread through the normal inter-dependence of institutions and markets due to real and payment system network relationships. Secondly, markets could experience significant propagation of financial stress stemming from asymmetries in information. [2]

Real financial linkage is dependent on the structure of financial institutions. Based on banks' function in maturity transformation and the fractional reserve system, a financial panic could create systemic stress and bank insolvency in the short run even if these institutions were independently fundamental solvent in the long run[3]. System-wide fragility may also depend on the extent of network exposures between banks and the reliance on interbank money market and payment systems. Similarly a system-wide liquidity freeze may be created if a large proportion of the payment of obligations is dependent on the payment of accrued debt by a small number of firms that are systemically important.

A main type of monetary linkage between banks is as a result of the co-movement of asset prices. Such coincidence of asset price movement could also stimulate contagion and crisis. As spill-over in the volatility of asset prices throughout industries or across markets increases, the co-movement in rates of returns across markets will enhance the mechanism of transmission

[2] (De Bandt & Hartmann, 2000)
[3] (Diamond & Dybvig, 1983)

of financial stress[4]. For example, efforts to mitigate crisis in one institution, such as through asset fire-sale, could lead to a substantial change in market prices impacting the portfolio of other institutions.

Beyond structure and interconnectedness of the system, inefficiencies due to asymmetric information can influence fragility. For example, asymmetric information could allow for insolvent banks to continue to operate based on the supply of loans available in an inter-bank money market. As a result other banks could develop substantial exposures to fundamentally insolvent institutions. Revealed information on the insolvency of such a bank could again lead to financial panic and market failures.[5]

Problems due to asymmetric information could also trigger adverse outcomes in other markets such as the foreign currency or stock markets. In these cases the market prices on assets could be overvalued for a prolonged period of time, or could have become fundamentally uncertain, or misaligned with economic fundamentals. Though bank runs can serve as the initial shock to the financial system, the process of contagion throughout the market can spread through real exposures or by an information effect, referred to as banking "panic" (Allen & Gale, 2000). Similarly shocks to various markets whether securities or government bonds have the potential to simultaneously impact various agents. Such that shocks to these markets can create even more widespread impact than those originating from institution-specific or interconnectedness structure.

There are multiple ways in which financial shocks may propagate through to the real economy. For example, declining asset prices will impact the value of collateral tightening credit and subsequently constrain production (Kiyotaki & Moore, 1997). There exist significant empirical evidence on these and other relationships between financial stability and an unstable macroeconomic environment.[6] With these realities in mind the paper utilizes principal components analysis to develop a monitor of financial fragility in Jamaica while identifying the banks and markets that centrally characterize this systemic risk.

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[4] (Pericolo & Sbracia, 2003)

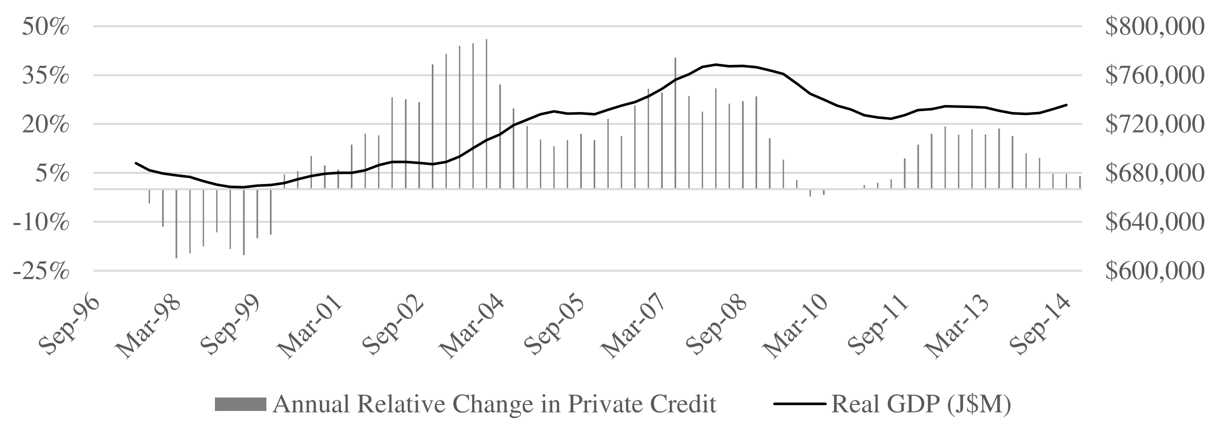
[5] (Chen, 1999)

[6] See, for example (Hardy & Pazarbasioglu, 1998)

Financial Soundness in the Jamaican Landscape

The financial system in Jamaica is predominantly comprised of deposit-taking institutions, securities dealers and insurance companies. These sectors account for 36%, 18% and 20% of financial system assets, respectively[7]. During the mid-1990's Jamaica experienced a major financial crisis involving contagion across the banking and insurance sectors. The effects of Jamaica's financial crisis is evident in the decline in private credit in which between December 1996 and June 1999 credit fell by 34% (see Figure 1).

Figure 1.



A stagnant banking sector is also evident between June 2009 and March 2011 during which the value of private sector credit issued each quarter declined. This financial outcome was associated with the U.S financial crisis. These observations demonstrate that over relatively short time periods the Jamaican financial system could be exposed to significant risk whether originating from domestic conditions or from international factors. Further, these difficulties will be reflected in, and have unwanted consequences for, real economic activity.

In recognition of these realities various approaches for developing measures useful for identifying systemic risks to financial markets in Jamaica have been developed. The development of composite indicators based on macro-financial and micro-financial variables, independently, was found useful for the signaling of financial crisis.[8] Composite indicators that combined both macro- and micro-financial variables were also found useful as early warning

[7] Central Bank assets account for 17 percent.
[8] See Langrin (2002)

measures of crisis.[9] These indicators which were developed from foreign exchange, equity, bond, and money market variables are also useful for macro-prudential surveillance.[10]

This paper contributes to this body of work by providing an additional approach to systemic monitoring of the financial sector. This approach is hinged on the fact that strong commonality in performances across institutions or markets within the financial system could serve as a source of systemic risk.

Figures 2 and 3 below display the average correlation and box plots of the net interest margin and return on assets respectively across deposit-taking institutions; [11] while Figure 4 displays the average correlation and box-and-whisker plots, of returns in the bond, stock, money, and foreign exchange markets.[12] The Figures show the potential for strong co-movement in performance across institutions and across markets. Average correlation in interest margins reached 0.62 and that in returns across markets climbed to 0.50 during the 2002 currency crisis period. Further the Figures show that the range in co-movement can show periods of tightening both across institutions and across markets. The interquartile range falls to a low of 0.11 and 0.14 for NIM and ROA, respectively. Likewise in returns across market the interquartile range demonstrated a tightening to 0.14 from a maximum spread of 1.59.

Given that strong co-movement of returns across institution or markets encapsulates a form of systemic risk the paper utilizes principal component methods for the application of an approach to identifying when such changes become a systemic concern. The section below describes the approach in more detail.

[9] See Morris (2010), (Lewis, 2006)
[10] See Milwood (2012) and Wallace (2013)
[11] The rolling correlation over five year periods is calculated for data beginning in 1989.
[12] The rolling correlation is taken over 3 year periods for the bond, stock, money, and foreign exchange markets for data beginning in 2002. Returns in the stock and foreign exchange market are measured as the log difference in the value of the Jamaica Stock Exchange index and the log difference in the weighted average buying rate at each quarter. Return in the bond and stock markets are the yields on GOJ 30 day issues and the average 30 day money market rate respectively.

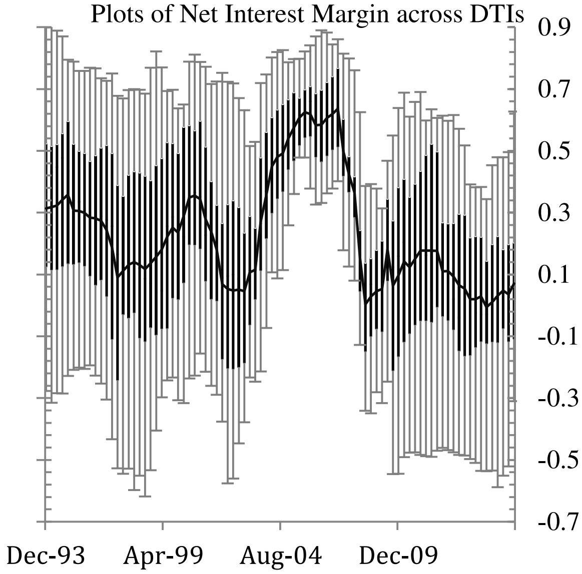


Figure 2. Average Correlation and Box Plots of Net Interest Margin across DTIs

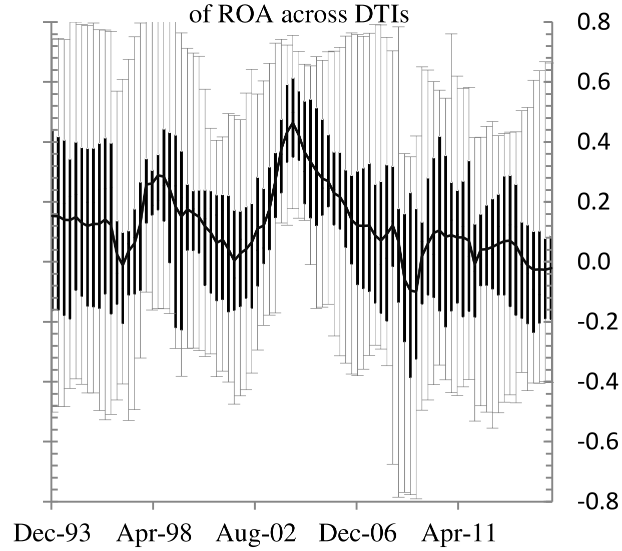


Figure 3. Average Corelation and Box Plots of ROA across DTIs

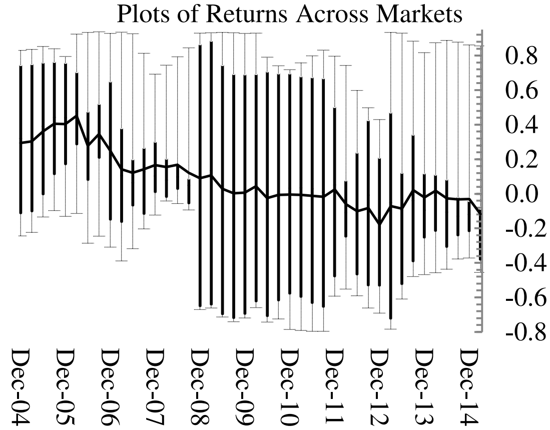


Figure 4. Average Correlation and Box Plots of Returns Across Markets

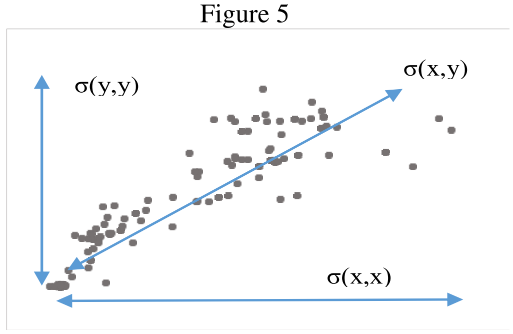
Principal Components Analysis and the Absorption Ratio

The ability to model the covariance structure of a system of variables can be used in various applications. This paper uses principal component analysis (PCA) as one such methodology. More specifically PCA is utilized to develop a measure for monitoring systemic financial developments. As an example of one of its applications PCA is able to identify the subset of variables that account for most of the variability within a broader system. In so doing it can be used to develop parsimonious models in which a single variable can capture most of the covariation in an estimated regression. In this context, an advantage of PCA over other applications is that it minimizes the dimensionality problem.

The PCA technique was first developed for geometric and numerical analysis by Pearson (1901) and further advanced by (Hotelling, 1993). To illustrate the procedure first consider the covariance matrix and the development of a set of eigenvectors. For two random variables x and y, the covariance matrix, $\sum$, presents information on the variability of x, the variability of y, and the variability along the diagonal association between x and y. These are given as σ(x, x), σ(y, y), and σ(x, y) respectively. Where $\sigma(x,x) = \frac{1}{n}\sum_{i=1}^{n}(x_i - \mu_x)^2$ and σ(x, y)= $\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu_x)\,(y_i - \mu_y)$.[13] See figure 4.

$$\sum = \begin{pmatrix} \sigma(x,x) & \cdots & \sigma(\mathrm{x,y}) \\ \vdots & \ddots & \vdots \\ \sigma(\mathrm{y,xy}) & \cdots & \sigma(\mathrm{y,y}) \end{pmatrix}$$

Figure 5



In other words the covariance matrix provides information on shape of the data as defined by the spread along each axis, variances σ(x, x) and σ(y, y), as well the spread and direction of variance along the diagonal, σ(x, y). Since the covariance matrix represents the shape of data along its multiple dimensions, as the number of variable dimensions increases, the identification of general patterns in the spread or similarities across variables become less obvious. PCA allows for identifying these similarities across data in which a visual examination of the spread or the calculated covariance matrix is not easily accomplished. In the context of this paper, PCA will be used to reveal patterns in returns across banks and across financial markets.

Figure 6 shows the eigenvectors v_1 and v_2 of the hypothetical covariance matrix. The eigenvectors and eigenvalues, like the covariance matrix, distinctively describe the shape of a set data.[14] In which the eigenvector points in the direction of the largest variation and the eigenvalue measures the length of the vector in that direction.

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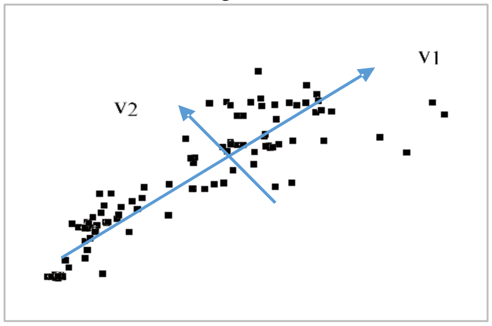
[13] μ represents the arithmetic mean.

[14] Recall that an eigenvector, v, of a square matrix A, is a vector such that Av=rv. Where r is the eigenvalue of A. That is, r is number that converts A to a singular matrix when subtracted from each diagonal such that A-rI is a singular matrix.

Figure 6



PCA in essence is the eigenvector decomposition of the covariance or correlation matrix of a system of variables. The principal components are selected through an algorithmic procedure such that vector v_i lies parallel to the direction in which the comovement of x and y is maximized, and subsequent v_{i+1}, are selected orthogonal to v_i.[15] These are ordered so that they progressively explain as much of the variation in the system. From an algebraic standpoint, if x is a vector of *p* random variables and α_1 is a vector of p constants. A linear function $\grave{\propto}_1\, x = \sum_{j=1}^{p} \alpha_{1j} x_j$ can be described such that elements of x_j have maximum variance. PCA is an iterative process that identifies a subsequent α_{j+1} that is uncorrelated with α_j, and has maximum variance. Then α_k is defined as the kth principal component of x. The objective of PCA is therefore to use some minimum set of principal components to explain as much of the variation of the data. In Figure 6 v_1 therefore represents the first principal direction in which data varies, and v_2 the second.

The ability to identify principal components becomes increasingly useful as the number of dimensions of the data increase. With this procedure variables with highly interrelated characteristic will demonstrate similar cluster patterns, and these patterns can be identified based on the variable's contribution to the direction of each component. The ability of PCA to decompose the variation within a system among different contributing sources is the key characteristic used in the approach used for systemic monitoring.[16] The section below describes the approach.

[15] In the two variable case this rotation amounts simply to finding the slope of the best fitted line of the data. The equation of this line then equates to the rotating vector v that points in the direction of the largest variance.
[16] See (Rovai, Baker, & Ponton, 2013).

The Absorption Ratio

In applications to banking, PCA is commonly applied to reduce of the dimensionality of a data set to those variables responsible for most of the variation.[17] This in an effort to minimize possible biases stemming from collinearity in regression models of bank performance that utilize various bank specific variables. In other financial studies, PCA's data reduction capabilities is used for the development early warning indicators of risk.[18] The loadings of each variable in the principal component indicator score is used to sum weight each original variable comprising the index. A linear composite of the optimally-weighted variables is then created. These component scores can then be used as predictor variables in a multiple regression model of aggregate financial stability.

Another financial sector application of PCA has been in the development of an "absorption ratio".[19] Technically, the absorption ratio is defined as the proportion of covariation between variables explained by a predetermined number of eigenvectors. Returning to Figure 6, a narrowing of the second principal component v_2 will reflect that the proportion explained by the first principal component has increased. Increases in the absorption ratio therefore show that a specific dimension is accounting for more of the co-movement of bank or market returns. Changes in the ratio then serves as an indicator of changes in how quickly, or the ease at which, an external shock could possibly propagate through the system.

The absorption ratio as an alternative to the examination of correlations between returns has a few potential advantages. Firstly, the derivation of the principal components accounts for the direction of the strongest variation, as such it accounts for the relevance of the asset correlations, which is not done in a simple average. As a result it is possible for the average correlation of asset return to decrease over time but for the absorption ratio to demonstrate increased value. Another added value of the absorption ratio is its ability to measure the proportion of the variation captured in specific directions as opposed to correlations that capture only bilateral congruence; the absorption ratio therefore captures secondary links between variable. Thirdly, the absorption ratio will reflect changes arising from co-movement between variables with high variance. However a simple average correlation between these assets will account for the levels of volatility implicit in each.

[17] See Saunders (1969) and Chiattelo (1974)
[18] See (Mingione, 2011) and (Wallace, 2013)
[19] See (Kritzman, Li, Page, & Rigobon, 2010) and (Avanzini & Jara, 2013)

Given these properties, an evaluation of changes in systemic risk as measured by the changes in the co-movement in returns along specific dimension over time is conducted. A one standard deviation shift in the proportion of variation explained by a fixed number of eigenvectors is used as a benchmark for identifying periods of increased fragility. Based on this methodology, institutions and markets that pose the greatest contribution to these risks are identified by the derivation of a "centrality score", which measures the degree to which a particular return drives aggregate system variance.

Procedure & Data

Key assumptions necessary for the completion of PCA are:

- variables are continuous;
- variables are in stationary form;
- the system is absent of outliers, and;
- the variability of the variables are comparable.

The absorption ratio measures the fraction of the total variance in returns explained by a subset of eigenvectors and is calculated according to the follow procedure:

i) Each variable is evaluated for unit root using Augmented Dickey-Fuller equations.[20]
ii) Returns are weighted by the relative asset size of the cross-sectional unit.[21]
iii) Each variable is converted to a standardized value by demeaning and presenting the demeaned value relative to the standard deviation such that $x_i^s = \frac{x_i - \mu_x}{\sigma_x}$.
iv) Standardized values greater than 3 are considered outliers and are removed from the series.
v) Principal components are calculated for the covariance matrix of the standardized values.
vi) The absorption ratio at time t is calculated as follows:

$$AR = \frac{\sum_{i=1}^{n} \sigma_{E_i}^2}{\sum_{j=1}^{N} \sigma_{A_j}^2}$$

[20] The test equation is given by $\Delta x_t = a_0 + \alpha x_{t-1} + \sum_{j=1}^{p} \beta \Delta x_{t-j} + \varepsilon_t$.With null H_o:α=0 ; the series contains unit root. If the series contains unit root it is converted to stationary series by first differencing.

[21] Langrin (2002) shows that in the case of Jamaica accounting for the relative size of financial institutions in macro-prudential indicators improves performance.

N = number of cross-sectional units

$\sigma_{E_i}^2$ = the variance of the ith eigenvector

$\sigma_{A_j}^2$ = the variance of the jth cross-sectional unit

PCA is applied to the performance indicators of 6 commercial banks between March 1989 and December 2014. Return on assets (ROA) calculated as net profits as a share of the 2 quarter average of total assets, and net interest margin (NIM), calculated as net interest income as a share of operating income, are used to measure bank performance.[22] Due to the consolidation of the commercial banking system in the 1990's, the data set considers any mergers and acquisitions that occurred during the period by taking the existing banks as at December 2014 and reconstructing backward their accounting statements such that these mergers and acquisitions are taken into account.[23]

The development of financial crisis might demonstrate increases in the co-movement of asset prices across markets.[24] PCA is also applied to the covariance of returns across major financial markets as an additional indicator of market fragility. These include the returns in the bond, money, equity, and foreign exchange markets. The average yield on the 30-day Government of Jamaica domestic bonds and the average 30-day money market interest rate each quarter are used to measure returns in the bond and money market respectively. Returns in the foreign exchange and equity markets are calculated as the log difference in JM/USD weighted average buying rate in the month ending each quarter and log difference of the period ending quarterly Jamaica Stock Exchange (JSE) Index value respectively.

Shift in the Absorption Ratio

The paper identifies periods of systemic concern as measured by significant changes in the absorption ratio over time. Significant shifts in absorption ratio indicates possible market fragility as returns across institutions and markets are behaving in a more unified manner.[25] The moving average of the absorption ratio is calculated over 4 quarters and is subtracted from the

[22] NIM provides a useful measure of banks' market performance since it occludes the effects of operational costs overheads or other accounting variations evident in the ROA. Whereby ROA is further driven by taxes, loan provisioning, regulations and changes in operational efficiency.

[23] Appendix 1 lists the banks included in this reconstructed series and provides a table of the variables utilized in other studies apply PCA to financial sector performance.

[24] See (Pericolo & Sbracia, 2003)

[25] See Kritzman et al. (2010), Kinlaw et al (2011) and Avanzini & Jara (2013) for a review of applications of the absorption ratio.

moving average of the absorption ratio over 12 quarters and then divided by the standard deviation of the absorption ratio over 12 quarters. This measure illustrates how the last 4-quarter average deviates from the 8-quarter average relative to the general volatility of the underlying series. A shift in the absorption ratio greater than 1, i.e., $\Delta AR_t > 1$, is interpreted as a period in which the system has demonstrated abnormal change and is further used to indicate a significant change in market fragility.

$$\Delta AR_t = \frac{\overline{AR}_{4\ quarter} - \overline{AR}_{12\ quarter}}{\sigma_{AR_{12\ quarter}}}$$

$\overline{AR}_{4\ quarter}$ = 4 quarter moving average of the absorption ratio

$\overline{AR}_{12\ quarter}$ = 12 quarter moving average of the absorption ratio

$\sigma_{AR_{12\ quarter}}$ = 12 quarter rolling standard deviation of AR.

Absorption ratios based on the covariance matrix of banks' quarterly return are calculated quarterly on a rolling basis over 5 year periods beginning March 1989. Absorption ratios based on market returns are calculated on a rolling basis over 12 quarters beginning March 2002. Given the shorter sample size for market returns, 12 quarter rolling periods are used to preserve time-periods available for analysis of the AR while sufficiently accounting for the dynamics of covariance

Centrality Score

PCA and the absorption ratio can be furthered utilized to provide a measure interpreted as contribution to systemic risk.[26] An institution's systematic importance reflected by the centrality score is given as:

$$CS_{it} = \frac{\sum_{j=1}^{n_t} AR_t^j \cdot \frac{\left|EV_{it}^j\right|}{\sum_{k=1}^{N_t}\left|EV_{kt}^j\right|}}{\sum_{j=1}^{n_t} AR_t^j}$$

AR_t^j= absorption ratio of the j[th] eigenvector

EV_{it}^j= exposure of the i[th] bank in the j[th] eigenvector

n_t = number of eigenvectors in the numerator of the absorption ratio

N_t = number of cross-sectional units

[26] See for example Kinlaw et al (2011) and Avanzini & Jara (2013)

First the absolute value of cross-sectional unit's loading in the eigenvector used in the absorption ratio is calculated. The absolute value of each cross-sectional unit's weight in each eigenvector is summed. The contribution to the eigenvector is then measured as a proportion of this sum and multiplied by the absorption ratio associated with the j^{th} eigenvector. Finally this weighted sum is presented as a share of the sum of the proportion of variation explained by all of the eigenvectors up to j.[27] The centrality score provides an ordinal score to those variable which will demonstrate the largest association in variation.

In an effort to know which institutions and markets contribute most when the absorption ratio is exceptionally high. For periods in which the shift in AR is greater than one, i.e, $\Delta AR_t > 1$, the CS of each bank and market is calculated. The average CS score is calculated for these periods and is used to rank contribution to risk during each period.

Results

Two separate sets of analysis are conducted for co-movement of return between commercial banks and the co-movement of returns between the money, foreign, bond and stock markets.

First the absorption ratio, its one standard deviation shift, and centrality scores are derived using NIM and ROA separately across six banks. The simple pairwise correlations of NIM and ROA between banks over the entire sample period are provided below.

Table 1 Correlation of NIM (**bold**) and ROA by DTI (1989Q1-2014Q4)

	BNS	NCB	CitiBank	TCB/FGB	CIBC/FCIB	RBTT
BNS		0.08	0.13	-0.10	0.03	0.05
NCB	**0.63**		0.19	0.00	0.20	0.04
CitiBank	**0.30**	**0.20**		0.19	0.50	0.23
TCB/FGB	**-0.12**	**-0.03**	**-0.36**		0.10	0.00
CIBC/FCIB	**0.54**	**0.69**	**0.17**	**-0.04**		0.09
RBTT	**0.62**	**0.79**	**0.33**	**-0.10**	**0.68**	

Table 1 shows that NIM generally shows stronger correlation between institutions over the sample period than does ROA. Only Citibank and CIBC/FCIB demonstrate moderate

[27] In the two variable example given in Figure 5. The equation of the line for eigenvector v_1 represents the factor loadings. Changes in the slope of this vector, for example a more steep v_1, will represent increased systemic importance of the x axis variable.

positive correlations in returns based on ROA, while multiple institutions demonstrate moderate to strong correlations in interest margin on average over the full sample period.

One fifth the number of cross sectional units is generally used to determine the number of eigenvectors employed in the analysis of the absorption ratio.[28] The Figures below present the absorption ratio based on the first, PC 1, and the first to second principal components, PC 1 to PC 2, overlaid with bar charts of the five year rolling correlations in returns.[29]

Figure 7 Absorption Ratio - NIM by DTI

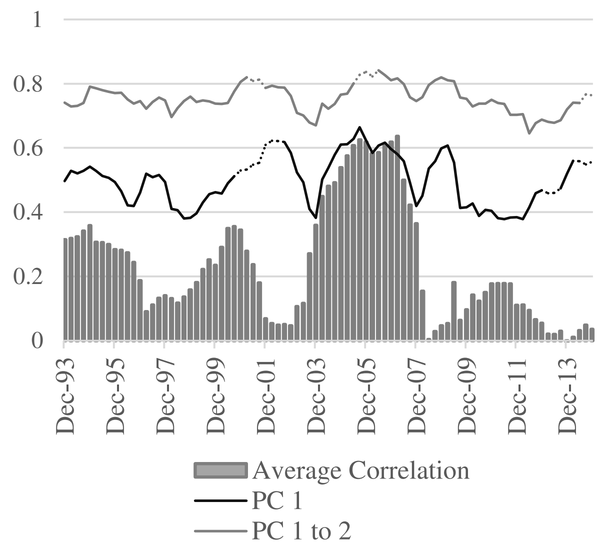
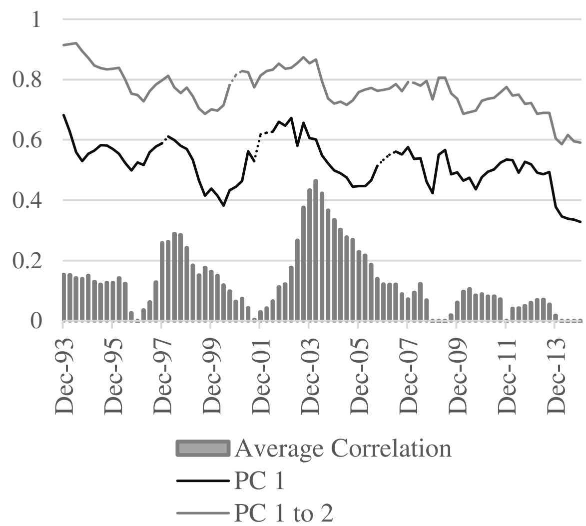


Figure 8 Absorption Ratio - ROA by DTI



Like the trend in correlations the movement in the absorption ratio over time shows periods of troughs and peaks, albeit with a smaller oscillating window. In addition the absorption ratio sometimes shows increases in value during periods of decline in the five-year average correlation.

The absorption ratio provides information on the dimensionality of covariance of returns across banking institutions overtime. It is the change in this dimensionality that provides useful information applicable for risk analysis. This shift in AR is used to indicate significant changes in market fragility but is not intended to signal the realization of crisis. Table 2 below presents the time periods in which AR>1 based on the first principal component and that derived up to the second principal component.

Significant shifts in the absorption ratio coincide with periods of noted weakness in the financial environment. Between 1993 and 1997 the absorption ratio showed a general decline in

[28] See Kritzman et al. (2010)

[29] The dotted portion represent periods in which ΔAR>1.

value with significant positive shift reflected by just the AR based on the first principal component of ROA.

Table 2 Periods of a Greater than One Standard Deviation Shift in the Absorption Ratio

Shift in AR based on NIM				
PC 1	---	Dec 00- Sep 02	---	Mar 13-Dec 14
PC 1 to 2	---	Jun 01-Dec 01	Sep 05 - Jun 06	Sep 14 to Dec 14
Shift in AR based on ROA				
PC 1	Jun-98	Mar 02 - Dec 02	Jun 07 - Dec 07	---
PC 1 to 2	---	Jun 01-Sep 01	Sep 08	---

[30]

Note however that Jamaica's experience with this financial crisis commenced in the early 1990's, and the decline in the absorption ratio mirrors the period in which the Government of Jamaica took management and control of a number of financial institutions.

Significant shifts in the AR based on both return measures are also observed between December 2000 and 2002. This period coincides with the U.S stock market crash of 2000 and subsequent recession in 2001 with the local backdrop of marked foreign exchange market instability experienced in Jamaica through to 2002.[31] The absorption ratio based on NIM signals market fragility between the 2013-2014 periods. The 2013 period includes the Jamaica's National Debt Exchange (NDX) involving the exchange of Government of Jamaica securities for lower coupon and extended maturities, which lead to a general reduction in interest rates. This period also reflected a time of significant foreign exchange uncertainty as in just one quarter, March 2013, the U.S dollar selling rate depreciated by 6 per cent. Further there was limited credit and tight liquidity conditions noted as well during the 2014 period. Market fragility during the periods of significant shift seem to reflect prevailing macroeconomic conditions.

Centrality Score

Centrality scores are derived from the loading of each bank in the principal component and reflect the degree to which the banks' return drives the market variance. The derivation of the score comprises a number of characteristics of the system including a banks vulnerability to

[30] An additional approach for identifying periods of fragility is also taken by calculating the growth rate of the absorption ratio over time. Fragility is measured as periods of growth rates within the 90th percentile. These dates of exceptional growth provide similar results as the standard shift in the ratio.

[31] Between December 2000 and December 2002 the weighted average selling rate fell by 10%.

failure, measured by the volatility of returns. The value of the centrality score also reflects how broadly and deeply a bank is connected to other banks, based on the strength of covariance with other banks, further accounting for the extent to which other banks are vulnerable. Conceptually there are concerns if a bank is vulnerable to failure and has strong co-movement with other banks that are vulnerable to failure. Table 3 below ranks each institution's centrality score for periods of significant shift of the absorption ratio.[32]

Table 3 Banks' Centrality Score and Percentile Rank during Periods of Significant Shift (score in bracket)

	NIM		ROA		
	Dec 00 - Sep 02	Mar 13- Dec 14	Jun-98	Mar 02- Dec 02	Jun 07- Dec 07
1	RBTT (0.67)	CITI (0.37)	NCB (0.39)	RBTT (0.49)	RBTT (0.32)
2	BNS (0.14)	CIBC_FCIB (0.20)	CIBC_FCIB (0.25)	BNS (0.31)	CITI (0.19)
3	CIBC_FCIB (0.10)	RBTT (0.18)	CITI (0.22)	CITI (0.15)	NCB (0.16)
4	NCB (0.05)	TCB_FGB (0.14)	BNS (0.11)	TCB_FGB (0.02)	TCB_FGB (0.14)
5	CITI (0.04)	NCB (0.07)	RBTT (0.01)	NCB (0.02)	CIBC_FCIB (0.14)
6	TCB_FGB (0.00)	BNS (0.02)	TCB_FGB (0.01)	CIBC_FCIB (0.00)	BNS (0.07)

The paper does not attempt to explain the institutional factors determining a particular centrality score or derived percentile rank of any one bank. However, a few important observations relating to systemic importance are made. Firstly, smaller banks can reflect centrality in systemic risk. In such cases the variation of returns of these institutions strongly co-varies with the returns of other institutions that show on aggregate significant variability. Further there can be instances of relative equi-contribution to systemic importance as is the case in the centrality score measured by ROA in the 2007 period. The results also show changes in systemic importance between periods of significant risk. For example, based on estimates derived from ROA, RBTT and BNS were the primary contributors to system variance in the 2002 period. This in contrast to 1998 in which NCB and CIBC were the major contributors.[33]

The Absorption Ratio across Markets-

The most frequent propagation of financial disturbance often takes place within financial sectors but there are sometimes significant spill-over across markets.[34] A therefore relevant

[32] Centrality score are calculated using the first eigenvector. This first eigenvector accounts for significant amount of the variation between bank returns often as much as 60%. See Figures 7 and 8.
[33] Appendix 2 provides centrality scores and ranks across the entire sample period.
[34] See (Ehrman, Fratzscher, & Rigobon, 2011)

objective for macro-prudential supervision is the monitoring of the extent to which financial markets on aggregate demonstrate joint behavior. The existence of which could create an accelerated diffusion of systemic risk, an "Asian flu".

There are various circumstances in which markets may demonstrate significant joint behavior. Portfolio theory often dictates allocation efficiencies through the diversification of funds across markets that demonstrate low cross correlations. Here asset holdings in one market serves as a hedge against unwanted asset price movement in another. In addition during financial nervousness there is often capital flight to safety between markets.[35] Also the contagion hypothesis demonstrate that price declines in one market, can increase aversion to risk in other markets, reducing positions, resulting in subsequent price declines and an observed realized contagion.[36]

Relationships between markets exists not only due to investor decision but could result from underlying macro fundamentals and monetary policy. For example, greater bond yields will make bonds more attractive compared to stocks and will be reflective in stock valuation through dividend discount approaches. Similarly bond yields might also be influenced by information on the future of stock performance and dividends. In addition the value of one asset price may impact other asset values simultaneously through, for example, the wealth channel. Further interest parity conditions can create interdependence between foreign exchange and money markets. These relationships can result in significant contemporaneous interactions between the various asset markets, in which returns in one market are correlated with that in others.[37]

In the case of Jamaica, evidence has been provided on significant cross market effects between stock, bond, and the foreign exchange market. As a result variables reflecting these markets have been used to create composite indices for the identification of financial stress.[38] To further the discourse on indicators of systemic risk the paper applies PCA in the development of absorption ratios, shifts in the absorption ratio and contribution to systemic risk based on the covariance of returns across the major asset markets in Jamaica. Again significant tightening of the dimensionality of the covariance structure serves as an indicator of system wide fragility.[39]

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[35] See (Hartmann, Straetmans, & G. De Vries, 2004)
[36] See (Ebrahim, 2000)
[37] See (Rigobon & Sack, 2003) and (Shiller & Beltratti, 1990)
[38] See (Milwood, 2012)
[39] (Billio, Getmansky, Lo, & Pelizzon, 2010) apply PCA to financial sectors to identify similarity in comovement of returns.

The average correlation between asset performance from March 2002 to December 2014 show strong pairwise correlations in the returns between bond and money markets, moderate pairwise correlations between the foreign exchange, bond and money market, and an inverse correlation between the foreign exchange and the equity market.

Table 4 Average Correlation of Asset Returns (2002Q1-2014Q4)

	Bond	*Money Market*	*F/X*
Money	0.79		
F/X	0.59	0.46	
Equity	0.12	0.18	-0.29

As it relates to the absorption ratio over time, Figure 9 shows that even though the rolling 3-year average correlation showed steady decline, the absorption ratio demonstrated some oscillating behavior, particularly evident when based on the first principal component. In fact, based on the shift in the absorption ratio, evidence of financial fragility similar to that provided based instructional returns is demonstrated in 2007 and again in 2013.

Figure 9 Absorption Ratio - Returns by Market

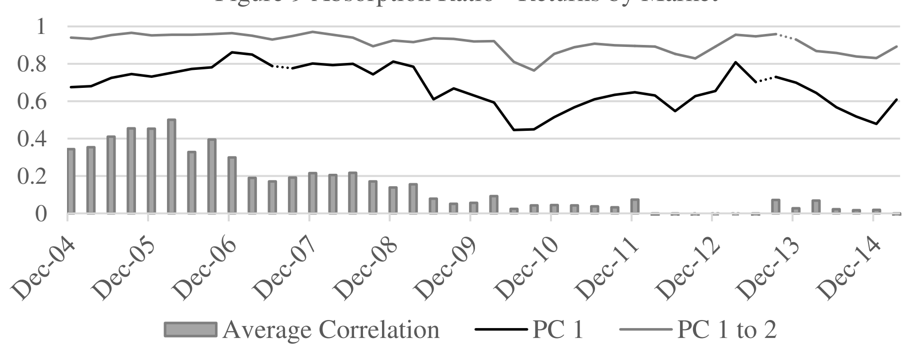

Table 5 Periods of a Significant Shift in the Absorption Ratio

<u>Shift in AR based on Market Returns</u>		
PC 1	Sep 07	Sep 13 --- Dec 13
PC 1 to 2		Dec 13

Measures of systemic contribution to risk based on the centrality score demonstrate that the equity market drove a large share of the covariance between markets in the 2007, while in 2013, the foreign exchange market demonstrates the largest contribution to risk.

Table 6 Markets' Centrality Score and Percentile Rank During Periods of Significant Shift (score in bracket)

	Market Return	
	Sep-07	Sep 13- Dec 13
1	Equity (0.81)	F/X (0.59)
2	FX (0.10)	Equity (0.31)
3	Bond (0.06)	Bond (0.06)
4	Money (0.03)	Money (0.02)

Closing and Future considerations

Macro-prudential oversight should undertake the measurement and analysis of risks stemming from both the structure and behavior of the financial system. The propagation of performance within and between markets, through pro-cyclical factor movements or herd behavior, is one way in which financial fragility and systemic weakness may arise as market players demonstrate commonalities in performance and exposures to risk. Early studies of financial conditions utilized the yield curve as a stand-alone measure of financial health and economic activity (Hatzius, Hooper, Mishkin, Schoenholtz, & Watson, 2010). A vast scope of macro prudential work now involves the creation of indices measuring financial conditions. Often the creation of indices entails the aggregation of a broad array of financial variables. Common among those are measures of the cost of capital or required rates of return, spreads between rates, asset volatility, industry performance or other financial measures specifically capturing unique country characteristics (Hakkio & Keeton, 2009).

This paper utilizes the principal components technique for the creation of measures of systemic vulnerability. These measures encapsulate the possibility that during periods of system-wide stress concurrent movement in the performance of banks will occur. Depending on the breadth and depth of the stress period, there may also be simultaneity in performance across markets. An absorption ratio is calculated which reflects the dimensionality of the co-movement of returns. Periods in which the dimensionality of the system becomes increasingly flat is measured by significant increase in the absorption ratio and a period of market fragility is calibrated as a shift in the absorption ratio. These shifts in the absorption ratio are calculated across the returns of commercial banks and across asset markets, separately. The paper shows that shifts in the absorption ratio captured accurately periods of financial stress in Jamaica.

PCA is also utilized as a method for identifying systemically important institutions during periods categorized as financially fragile. The loadings of cross-sectional units in the first eigenvector is sum-weighted and used to reflect those institutions and markets that contribute most to the shape of the dimensionality of co-movement in returns. This centrality score demonstrated that contribution to vulnerability changes over time and that multiple banks can contribute generally equally to risk regardless of size. The centrality score also demonstrated that equity and foreign exchange markets drove much of the financial fragility in Jamaica during its stress periods.

In total, the paper shows that changes in the absorption ratio can serve useful for monitoring and measuring financial conditions in Jamaica. Some future considerations in its use are undertaking a signal-extraction approach for evaluating its performance over time. Some modifications to its development could also be considered by adjusting the moving average window in the calculations of shifts in the ratio, possibly weighting the covariance matrix of returns to adjust for possible market persistence over time, and calculating of centrality scores based on the first and second principal components.[40]

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Appendix 1

Table A1 Reconstructed Banking Series

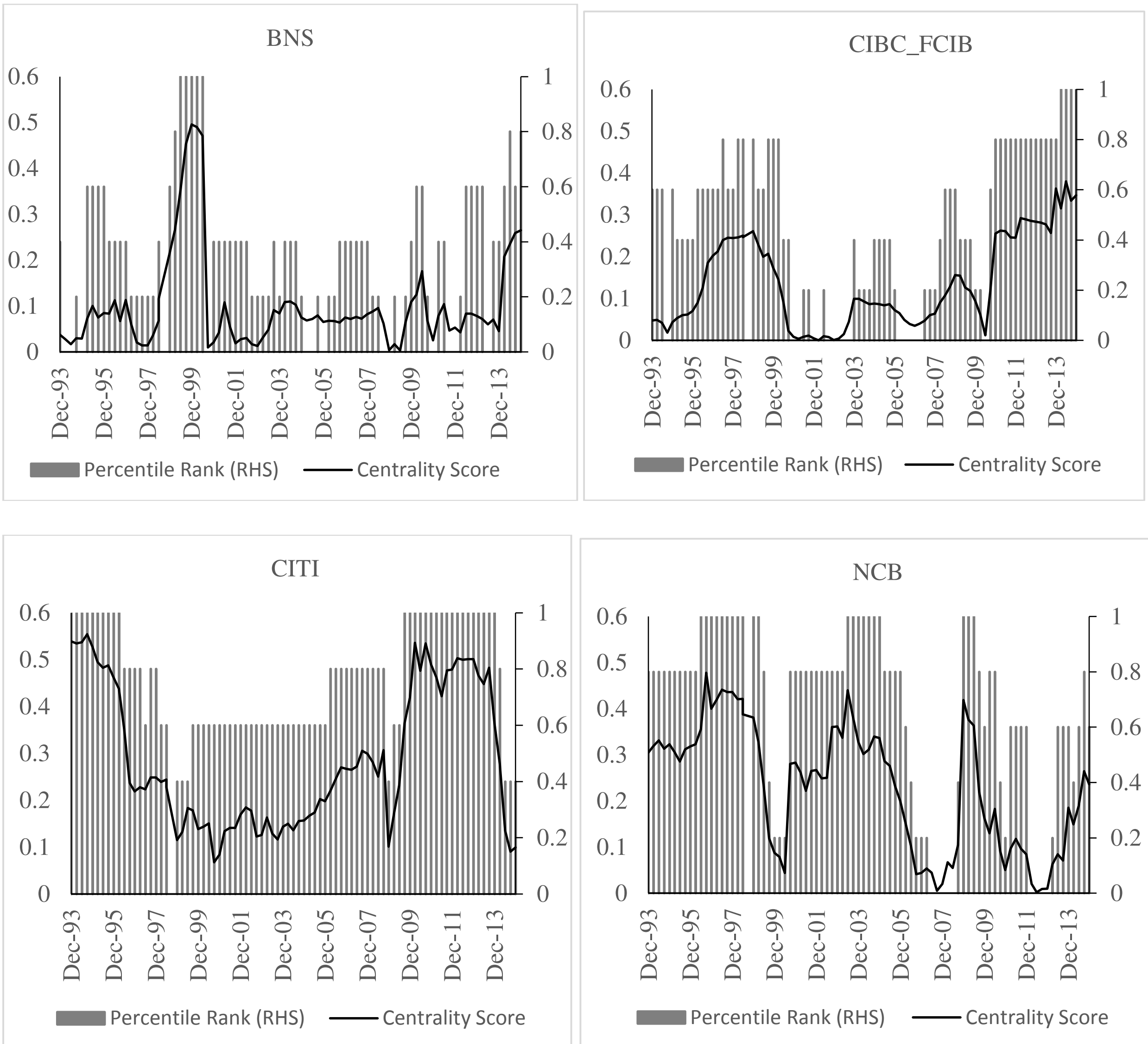
	Commercial Banks	Merger/ Acquisition
1	Bank of Nova Scotia	
2	National Commercial Bank	
3	CitiBank	
4	First Global Bank	Trafalgar Commercial Bank was thereafter renamed First Global Bank Limited on January 2002
5	First Caribbean Bank	First Caribbean was formed in 2002 with the merger of CIBC West Indies Holdings and Barclays Bank PLC Caribbean operations.
6	RBTT	Union Bank was the result of a merger of the business of *four (4) FINSAC controlled commercial banks* and their *three (3) allied merchant banks*: (Citizens Bank Ltd; Eagle Commercial Bank ltd; Island Victoria Bank Ltd; Workers Savings & Loan Bank; Citizens Merchant Bank Ltd; Corporate Merchant Bank Ltd; Island Life Merchant Bank) In 2000 RBTT acquired FINSAC's 99.9% shareholding in Union Bank of Jamaica and its name to RBTT RBTT was re-branded to RBC Royal Bank in 2011, three years after they were acquired by Royal Bank of Canada. RBC Royal Bank was re-branded to Sagicor bank in late 2014, after it was acquired by the Sagicor Group. The RBTT series from 1989 to 1996 is creating based on the accounting statement of Citizens Bank, Eagle Commercial Bank Ltd., and Workers Savings and Loans Bank. Net interest margins for RBTT include the accounts of Island Victoria starting June 1992.

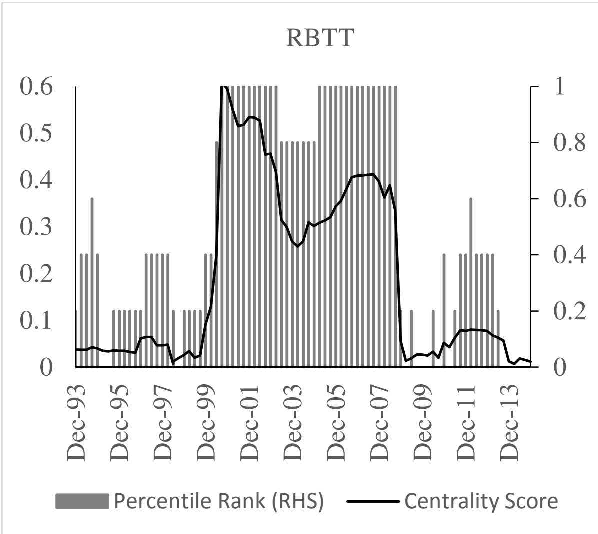
Table A2 PCA Related Studies

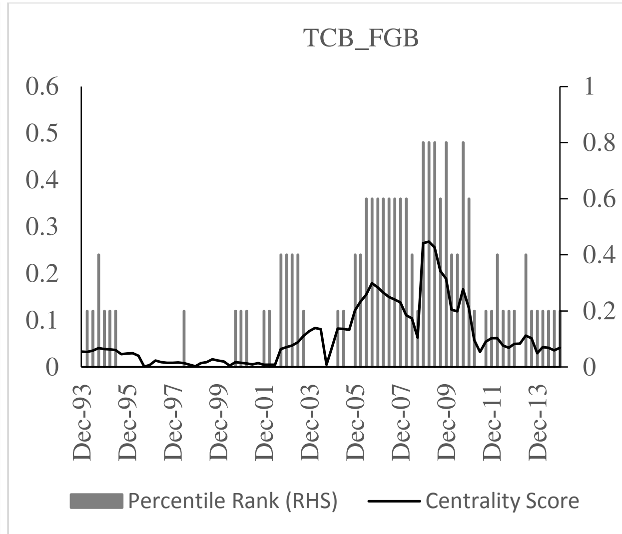
Saunders 1969	bank operating and balance sheet variables used to identify common aspects in determining returns
Billio et al.	monthly 1994-2008 index returns of hedge funds, brokerage, banks, and insurance to see commonality
Kritzman et al (2010)	500 day overlapping return of MSCI US index covering 51 industries between 1998-2010
Avanzini and Jara (2013)	5 year moving average 1989-2012 of return on assets and net interest margin for 15 banks

Appendix 2

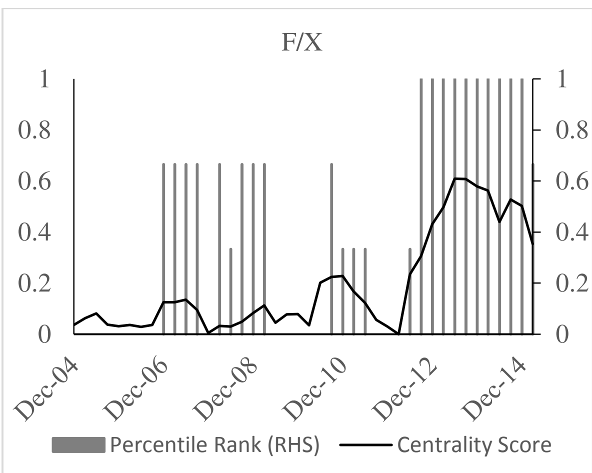
Centrality Scores Over Time by Bank Performance

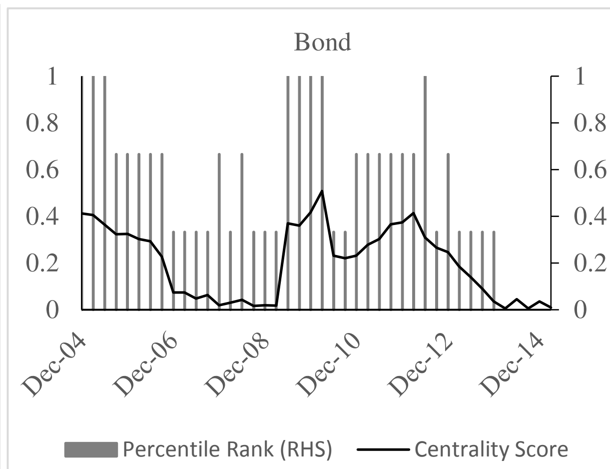


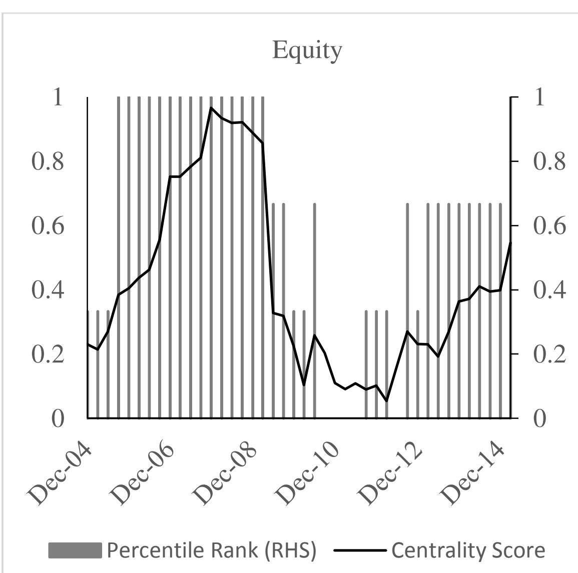


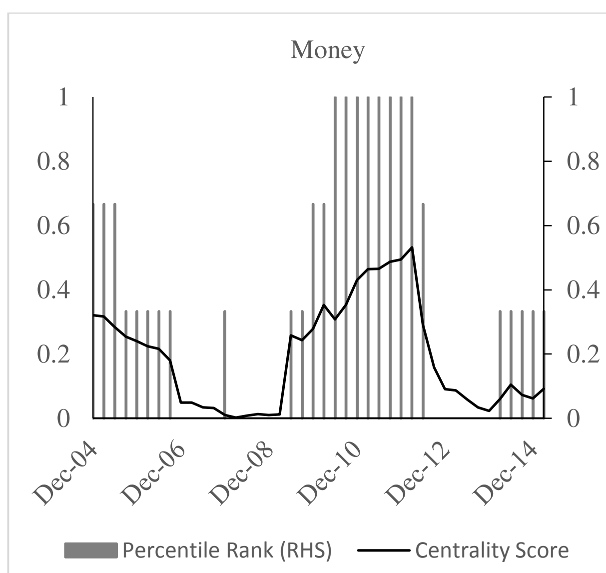


Centrality Scores Over Time by Market Performance









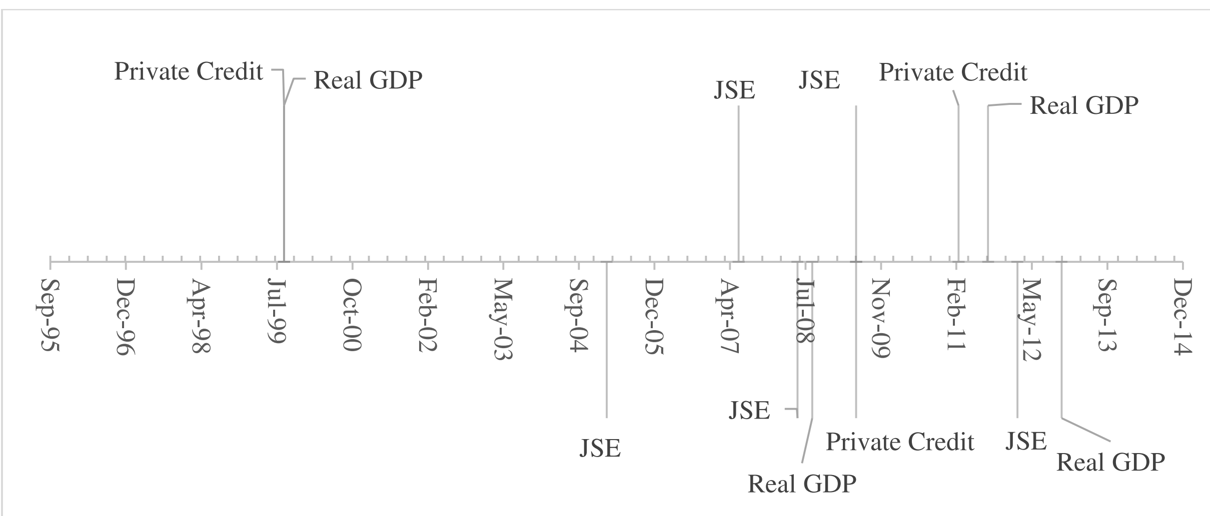
Appendix 3

Appendix 3 provides a description of some further assessments of the association of the absorption ratio with real economic activity. Does a shift in AR precede turning points in indicators of real financial and economic activity? Do the indicators of real activity perform worse during periods of high market fragility compared to periods of financial soundness as measured by shifts in the absorption ratio? Is there econometric evidence that the absorption ratio can serves significantly as leading indicator of real financial and economic activity?

Turning points

The 2 quarter moving average of private credit, real GDP, and the Jamaica Stock Exchange (JSE) Main Index are calculated. The difference in the two quarter moving average is then calculated. A change in the direction of the difference for at least 4 quarters is used to signal a turning point in the level of the indicator. Indicators above the timeline reflect a positive turning point those below the timeline reflect a negative turning point. The time periods of negative turning points generally mirror the periods of concerning shift in the absorption ratio.

Figure A2 Date of Turning Point by Indicator



The table below presents the quarterly percent change in economic indicators during periods 1 quarter, 2 quarters and 4 quarters after both a negative and positive shift in the absorption ratio. It is expected that the quarterly growth rates in periods immediately after a shift in ΔAR>1 (financial fragility) should be generally lower than that after ΔAR<-1 (relative stability). The analysis supports this expectation as the difference in these growth rate are generally positive.

Table A3 Growth Rates of Economic Indicators after an AR Shift

	ARROA			ARNIM		
	ΔAR>1	ΔAR<-1	difference	ΔAR>1	ΔAR<-1	difference
	RGDP					
1 qtr	0.26%	0.26%	+	0.14%	0.33%	+
2 qtr	0.14%	0.25%	+	0.08%	0.26%	+
4 qtr	0.34%	0.34%	+	0.33%	0.03%	-
	JSE Volume					
1 qtr	19.71%	92.54%	+	72.67%	138.32%	+
2 qtr	22.70%	55.95%	+	54.22%	6.01%	-
4 qtr	221.06%	247.90%	+	75.04%	184.96%	+
	JSE Value					
1 qtr	36.42%	44.07%	+	59.78%	89.82%	+
2 qtr	40.91%	13.60%	-	54.24%	8.25%	-
4 qtr	76.32%	154.69%	+	53.00%	61.15%	+

Econometric Lead-Lag Model

None of the referenced papers on the use and development of the absorption ratio undertake econometric assessment of its use. The appendix presents a lead lag model of real financial indicators. The specification is provided below and informs an assessment of whether changes in the absorption ratio provides useful information on the future changes in real economic activity.

$$y_t = \beta_0 + A(L)y_{t-1} + B(L)z_{t-1} + \varepsilon_t$$

Where

A(L) and B(L) are lag operators.[41]

y_t = the value of the real economic indicator

z_{t-1} = the absorption ratio

ε_t = a white-noise disturbance, with $E[\varepsilon_t]=0$ and $var[\varepsilon_t]=\sigma$

Equation assumes that z_t is strictly exogenous and evolves independently of y_t and that y_t has no effect on z_t, such that $E[z_t\ \varepsilon_t]=0$. Since B(L) is defined as $b_0+ b_1L+ b_2L^2+\ldots$, if $b_0=0$ then the value of z has no contemporaneous association with y. If $b_1, b_2, \ldots, b_t \neq 0$, then z can be considered a leading indicator of y. If so the leading indicator z will be a delay in the association with y.

[41] The lag operator is defined such that $L^i y_t \equiv y_{t-I}$.

Private credit to GDP, real GGP , values and volumes of Jamaica stock activity are used real economic indicators y, and z reflects the absorption ratio.

To determine the parameters of the polynomial we first evaluate the stationarity of the individual variables. If unit roots are present the variable is converted to its stationary form. Secondly, the best lag order y of is determined by evaluating the appropriate AR(p) for y. The Schwartz Bayesian Criterion is used to select an efficient parsimonious model of y. The $B(L)z_{t-1}$ is then added to the appropriate AR(P) structure of to evaluate whether it provided additional information in the variation of the series. The significance of the coefficients are evaluate by standard t-test of the null B(L)=0.

A second approach is taken as additional assessment of possible use of absorption ratios as indicators of real economic activity. The previous methodology assumed strict exogeneity of z_t. Since the absorption ratios were developed compositely from principal components analysis of financial indicators, we relax this assumption of pure exogeneity. A system of equations is specified that allows for y_t to be influenced by z_t , and as well z_t to be influenced by y_t. The vector autoregressive model is presented below.

$$y_t = \beta_{10} + \sum_{i=1}^{n} a_i y_{t-i} + \sum_{j=1}^{n} b_j z_{t-i} + \varepsilon_{1t}$$
$$z_t = \beta_{20} + \sum_{i=1}^{n} \alpha_i y_{t-i} + \sum_{j=1}^{n} \beta_j z_{t-i} + \varepsilon_{2t}$$

Here ε_{1t} and ε_{2t} are uncorrelated disturbances with constant variances σ_y and σ_z and $E(\varepsilon_{1t}) = E(\varepsilon_{2t}) = 0$. This system of equations is used to evaluate whether current or past values of the absorption ratios, z_t, help forecast future values of the indictors of the real environment. As such hypothesis testing does not test for contemporaneous associations between current period values. Each equation is estimated using ordinary least squares and the appropriate lag length is selected using Schwartz information criterion. The joint null hypothesis H_0: $\sum a_i=0$ is evaluated via F-Test.[42]
The results of both econometric exercises did not provide strong evidence that shifts in the absorption ratio provide useful information for setting expectations on the realization of the indicators of the real environment.

[42] These reflect Granger Causality testing (Granger, 1969).