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DOES THE CREDIT-TO-GDP GAP PREDICT FINANCIAL CRISIS IN NIGERIA?

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ⓘD Ihejirika, Peters. O

Department of Banking and Finance, Faculty of Management Sciences, Imo State University Owerri Imo State, Nigeria.
Email: ihejirikap@yahoo.com Tel: +2347035073297

(+ Corresponding author)

ABSTRACT

This study investigated the Credit-to-GDP Gap as an Early Warning Indicator (EWI) of banking/systemic crisis in Nigeria. Annual data on domestic credit to the private sector as a ratio of gross domestic product for the period 1981 to 2019 was used. The credit-to-GDP gap was calculated using the one-sided Hodrick-Prescott filter with Lamda set at 1600. The performance was analyzed using a couple of interrelated methods - the signal approach and the area under the receiver operating characteristic (AU-ROC) curve as well as graphical analysis for visualization. The results indicate that Credit-to-GDP Gap performs poorly in Nigeria with an area under the receiver operating characteristic (AU-ROC) curve of 63.68%. Further, this study shows that the Basel Committee on Banking Supervision's (BCBS) recommendation that the prudential authorities set lower thresholds (L) at 2% above trend may not work for Nigeria as this study suggests an optimal threshold of 0.98%. This result emphasizes the need for prudential authorities to employ informed judgement in setting thresholds with a view to activating the countercyclical capital buffer on time before crisis occurs.

Contribution/ Originality: This study is one of very few studies which have investigated the performance of the credit-to-GDP gap as an early warning indicator of financial/banking crisis in Nigeria.

1. INTRODUCTION

The aggregate private sector credit-to-GDP gap has been subjected to various scrutiny for its properties as a warning indicator for impending financial crisis. For instance, Schlarick and Taylor (2009) examine the long run behavior of money, credit, and macroeconomic indicators for 14 developed countries from 1870-2008 and show that credit growth is a significant predictor of financial crises with the conclusion that policymakers ignore credit growth at their own risk. With a growing argument but not denying the importance of the credit-to-GDP gap as a predictor of financial crisis, researchers (Hamilton, 2017) have queried the filter method (one-sided Hodrick-Prescot filter) used in generating the credit gap. Thus, Drehmann and Yetman (2020) embarked on a study with the soul aim of discovering which credit gap is better at predicting financial crises using different filter methods. The results of their investigation suggest a statistically small difference with limited relevance. All these lead to a greater desire to understand the role of credit-to-GDP as an early warning indicator and whether it can be applied to the Nigerian financial landscape as a macroprudential policy instrument.

The evolution of total credit, especially credit to the non-financial private sector over time may fall short of what is required by the real sector to grow and therefore dampen the growth of the economy in general while at

other times, credit growth may just be adequate. However, there are periods when credit growth becomes excessive and threaten the financial stability of the system. This scenario defines what has been referred to as the credit or financial cycle. Borio (2014) in Borio, Drehmann, and Xia (2018) defining "financial cycle" as the "self-reinforcing interactions between perceptions of value and risk, risk-taking, and financing constraints" observe that "this mutually reinforcing interaction" has "historically tended to cause serious macroeconomic dislocations". According to the Bank for International Settlements (Basel Committee on Banking Supervision (BCBS), 2010a) periods of excess aggregate credit growth is often associated with the build-up of system-wide risk.

To forestall the negative effect of both inadequate credit growth and excess aggregate credit growth with systemic wide risk implications, the Basel Committee on Banking Supervision (BCBS) (2010a) introduced the Countercyclical Capital Buffer in addition to other macro-prudential policy instruments - the Minimum Regulatory Capital requirement and the Capital Conservation Buffer. Whereas the Minimum Regulatory Capital requirement and the Capital Conservation Buffer are mandatory, the Countercyclical Capital Buffer is left to national jurisdictions to decide when to activate or release it as credit situations demand. Thus, the objective of the Countercyclical Capital Buffer is to ensure a more resilient banking system that can withstand financial stress and maintain adequate credit flow in the economy (Basel Committee on Banking Supervision (BCBS), 2010a). Simply, suppose a financial crisis occurs, banks acting on the side of safety may stop or reduce lending to borrowers. This will affect economic agents who need funds for their business activities which in turn affect the output of the economy in general. To prevent this type of situation, the Countercyclical Capital Buffer was introduced such that when signs of crisis appear, such as excessive credit growth, banks will be notified by the prudential authorities to begin to accumulate capital which will be deployed to service the system if eventually financial crisis occurs.

The question is, how do central banks know that credit growth is tending towards systemic wide risk? The operation or rather the decision to impose the countercyclical capital buffer demands that regulatory authorities be able to track aggregate credit growth and decide whether such growth is excessive and tending towards system-wide risk (Basel Committee on Banking Supervision (BCBS), 2010a). To track the financial fragility or build-up of system-wide risk, the BIS through its Basel Committee on Banking Supervision recommends a "common reference guide based on the aggregate private sector credit-to-GDP gap". The aggregate private sector credit-to-GDP gap is the deviation of the aggregate private sector credit-to-GDP ratio from its long-term Hodrick- Prescott (HP) filtered trend. Although the BIS warned that "the guide does not always work well in all jurisdictions at all times", studies have shown that the aggregate private sector credit-to-GDP gap is a good warning indicator for impending financial crisis (Corder & Weale, 2011; Drehmann, Borio, Gambacorta, Jiménez, & Trucharte, 2010; Drehmann, Borio, & K, 2011; Schlarick & Taylor, 2009; Valinskytė & Rupeika, 2015). Several more studies have gone ahead to consider other early warning indicators including Basel Committee on Banking Supervision (BCBS) (2010a) property prices, banking system aggregate profits and spreads. Dieter, Gavin, Mikhail, and Stephen (2010) provide a critical review of early warning systems for systemic banking risk while Aldasoro, Borio, and Drehmann (2018) incorporate debt service ratio, cross border or foreign currency debt ratio and household debt ratio into the list of possible early warning indicators. Furthermore, other studies (Bakhuashvili, 2017; Hamilton, 2017) expand the literature on methodological grounds arguing against the use of the one-sided Hodrick Prescott filter recommended by the Bank for International Settlements for the calculation of the credit to GDP gap.

However, Caggiano, Calice, and Leonida (2013), cried out in their study "Early Warning Systems and Systemic Banking Crises in Low Income Countries" published by the African Development Bank, that "while most of the focus has been on advanced economies, the relevant empirical literature has devoted scant attention to low income countries". Again, Borio et al. (2018) writing on "The financial cycle and recession risk" add that research such as Liu and Moench (2016); Ponka (2017) and Guender (2018), exploring how financial expansions affect recession risk is scant and predominantly focused on the United States. In Nigeria, the Central Bank of Nigeria uses as early warning system the composite score model and the logit model centered around financial soundness indicators

developed by the Central Bank of Nigeria in conjunction with the International Monetary Fund to predict bank failure over a 12-month period. While the composite score model does not predict bank failure (CBN, 2016), (Kama, Adigun, & Adegbe, 2013) observe that "it is more concerned with the solvency of individual institutions rather than the resilience and stability of the financial system as a whole". On the other hand, the Nigerian Deposit Insurance Corporation (NDIC) was using bank ratings (financial ratios) based on returns submitted by banks through Electronic-Financial Analysis Surveillance System (eFASS) but currently uses Early Warning Systems based on statistical, econometric and artificial intelligence techniques that utilize both regulatory information and market data as input to produce estimates of bank failure. This paper re-echoes the observation by Caggiano et al. (2013) and affirms that the gap has hardly been filled as literature search still reveal very scanty studies on the credit-to-GDP gap as an early warning indicator to financial crisis in Nigeria. This paper sets out to bridge this gap. Following the above introduction, the rest of paper is organized as follows. Section two reviews related literature, section three states the methodology, analysis is covered in section four while the paper concludes in section five.

2. REVIEW OF RELATED LITERATURE

2.1. Minimum Regulatory Capital, Capital Conservation Buffer and the Countercyclical Capital Buffer

The banking sector arising from the nature of its business is faced with several types of risks including (a) credit risk (b) market risk and (c) operational risk. To protect the financial system's assets from these risks, regulatory authorities stipulate some level of capital that could be used to absorb losses when these risks materialize. Ihejirika (2015) observe that the Basel Capital Accords envisages that the higher the risk of loss, the higher the qualifying capital base of banks to maintain the stipulated capital adequacy ratios. The components of capital as specified by BCBS (2012) in the Basel framework effective from 2019 comprise of Tier 1 (common shares, share premium, retained earnings, accumulated other comprehensive income and other disclosed reserves, minority interests and regulatory adjustments to common equity tier 1) which must be at least 6.0% of Risk Weighted Assets (RWA). The framework also stipulates that common equity tier 1 must be at least 4.5% of RWA. The other component is the tier 2 capital (revaluation reserves, hybrid capital instruments – cumulative preferred stocks and convertible bonds, subordinated term debt, general loan-loss reserves, undisclosed reserves). According to the Basel framework, total capital must be at least 8.0% of RWA. This constitutes the minimum risk-based capital requirements of banks.

To further strengthen the banks, an additional capital above the minimum regulatory capital called the Capital Conservation Buffer of 2.5% of RWA was stipulated by the BCBS (2012). This capital conservation buffer is designed to ensure that adequate capital is accumulated from Common Equity Tier 1 by banks during "stress free" periods which can be used to absorb losses when they occur. It is a layer of security to maintaining the minimum regulatory capital.

A second layer of security against losses though for entirely different purpose is the Countercyclical Capital Buffer. The Basel committee on banking supervision recognizes that banks faced with down-side risk will tighten credit which may not augur well for the real economy. Thus, to ensure a more resilient banking system, the BIS in Basel 111 provides that supervisory authorities monitor the credit cycle against aggregate excess credit that may result to system wide risks. To this end, the regulatory authorities are required to initiate capital build-up by the banks of between $0 - 2.5$ of RWA which banks can use to still perform the intermediation role especially extension of credit to the real sector even in periods of crisis. This is the essence of the countercyclical capital buffer.

2.2. Credit-to-GDP Ratio, Credit-to-GDP long-term trend and Credit-to-GDP Gap

In their work "Why you should use the Hodrick-Prescott filter – at least to generate credit gaps", Drehmann and Yetman (2018) reported that Borio and Lowe (2002) proposed a credit-to-GDP gap measured by the deviations of the credit-to-GDP ratio from a one-sided Hodrick-Prescott (HP) filter with a large smoothing parameter (400

000 for quarterly data) as an indicator to system-wide risk build up. The credit-to-GDP gap according to Drehmann et al. (2011) as well as BIS (2019) is the deviations of the credit-to-GDP ratio from its long-term trend.

However, literature on the credit-to-GDP gap dwells on the definition of credit and the appropriateness of the one-sided Hodrick-Prescott filter to the calculation of the gap. On the definition of credit, the Basel Committee on Banking Supervision (BCBS) (2010a) "Guidance for national authorities operating the countercyclical capital buffer" used a broad definition of credit that include all sources of debt funds for the private sector in addition to funds raised abroad. The definition of credit BIS say, should include all credit given to households and private, non-financial sector in an economy no matter its origin and type. In other words, it should not be credit as extended by banks alone. It also observed that available credit data differ across prudential jurisdictions. Apparently, the BCBS applied different Credit series for the countries in its empirical analysis chiefly among them is the total domestic credit to the private sector (see Basel Committee on Banking Supervision (BCBS) (2010b)).

2.2. Episodes of Financial Crisis in Nigeria

The World Bank. (2020) explains that systemic banking crisis occurs when many banks in a country are in serious solvency or liquidity problems at the same time. In Nigeria, the CBN/NDIC (2002) cited in CBN (2013) defined systemic banking crisis as a situation in which banks that are distressed holds 20.0 per cent of the total assets in the banking system; and, secondly, 15.0 per cent of total deposits are exposed; and, 35.0 per cent of banks' total loans are non-performing.

Goldstein, Kaminsky, and Reinhart (2000) provide two approaches to define what a crisis is. The first approach uses three criteria:

(i) the ratio of non-performing loans to total loans in the banking system exceeded ten percent; (ii) the cost of the bank rescue operation was a least two percent of GDP; (iii) the rescue episode involved either a large-scale nationalization of banks, or extensive runs on bank deposits, measures like deposit freezes, bank holidays and or the issuance of government blanket guarantees.

The second approach is to call an episode a banking crisis if you see large-scale bank runs, bank closures, mergers, or large public-sector takeovers of banks. Goldstein et al. (2000) choose the second approach.

Similarly, banking crises episodes according to Laeven and Valencia (2012), is defined as systemic if two conditions are met: (1) Significant signs of financial distress in the banking system (as indicated by significant bank runs, losses in the banking system, and/or bank liquidations) and (2) Significant banking policy intervention measures such as: extensive liquidity support, bank restructuring gross costs (at least 3 percent of GDP), significant bank nationalizations, significant guarantees put in place, significant asset purchases and deposit freezes and/or bank holidays in response to significant losses in the banking system.

2.2.1. Some Crisis Events in the Nigerian Banking System

1991 eight banks in Nigeria were officially classified as distressed, or technically insolvent.

1992 the number of banks officially classified as distressed rose to fifteen.

1993 the number of banks officially classified as distressed rose to twenty-seven.

1994 the number of banks officially classified as distressed rose to forty-seven.

1994 non-performing loans/bad accounts represented 567.7%, of shareholders' funds.

1995 60 banks were considered distressed.

1995 five banks were under interim management boards.

1995 seventeen banks had been taken over by the CBN.

1996 non-performing loans/bad accounts represented 419.8% of shareholders' funds.

2003 The number of unsound banks rose from 9 to 11.

2004 non-performing loans/bad accounts represented 105.3% of shareholders' funds.

2005 At the end of the consolidation exercise, 19 of the new banks arose from mergers and acquisitions.

2007 Nigerian banking system had a Banking System Indicator (BSI) rating of D for Poor system quality.

2007/2008 financial crisis, CBN Bailed out banks to the tune of over 720 billion naira.

2009 Nigeria deployed significant liquidity support and guarantees on bank liabilities.

2009 takeover of 5 banks, significant nationalizations and extensive liquidity support.

2010 Nigeria established an asset management company.

2011 a significant transfer of nonperforming loans and merger of four banks took place.

2011 significant guarantees on liability, significant restructuring costs, significant asset purchases.

2018 Polaris Bank was established by the Central Bank of Nigeria (CBN).

Table-1. Number of banks closed and year of closure.

Crisis Periods	Number of closed banks
1994	4
1995	1
1998	27
2000	3
2006	10
2011	3
2013	1

The above crisis events were extracted from several sources including but not limited to Alashi (2002); Ebong (2005); Soludo (2004); Burgis (2009); IMF (2013); Ugoani (2015); Iyede, Onah, and Osusu (2018); Laeven and Valencia (2018); IMF Staff reports; IMF Financial Soundness Indicators; CBN/NDIC Banking Supervision Annual Report several years, CBN Financial Stability Report several years and Nigerian Deposit Insurance Corporation annual reports several issues.

Table 1 show the number of banks closed by the central bank of Nigeria and the years they were closed. According to Goldstein et al. (2000) any year bank closures occurs is counted as banking crisis period.

2.3. Empirical Review of Related Literature

Several researchers have attempted to examine the potency of the credit-to-GDP gap as an early warning indicator.

Bonfim and Monteiro (2013) study the implementation of the Countercyclical Capital Buffer with particular attention to Rules Versus Discretion for Belgium, Finland, France, Germany, Ireland, Italy, Portugal, Spain and United Kingdom starting from 1977 to 2011. One of the aims of their study was to examine the implementation of the capital buffer based on the credit-to-GDP gap calculated using a one-sided Hodrick-Prescott filter as well as identifying other indicators well suited to guide buffer decisions. They used quarterly credit data collected from BIS' website and defined data as credit to private non-financial sectors while their annualized GDP data based on national official statistics came from Thomson Reuters. They performed a sensitivity analysis to the calibration of the "buffer guide" that is, the credit-to-GDP gap, showing that the results were sensitive to the methodologies used and to the assumptions made. Furthermore, they analyze several other indicators with "leading and near-coincident properties", which may potentially be relevant in guiding buffer decisions. Their analysis confirms that the credit-to-GDP gap is amongst the best performing indicators in predicting banking crises, but shows that other indicators also display good signalling properties

Giese et al. (2014) examined the credit-to-GDP gap and complementary indicators for macroprudential policy in the UK. Their dataset began in the late 1960s for most series, covering the secondary banking crisis from Q4 1973 to Q4 1975, the small banks' crisis from Q3 1990 to Q2 1994 and the current crisis from Q3 2007 onwards up to 2012. They defined their data in two ways following Basel Committee on Banking Supervision (BCBS) as (1)

broad credit to the households and private non-financial corporate sector, non-banks and lending from abroad and (2) the narrow measure as UK resident bank lending to resident households and private non-credit financial corporations. For this, they constructed an approximation of the credit-to-GDP gap back to the 1960's by extrapolating the credit sales data. They detrended the credit to GDP ratio using the Hodrick-Prescott filter as suggested by bank of international settlements Basel Committee on Banking Supervision (BCBS) (2010a) with a smoothing parameter of 400,000. They calculated the credit-to-GDP gap as the difference between credit growth and its long-term trend. Giese et al. (2014) report that the credit-to-GDP gap worked well in providing an advance signal of past UK episodes of banking system distress but suggested that it should not be used in isolation.

Farrell (2014) investigated Countercyclical capital buffers and real-time credit-to-GDP gap estimates based on South African perspective. Credit-to-GDP gaps were estimated by applying a range of Hodrick-Prescott filters to real-time South African data. The properties of these estimates are compared, and the calibration of the lower and upper thresholds of the buffer in the South African case was also investigated. Farrell (2014) indicates that the mechanical application of the credit-to-GDP guide is not advisable, and raises a number of issues that policymakers will have to consider when implementing the countercyclical buffer guidance.

Nicole (2016) "Predicting financial crises" explored the significance of aggregate indicators in predicting banking crises in advanced economies. The paper assessed the importance of 26 indicators in forecasting crises, two years in advance, for twenty high income countries for the period 2006 to 2016, using machine learning techniques and classification tree models. The results indicate that domestic credit to the private sector, as a percent of GDP, is the most common significant indicator in forecasting banking crises while bank lending deposit spread became the most significant indicator when classification models inclusive of all countries, however, more data is needed to build upon these models to ensure their robustness.

Aikman, Lehnert, Liang, and Modugno (2017) studied "Credit, Financial Conditions, and Monetary Policy Transmission" with the objective to examine the role of private nonfinancial credit in conditioning the response of the U.S. economy to impulses to financial conditions and monetary policy. Their data consisted of a broad measure of credit to households and nonfinancial businesses provided by banks, other lenders, and market investors. They measured high credit as when the credit gap (credit-to-GDP ratio minus its estimated long-run trend) is above zero as in Borio and Lowe (2002); Borio and Lowe (2004); Borio and Drehmann (2009) and also when growth in the credit-to-GDP ratio is above its average. They also constructed a financial condition index (FCI) by combining information from asset prices and non-price terms, such as lending standards, for business and household credit, following (Aikman, Kiley, Lee, Palumbo, & Warusawitharana, 2017). They applied a threshold vector autoregression (TVAR) model to their data series starting from 1975 to 2014. Aikman et al. (2017) results show that the effects of financial conditions and monetary policy on U.S. economic performance depend nonlinearly on non-financial sector credit.

Bakhuashvili (2017) examined credit to GDP gap as an indicator for upcoming financial crisis using data for Georgia with a sample period ranging from 2000 to 2016. The researcher used four variables: seasonally adjusted real GDP, the real estate price index, the Credit to private sector and the nominal GDP. For comparative reasons, the study generated gaps using both nominal and real GDP as denominators as well as detrended the series using HP filter and the Kalman filter. The study reports that the gaps calculated using the Kalman filter out performed the HP filter as an early warning indicator.

Odeta (2017) study "Credit-to-GDP gap as an early warning indicator of banking stress in Albania". Quarterly data on three gap series - total credit to private sector–to-GDP gap from Q4 1996 to Q4 2015, credit to households and credit to firms that covered the period Q4 2001 to 2015Q4) were used. The study employed (Kaminsky. & Reinhart, 1999) signal extraction approach to test the early warning abilities of the indicators generated using one sided Hodrick-Prescott filter with varying smoothing parameters. The study indicates that credit to GDP gap for total credit to private sector, computed using HP filter $\lambda = 25000$ or 400000 work best as early warning indicator in

terms of the study's evaluation criteria and up to two periods ahead of a potential episode of distress or crisis. For the other gap series, the study asserts that the performance of credit to households-to-GDP gap, and firms' credit to-GDP- gap, were weak as they failed in predicting most part of the stress episodes although these indicators generate low noise rates.

Barrell, Karim, and Macchiarell (2017) paper "Towards an understanding of credit cycles: do all credit booms cause rises?" considered the calculation of the credit-to-GDP gap by examining several ways of extracting the cyclical indicator for excess credit. They compared different smoothing parameters for the credit gap, and show that some countries require an AR(2) process while others do not. They arrived at this conclusion by using Logit models of financial crises, and further state that the AR(2) cycle is a much better contributor to their explanation than is the HP filter suggested by the BIS. Their study covered Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Spain, Sweden, UK and US with data that ranged from $1978 - 2016$.

Alessi and Detken (2018) exploring "identifying excessive credit growth and leverage" insist that unsustainable credit developments endanger financial stability. Their data consisted of broad credit aggregates sourced from BIS and considered (i) the year-on-year rate of growth, (ii) the ratio to GDP, and (iii) the deviations of such ratios from its trend (i.e. the 'gap'). The gaps were detrended using Hodrick-Prescott filter with the smoothing parameter set equal to 400,000 and 26,000 (i.e. λ = 400,000 and 26,000) alternatively to address the duration disparity between financial cycle and business cycle. They constructed three models- a modern classification tree ensemble technique, "Random Forest", as well as logit models and included (global) credit as well as real estate variables as predictors. The results highlighted that the main drawback of the tree technology is its non-robustness when additional predictors or observations are included. While the Random Forest turned out to be an extremely powerful predictor, and could be used as a regular tool for policy purposes.

Aldasoro et al. (2018) study on Early warning indicators of banking crises confirm that credit-to-GDP gap provide information to the build-up of vulnerabilities but assert that combining the EWI used by the BIS with Household and international debt gaps improves performance of the EWIs. Their study covered 42 countries with data ranging from 1980Q1 to 2017Q2. Their credit-to-GDP gap was measured as the difference between the ratio of total non-financial sector credit to GDP and its trend based on a one-sided Hodrick-Prescott (HP) filter with the smoothing parameter equal to 400,000 (i.e. λ = 400,000).

Drehmann and Yetman (2018) study titled "why you should use the Hodrick-Prescott filter – at least to generate credit gaps" in response to Hamilton (2017) paper: "why you should never use the Hodrick-Prescott Filter", argue that gaps serve as indicators and not cause. That HP filter results in spurious dynamics, has end-point problems and its typical implementation is at odds with its statistical foundations as propagated by Hamilton (2017) should not deter jurisdictions from using the HP filter. Drehmann and Yetman (2018) while agreeing with criticisms of the HP filter set up a comparative study to empirically compare which measure performs best as an early warning indicator for crises between the use of linear projections proposed by Hamilton and the Hodrick-Prescott filter detrended series recommended by the BIS. Using quarterly data from 1970 to 2017 for 42 economies, they considered eight gaps and used two methods of normalizing nominal credit (either by nominal GDP or by calculating real-credit-per-capita), as well as four methods of deriving "gaps" relative to an HP trend including linear projections. The results of their study indicate that no other gap outperforms the Basel recommended credit-to-GDP gap while credit gaps based on linear projections in real time performed poorly.

Giordani and Simon (2019) "Tracking financial fragility," was concerned with the performance of credit-to-GDP gap when detrended using the HP filter compared to using a moving average and what they called the local level filter. Though the present study is not about methodology, the take away from their study is that credit-to-GDP is a veritable tool for managing financial fragility.

3. METHODOLOGY

This study is modelled following the recommendation of the Basel Committee on Banking Supervision (BCBS) on the derivation of the credit-to-GDP gap. To derive the credit-to-GDP gap the Basel Committee on Banking Supervision (BCBS) (2010a) calculate the credit to GDP gap in period t as the actual credit-to-GDP ratio minus its long-term trend (see Equation 3) calculated using the one-sided Hodrick-Prescott filter. The Hodrick-Prescott filter divides the Credit to GDP Ratio (ratio) into two components: the trend (trend) and the gap (gap) as shown in Equation 1 such that:

$$ratio_t = trend_t + gap_t \qquad (1)$$

While the Credit-to-GDP ratio is calculated by dividing domestic credit to the private non-financial sector at time t with gross domestic product at time t. this is expressed in Equation 2.

$$ratio_t = \frac{credit_t}{GDP_t} \times 100\% \qquad (2)$$

the Credit to GDP Gap results from the difference between the ratio and the trend. Thus,

$$gap_t = ratio_t - trend_t \qquad (3)$$

The trend ($trend_t$) was calculated using the one-sided Hodrick-Prescott (HP) filter (see Equation 4 below) which is expressed as:

Minimize $trend_t$:

$$\left\{ \sum_{t=1}^{T}(ratio_t - trend_t)^2 + \lambda \sum_{t=2}^{T-1}\big((trend_{t+1} - trend_t) - (trend_t - trend_{t-1})\big)^2 \right\} \qquad (4)$$

Where,

$\sum_{t=1}^{T}(ratio_t - trend_t)^2 = $ *is the sum of the squared deviations of trend from ratio*

$\sum_{t=2}^{T-1}\big((trend_{t+1} - trend_t) - (trend_t - trend_{-1})\big)^2 = $ *sum of the squares of 2nd difference of $trend_t$*

$\lambda = $ *is a smoothing parameter. BCBS (2010) suggests 1600 for annual data.*

also, see Drehmann, Borio, Gambacorta, Jimenez and Trucharte (2010).

3.1. Data

The literature show that most studies in this area used quarterly data. The Basel Committee on Banking Supervision (BCBS) (2010a) however, while using quarterly data for most of the countries in its study, also used annual data for Saudi Arabia and calculated the gap using a one-sided HP filter with a smoothing factor - lambda of 1,600. In Nigeria, quarterly data is not evenly available across variables but annual data on Domestic Credit to private sector to GDP ratio is available from World Development Indicators (WDI) for the period 1960 to 2018 and Central Bank of Nigeria (CBN) Statistical Bulletin 1981 to 2019. This study used the already published annual data on Domestic Credit to private sector to GDP ratio as published by the Central Bank of Nigeria to generate the credit to GDP Gap (a test of equality of variances between WDI and CBN data 1981 - 2018 indicate no significant

difference see Appendix 1). For data on episodes of financial crisis, this study adopted the updated episodic banking and systemic crisis binary data sourced from Harvard Business School's (HBS) Global Crises Data bank which relies on data "collected over many years by Carmen Reinhart with her coauthors Ken Rogoff, Christoph Trebesch, and Vincent Reinhart". However, the categorization of crisis into "Banking Crisis" and "Systemic Crisis" by HBS was merged to arrive at a consolidated episodic crisis binary data. In addition, years of bank closures, mergers, or large public-sector takeovers of banks (1998, 2000, 2006,2017 and 2018) not captured in the HBS data base were incorporated (see (Goldstein et al., 2000; Reinhart & Rogoff, 2009)).

3.2. Performance Evaluation

Previous studies have applied various methods such the signal approach, area under the curve (AUC) employing the receiver operating characteristic (ROC) curve, logistic and multi-variate models among others to evaluate the performance of early warning indicators. In this study, the analysis was done using a couple of interrelated methods such as the signal approach and the area under the ROC curve. Graphical analysis was also used to visualize some elements of Credit-to-GDP Gap as an Early Warning Indicator (EWI).

3.2.1. Classification Table/Confusion Matrix

First, the researcher classified the credit-to-GDP Gap signals into True Positives, False Positives, False Negatives and True Negatives based on several thresholds (see Table 2 and 4 below)

Table-2. Classification table.

		Actual outcome	
		Crisis occurs	No crisis
Prediction	Signal	True Positive (TP)	False Negative (FP)
		(A)	(B)
			Type 1 Error
	No signal	False Positive (FP)	True Negative (TN)
		(C)	(D)
		Type 11 Error	

Where

A = Credit-to-GDP issues signal and crisis occurs within the timeframe =True Positive (TP).

B = Credit-to-GDP issues signal but no crisis occurred within the timeframe = False Negative (FP).

C = Credit-to-GDP issues no signal but crisis occurs within the timeframe False Positive (FP).

D = Credit-to-GDP issues no signal and no crisis occurs within the timeframe (true Negative).

The outcomes of the classifications were used to calculate True Positive Rate (Sensitivity) and True Negative Rate (Specificity) for the ROC curve, as well as Accuracy, Noise-to-Signal ratio, the Youden Index, Distance to Corner and Positive Predictive Value or Precision. The formula for the calculations are provided below.

Table 3 Formula for: False Positive Rate (Type 11 error), False Negative Rate (Type 1 error), True Negative Rate or Specificity, Positive Predictive Value or Precision, Accuracy (Proportion Correctly Classified), Youden Index, Distance to Corner and Noise to Signal Ratio (NTSR).

3.2.2. Noise-to-Signal Ratio

Supriyadi (2015) states that a generally accepted method to evaluate the performance of an indicator is the Signaling Approach. According to Kaminsky, Lizondo, and Reinhart (1998), this is the ratio of false signals (noise) to good signals. The noise to signal ratio is obtained by dividing Type 11 error with 1- Type 1 error. As a guideline, the lower the noise to signal ratio the better the indicator (Kaminsky et al., 1998).

Table-3. Formula for the calculation of True Positive Rate or Sensitivity, False Positive Rate (Type 11 error), False Negative Rate (Type 1 error), True Negative Rate or Specificity, Positive Predictive Value or Precision, Accuracy (Proportion Correctly Classified), Youden Index, Distance to Corner and Noise to Signal Ratio (NTSR).

Statistic	Formula
True Positive Rate or Sensitivity	$TPR \ or \ Sensitivity = \dfrac{A}{A+C}$
False Positive Rate (Type 11 error)	$FPR = \dfrac{B}{B+D}$
False Negative Rate (Type 1 error)	$FNR = \dfrac{C}{A+C}$
True Negative Rate or Specificity	$TNR \ or \ Specificity = \dfrac{D}{B+D}$
Positive Predictive Value or Precision	$PPV = or \ Precision = \dfrac{A}{A+B}$
Accuracy (Proportion Correctly Classified)	$Accuracy = \dfrac{A+D}{A+B+C+D}$
Youden Index	YI = Sensitivity + Specificity - 1.
Distance to Corner (distance from the top left corner of the ROC curve to the point on the ROC curve)	$d = \sqrt{(1 - sensitivity)^2 + (1 - specificity)^2}$
Noise to Signal Ratio (NTSR)	$NTSR = \dfrac{Type \ 11 \ error}{1 - type \ 1 \ error} = \dfrac{B/(B+D)}{A/(A+C)}$

3.2.3. Empirical ROC Curve

This is a graph showing the plots of the true positive rate (TPR) or sensitivity on the Y-axis against the false positive rate (FPR) or (1 − specificity) on the X-axis. TPR and FPR are derived from the counts of True Positives, False Positives, False Negatives and True Negatives for all possible threshold values.

3.2.4. Area under the ROC Curve (AUC)

This is a popular measure of the accuracy of a warning indicator. Generally, higher AUC values indicate better performance (see Drehmann and Juselius (2014) for benefits of the AUC). The values of AUC range from 0.5 (no prediction ability), 0.7 - 0.8 (acceptable), 0.81 − 0.9 (excellent) and above 0.9 is considered outstanding (see Mandrekar (2010)).

3.2.5. Youden Index, (Sensitivity + Specificity) and Distance to Corner

These statistics are used to determine the optimal threshold. Higher values of the Youden Index and Sensitivity + Specificity are better than lower values. While Lower distances to the corner are better than higher distances.

4. RESULTS

4.1. Comparism of CPS/GDP Gap Generated Using Lambda of 100 and 1600

A test for equality of variances between series on the CPS/GDP gap generated using Lambda of 100 and 1600 respectively show that there is marginal significant difference at 95% confidence level between the gaps (see Appendix 2). Presented in Figure 1 below is the graphical view of the movement of CPS/GDP Gap generated using Lambda of 100 and 1600 respectively. However, since this study follows the (Basel Committee on Banking Supervision (BCBS), 2010a) model, the CPS/GDP gap in this study was generated using Lambda = 1600 for annual data.
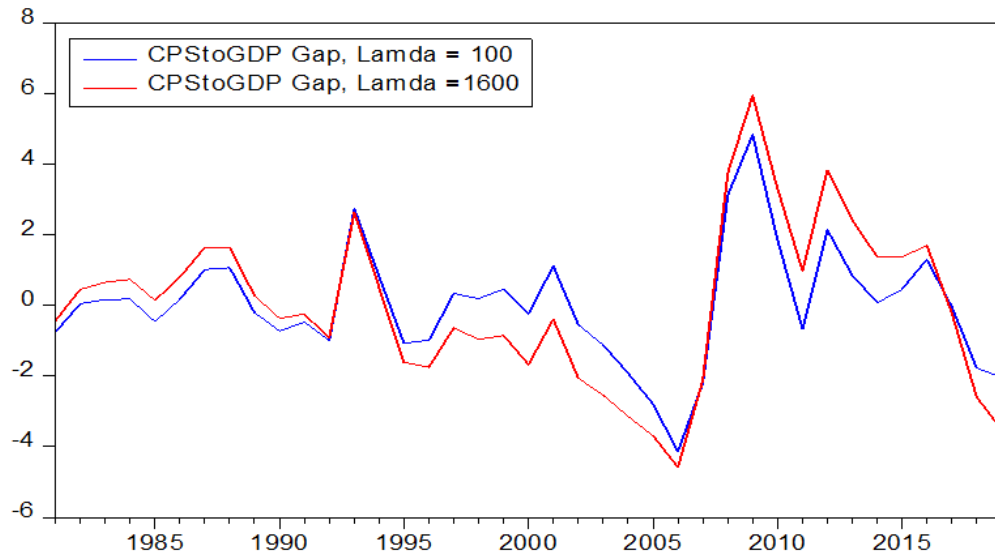
Figure-1. CPS/GDP gaps with different lambda values.

The idea behind early warning indicators is to predict financial crisis long enough (2 or 3 years) before it happens. According to the Basel Committee on Banking Supervision (BCBS) (2010a), there is need to determine when the gap begins to signal crisis at which point the countercyclical capital buffer is activated. The Basel Committee on Banking Supervision (BCBS) (2010a) suggests setting the minimum threshold (L) at 2% above the trend (i.e. if the gap exceeds the trend by 2%) but this depends on Lambda used to calculate the gap and the peculiarities of the prudential jurisdiction. A general consideration would be to set L "low enough, so that banks are able to build up capital in a gradual fashion before a potential crisis" (Basel Committee on Banking Supervision (BCBS), 2010a). Also, Basel Committee on Banking Supervision (BCBS) (2010a) recommends that "L should be high enough, so that no additional capital is required during normal times and the maximum threshold (H) should be low enough (Basel Committee on Banking Supervision (BCBS), 2010a) suggested 8%), so that the buffer would be at its maximum prior to major banking crises".

The process to implementing an early warning indicator using the credit-to-GDP gap begins with calculating the credit-to-GDP ratio, credit-to-GDP ratio trend using a chosen filter and Lambda value and extracting the credit gap. Figure 2 below show the movement of Credit-to-GDP ratio, Credit-to-GDP HP Trend and Credit-to-GDP Gap during the period covered by this study.
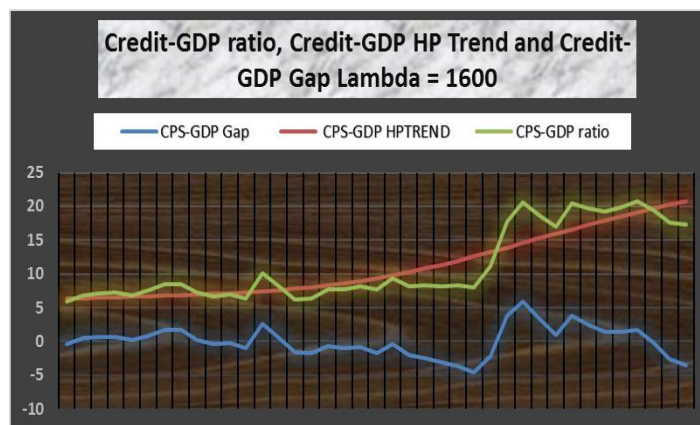

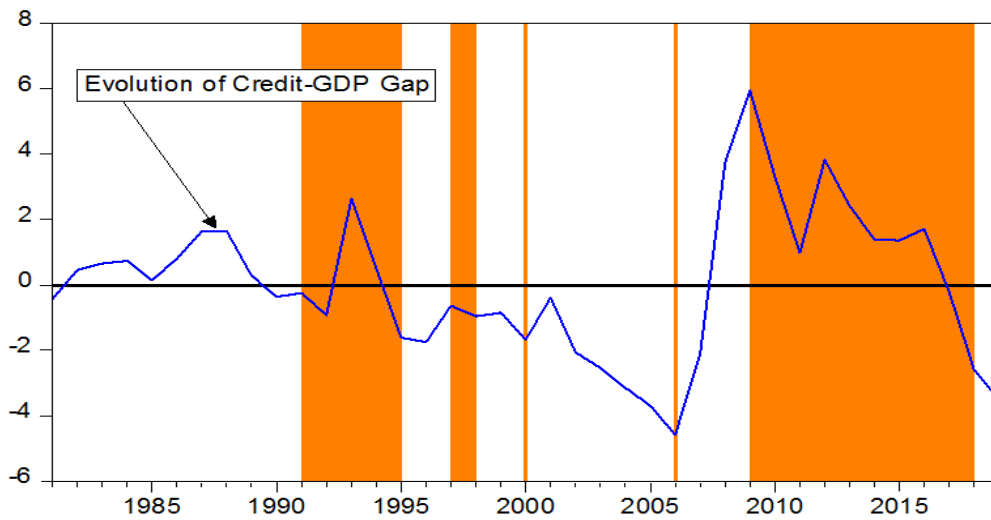**Figure-2.** Credit-GDP ratio, Credit-GDP HP Trend and Credit-GDP Gap.

Figure-3. CPS-GDP GAP, Lambda=1600.

In Figure 3 above, the blue line shows the movement of the credit-GDP gap while the shaded portions indicate systemic crisis periods. The Y-axis show possible thresholds in percentages above or below the trend line labelled '0' (zero). Values above zero indicate credit build-up but it is important to determine the threshold at which credit buildup becomes excessive that will warrant prudential authorities to activate the countercyclical capital buffer. Since the indicator is supposed to have a 3 to 2-year lead to a crisis, Figure 4 below presents the combination of 3-year window and crisis periods in Nigeria.

In Figure 4 below, the black dotted lines with arrows in-between indicate the 3 years signal window before a crisis occurs.
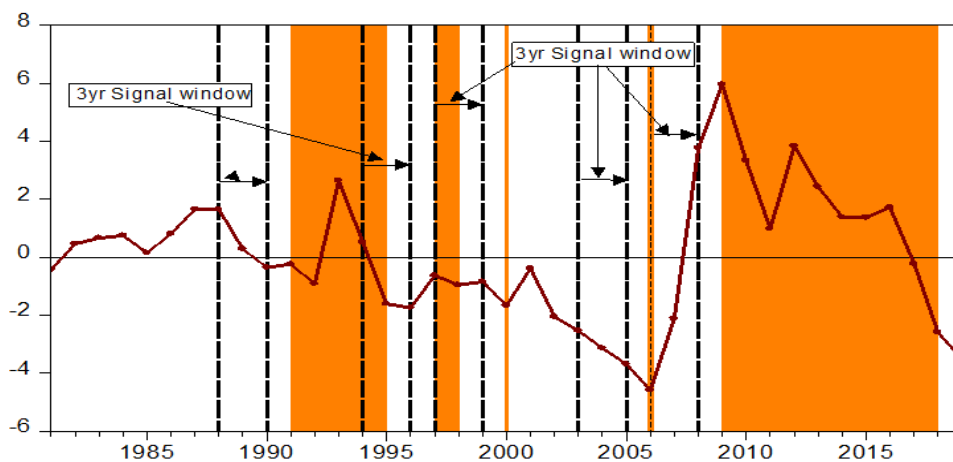

Figure-4. CPS-GDP GAP, Lambda=1600.

A visualization of Figure 5 below with a lower threshold (L) of 0.98 (0.98 was actually determined as the optimal cut-off threshold using a combination of Accuracy and the sum of Sensitivity and Specificity, as well as Youden Index and Distance to corner ROC Curve) shows that for the 1991 − 1995 systemic crisis, credit to GDP gave a signal outside the 3 year window. It was already at its maximum at the beginning of the 3-year window. Nevertheless, it issued another signal towards the end of 1992 which climaxed in 1993. This however was still outside the 3-year window before the 1997/98 banking crisis. For the year 2000 banking crisis, the credit-to-GDP Gap did not issue any warning as it remained below the trend line. For the 2009 − 2018 systemic crisis, the credit-to-GDP Gap crossed the threshold sometime late in 2007 and remained above the threshold till 2016. Thus, for the observed four banking/systemic crisis, the credit-to-GDP Gap was only able to predict one (2009 − 2018) within the 3-year signal window.
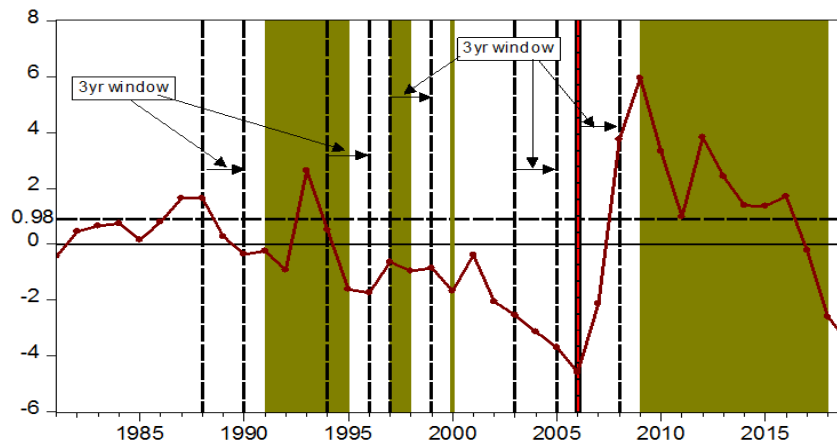
Figure-5. CPS-GDP GAP, Thresholds, crisis period and 3yr window.

4.2. Empirical Results

Below in Table 4 are shown the values of the statistics in Table 3 above for positive data only. Credit-to-GDP Gap values below the trend line do not count in the setting of the countercyclical capital buffer. The cut-off (threshold) values are based on actual Credit-to-GDP data.

The True Positive Rate (TPR) and the False Positive Rate (FPR) statistics for respective thresholds were used to plot the ROC Curve shown in Figure 6.

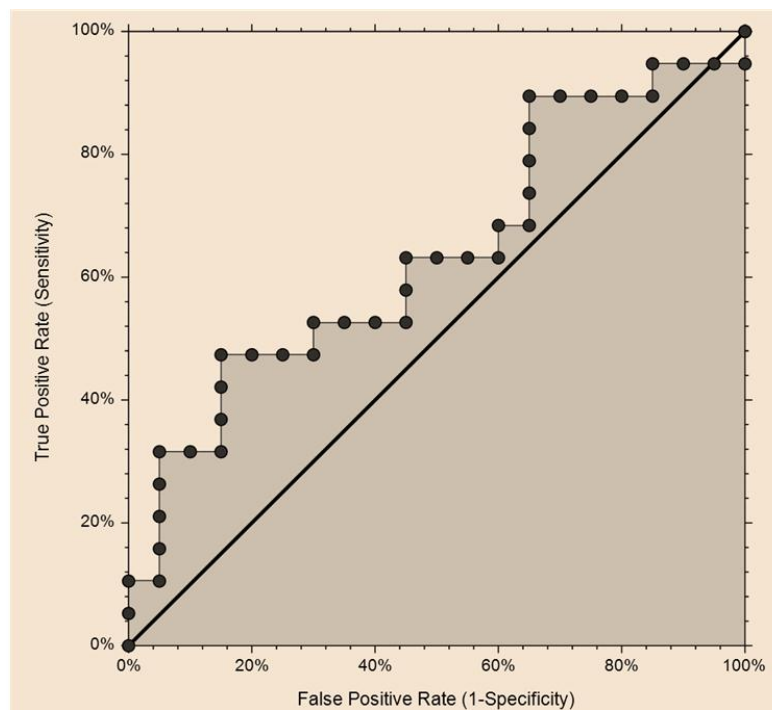**Figure-6.** ROC curve of CPS-to-GDP gap as EWI of crisis episodes.

Table-5. Area under ROC curve analysis (empirical estimation).

Criterion	Count	AUC	Standard Error	Z-Value to Test AUC > 0.5	Upper 1-Sided P-Value	95% Confidence Limits	
						Lower	Upper
CPS_GDP Gap	39	0.6368	0.0919	1.49	0.0682	0.4219	0.784

Table-4. Variables are as defined above.

Cutoff	TPs	FPs	FNs	TNs	TPR	TNR	PPV	Accuracy	TPR + TNR	FNR	FPR	Incorrectly Classified	Youden Index	Dist. to Corner	NTSR
Value	A	B	C	D	(Sens.)	(Spec.)	-	-	-	-	-	-	-	-	-
≥ 0.15	10	9	9	11	0.53	0.55	0.53	0.54	1.08	0.47	0.45	0.46	0.08	0.65	0.86
≥ 0.28	10	8	9	12	0.53	0.6	0.56	0.56	1.13	0.47	0.4	0.44	0.13	0.62	0.76
≥ 0.46	10	7	9	13	0.53	0.65	0.59	0.59	1.18	0.47	0.35	0.41	0.18	0.59	0.67
≥ 0.51	10	6	9	14	0.53	0.7	0.63	0.62	1.23	0.47	0.3	0.38	0.23	0.56	0.57
≥ 0.66	9	6	10	14	0.47	0.7	0.6	0.59	1.17	0.53	0.3	0.41	0.17	0.61	0.63
≥ 0.74	9	5	10	15	0.47	0.75	0.64	0.62	1.22	0.53	0.25	0.38	0.22	0.58	0.53
≥ 0.81	9	4	10	16	0.47	0.8	0.69	0.64	1.27	0.53	0.2	0.36	0.27	0.56	0.42
≥ 0.98	9	3	10	17	0.47	0.85	0.75	0.67	1.32	0.53	0.15	0.33	0.32	0.55	0.32
≥ 1.37	8	3	11	17	0.42	0.85	0.73	0.64	1.27	0.58	0.15	0.36	0.27	0.6	0.36
≥ 1.38	7	3	12	17	0.37	0.85	0.7	0.62	1.22	0.63	0.15	0.38	0.22	0.65	0.41
≥ 1.65	6	3	13	17	0.32	0.85	0.67	0.59	1.17	0.68	0.15	0.41	0.17	0.7	0.48
≥ 1.65	6	2	13	18	0.32	0.9	0.75	0.62	1.22	0.68	0.1	0.38	0.22	0.69	0.32
≥ 1.71	6	1	13	19	0.32	0.95	0.86	0.64	1.27	0.68	0.05	0.36	0.27	0.69	0.16
≥ 2.43	5	1	14	19	0.26	0.95	0.83	0.62	1.21	0.74	0.05	0.38	0.21	0.74	0.19
≥ 2.64	4	1	15	19	0.21	0.95	0.8	0.59	1.16	0.79	0.05	0.41	0.16	0.79	0.24
≥ 3.32	3	1	16	19	0.16	0.95	0.75	0.56	1.11	0.84	0.05	0.44	0.11	0.84	0.32
≥ 3.76	2	1	17	19	0.11	0.95	0.67	0.54	1.06	0.89	0.05	0.46	0.06	0.9	0.48
≥ 3.83	2	0	17	20	0.11	1	1	0.56	1.11	0.89	0	0.44	0.11	0.89	0
≥ 5.96	1	0	18	20	0.05	1	1	0.54	1.05	0.95	0	0.46	0.05	0.95	0

The results in Table 5 show an Area under ROC Curve (i.e. the shaded portion in Figure 6 above) of 0.6368 (63.68%) with a z-value probability of 0.0682. As was stated earlier, the values of AUC range from 0.5 (no prediction ability), 0.7 - 0.8 (acceptable), $0.81 - 0.9$ (excellent) and above 0.9 is considered outstanding. Thus, with 63.68% as the Area Under ROC Curve, the Credit-to-GDP Gap therefore performs poorly as an early warning indicator of banking crisis in Nigeria.

5. CONCLUSION

The analysis to determine the predictive power of credit-to-GDP gap as an early warning indicator show clearly that it performs poorly in Nigeria as indicated by the area under the receiver operating characteristic (AU-ROC) curve. Further, this study shows that the BCBS recommendation that the prudential authorities set lower thresholds (L) at 2% above trend may not work for Nigeria as this study suggests an optimal threshold of 0.98%. This result emphasizes the need for prudential authorities to employ informed judgement in setting thresholds with a view to activating the countercyclical capital buffer on time before crisis occurs (Basel Committee on Banking Supervision (BCBS), 2010a). At the recommended threshold, the credit-to-GDP gap signal was correctly classified 67% of the time with a noise to signal ratio of 32%. In the future, other variables, filter methods and panel linear projections (Drehmann & Yetman, 2020) will be considered as the search for early warning indicators for financial crisis in Nigeria continues.

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Appendix 1

Test for Equality of Variances Between Series
Date: 08/25/20   Time: 12:46
Sample: 1981 2019
Included observations: 39

Method	df	Value	Probability	
F-test	(38, 38)	1.613269	0.1450	
Siegel-Tukey		0.479682	0.6315	
Bartlett	1	2.124628	0.1449	
Levene	(1, 76)	6.511998	0.0127	
Brown-Forsythe	(1, 76)	1.039985	0.3111	
Category Statistics				
			Mean Abs.	Mean Abs.	Mean Tukey-
Variable	Count	Std. Dev.	Mean Diff.	Median Diff.	Siegel Rank
CBNCPSGDP	39	5.399504	4.794233	3.979512	40.74359
WDICPSGDP	39	4.251091	3.386666	3.041550	38.25641
All	78	4.890871	4.090450	3.510531	39.50000
Bartlett weighted standard deviation: 4.859343					

Source: Researcher's desk e-views 10 output).

Appendix 2

Test for Equality of Variances Between Series
Date: 08/25/20   Time: 13:35
Sample: 1981 2019
Included observations: 39

Method	df	Value	Probability	
F-test	(38, 38)	1.874582	0.0563	
Siegel-Tukey		1.858769	0.0631	
Bartlett	1	3.643174	0.0563	
Levene	(1, 76)	3.984263	0.0495	
Brown-Forsythe	(1, 76)	3.835140	0.0539	
Category Statistics				
			Mean Abs.	Mean Abs.	Mean Tukey-
Variable	Count	Std. Dev.	Mean Diff.	Median Diff.	Siegel Rank
CPS/GDGapP100	39	1.651157	1.183563	1.182240	44.28205
CPS/GDPGap1600	39	2.260687	1.757829	1.752208	34.71795
All	78	1.966627	1.470696	1.467224	39.50000
Bartlett weighted standard deviation: 1.979523.					

Source: Researcher's desk (e-views 10 output).