Predicting financial fragility in Nigeria: does the filter method matter?

Abstract

This study has applied two distinct methods of analysis to evaluate and compare the predictive ability of certain EWIs of financial crisis when gaps are generated using two filter methods – the Hodrick – Prescott and Kalman Filters. First, the receiver operating characteristics curve where the area under the receiver operating characteristic (AU-ROC) curve and distance to corner were the basis of evaluation and 2, the logistic regression encompassing the estimates for individual indicator parameters, the model Expectation-Prediction Evaluation and the Hosmer-Lemeshow (HL) and Andrews Tests for goodness-of-fit. On the basis of the AU-ROC and Distance to Corner, the study concludes that the credit-to-GDP gap is a predictor of financial crisis in Nigeria. On the other hand, the Logit regression leads to the conclusion that none of the EWIs tested (Credit-to-GDP gap, Nonperforming loans, Loan-to-Deposit ratio and asset prices) could predict financial crisis at the 5% level of significance although credit-to-GDP gap could at 10%. Nevertheless, both the AU-ROC and Logit regression, suggest that credit-to-GDP gap outperforms Non-performing loans, Loan to deposit ratio and asset prices as EWIs of financial crisis in Nigeria. Going by the results of the AU-ROC curve and the Logistic regression, we do not find any significant difference whether gaps are from HP filter or Kalman filter. It is hoped that regulatory authorities apply the EWIs of financial crisis with caution, explore the different methodologies available and identify which EWI, filter method as well as the analytical model suitable for their jurisdiction.

Keywords: Early warning indicators, Financial Fragility, Kalman filter, AU-ROC curve, Logit, Nigeria

1.0 Introduction

When will the next financial crisis occur? The answer to this question has been on the mind of researchers (e.g. Borio & Lowe, 2002; BCBS, 2010; Drehman & Yetmahn, 2020; Ihejirika, 2020; Du, 2021; Sally & Katsiaryna, 2021) in search of early warning indicators of financial crisis across financial jurisdictions the world over. The consequences of a financial crisis as happened in 2007 – 2010 are dreadful and thus demands some level of preparedness. Even more dreadful is the continuing and unabated danger of another financial crisis that may be ignited and aggravated by COVID 19 and its OMICRON variants.

To prepare and articulate adequate response to impending financial crisis, the Basel Committee on Banking Supervision (BCBS)an arm of the Bank of International Settlements (BIS) recommends that monetary authorities should bench-mark the "credit-to-GDP gap" defined as "the deviation of the aggregate private sector credit-to-GDP ratio from its long-term Hodrick-Prescott (HP) filtered trend". According to BCBS (2010), credit built up at certain levels has the potential to ignite financial crisis. Thus, the BCBS recommend activating the counter cyclical capital buffer (a macro-prudential policy instrument) at a threshold (2%) above the credit-to-GDP gap. However, results of investigations into the efficacy and efficiency of credit-to-GDP gap to predict financial crisis are far from conclusive (see, Hamilton, 2017). The BCBS (2010) indeed observed that credit-to-GDP gap might not "work well at all times in all jurisdictions".

Given the controversy on the effectiveness of credit-to-GDP gap to predict financial crisis and the criticism around the use of the Hodrick- Prescott (HP) filtered trend (see Hamilton, 2017; Drehmann & Yetman, 2020), a flurry of studies has emerged with other likely early warning indicators and filter methods. For instance the BCBS (2010a) explored property prices, banking system aggregate profits and spreads 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. Bakhuashvili, (2017), Hamilton, (2017), Guender (2018) among others extend the literature on methodological grounds arguing against the use of the one-sided Hodrick Prescott filter recommended by the Bank for International Settlements (BIS) for the calculation of the credit to GDP gap or any other gap.

Elsewhere, researchers are contributing to the management of systemic wide risk through unearthing macroeconomic variables that act as barometers or indicators to financial fragility. The same may not be said about Nigeria as studies dwelling on early warning indicators of financial crisis are very few, far between and hard to find (Caggiano, Calice, & Leonida, 2013; Borio, Drehmann & Xia, 2018). Following Ihejirika's, (2020) finding that Credit-to-GDP Gap performs poorly as a predictor of Financial Crisis in Nigeria, this study sets out in search of other potential early warning indictors of financial crisis in Nigeria using several methodological approaches. Specifically, it examines Asset Prices, Non-Performing Loans, Credit-to-GDP Gap and Loan to Deposit Ratio as potential Early Warning Indicators. We explore and compare the Hodrick-Prescott and Kalman filtered gaps as well as estimate a logistic regression. Following the above introduction, the structure of the rest of the paper show review of related literature in section two, section three covers the methodology; analysis occupies section four while the paper concludes in section five.

2.0 Review of related literature

2.1 Early warning indicators (EWIs)

Simply, early warning indicators foretell the occurrence of an event. They act as road signs to warn financial regulators of impending financial crisis or worsening financial fragility. To the extent that the predicted crisis may not be averted, the purpose is to alert financial regulators and operators to begin to prepare in the best possible way to ride over the financial storm. The best possible way here according to the BCBS, (2010) is by activating the "counter cyclical capital buffer" which means the accumulation of extra capital. The "counter cyclical capital buffer" ensures that in the face of financial crisis, financial intermediation will not be hampered. As observed earlier, several macro-economic and financial variables have been brought into the analysis including asset prices, Non-Performing Loans, Loan to Deposit Ratio, property prices, banking system aggregate profits and spreads; debt service ratio, cross border or foreign currency debt ratio and household debt ratio (BCBS,2010a; Dieter, Gavin, Mikhail, & Stephen, 2010; Aldasoro, Borio, & Drehmann, 2018). This study focuses on asset prices, Non-Performing Loans and Loan to Deposit Ratio. The literature on credit-to-GDP ratio and the derived gap has received much attention from scholars (see Borio & Lowe 2002, BCBS 2010, Drehman & Yetmahn, 2020; Ihejirika, 2020; Du, 2021; Sally & Katsiaryna, 2021 among others)

2.2 Asset Prices

Economists say that a financial asset exhibits a bubble when its price exceeds the present value of the future income that would be received by owning it to maturity. As many investors buy the asset with hopes of selling it at higher price, there is a bubble. They say if there is a bubble, there is also a risk of a crash in asset prices. Anne (2000) examined the association between equity market crises and banking crises for 14 developed countries over the period 1970–99 and found the association to be relatively weak. Bordo and Jeanne (2002) and Goetzmann, (2015) among others argue that not all rising asset prices in the stock and housing markets lead to financial crisis. But, Reinhart and Rogoff (2009) assert that rising asset prices in the stock and housing markets are symptoms of financial crisis. Heung's (2017) "Asset Price Booms, Busts and Financial Crises", assert that the probability of a bust conditional on a boom is only slightly higher than the unconditional probability and concludes "that stock and housing price booms are not strong indicators of impending busts or financial crises".

2.3 Non-Performing Loan ratio

The Central Bank of Nigeria's loans classification indicates that loans that are performing are those for which the borrowers/beneficiaries are up to date in respect of payments of both principal and interest (CBN 2010). On the contrary, non-performing loans ratio represents the proportion of total loans that are in default. The EU definition of a non-performing loan is one whose instalments are not paid for over 90 days (European Commission, 2017). In Nigeria, and other financial jurisdictions, banks usually report their ratios of non-performing loans to total loans as a measure of the quality of loan balance. Reinhart and Rogoff (2011) states that non-performing loan (NPL) is one of the most common indicators for assessing loan quality and can be used to mark the onset of a banking crisis. Low levels of NPLs portray a relatively stable financial system whereas high levels of NPLs points to the existence of financial stress. High Non Performing Loans weaken bank balance sheets, depress credit growth, and delay output recovery (Aiyar & Monaghan, 2015; Kalemli-Ozcan, Laeven, & Moreno, 2015). Sorge (2004) and Aiyar and Monaghan, (2015) agree that there is a connection between NPLs and financial crisis.

2.4 Loan to Deposit Ratio

According to Murphy (2020), the loan-to-deposit ratio (LDR) assesses the liquidity of banks. A high LDR indicates that the bank is illiquid and may cause bank runs. On the other hand, a too low LDR suggests low earning ability. Muhammad (2014) show "that banks which sustain the LDR were able to successfully pass through the liquidity crisis of 2008, and other banks which rely more on borrowed funds or banks with increasing LTD ratio, became the victim of the financial crisis". Earlier, Fadare (2011) in his study "Banking Sector Liquidity and Financial Crisis in Nigeria" reports that lagged loan-to-deposit ratio is significant for predicting Banking Sector liquidity and by extension financial fragility.

2.5 Methodological issues

Several studies, for instance Liu and Moench, (2016), Bakhuashvili, (2017), Hamilton, (2017), Ponka, (2017), Guender, (2018) argue against the use of the one-sided Hodrick and Prescott (1997) filter recommended by the Bank for International Settlements (BIS) for the calculation of the credit to GDP gap or any other gap. Hamilton, (2017) put it pointedly in his work: "WHY YOU SHOULD NEVER USE THE HODRICK-PRESCOTT FILTER". Hamilton proffered about four grounds for the rejection of the Hodrick – Prescott (HP) filter:

> "Here's why. (1) The HP filter produces series with spurious dynamic relations that have no basis in the underlying data-generating process. (2) Filtered values at the end of the sample are very different from those in the middle, and are also characterized by spurious dynamics. (3) A statistical formalization of the problem typically produces values for the smoothing parameter vastly at odds with common practice, e.g., a value for λ far below 1600 for quarterly data. (4) There's a better alternative. A regression of the variable at date t+h on the four most recent values as of date t offers a robust approach to detrending that achieves all the objectives sought by users of the HP filter with none of its drawbacks".

Following this, Drehmann and Yetman, (2018) responded with: "Why you should use the Hodrick-Prescott filter – at least to generate credit gaps". Drehmann and Yetman, (2018) agree with Hamilton's criticisms but argue that "in the absence of clear theoretical foundations, all proposed gaps are but indicators". They assert that it is "an empirical question which measure performs best as an early warning indicator for crises" and went ahead to "run a horse race using quarterly data from 1970 to 2017 for 42 economies". Drehmann and Yetman, (2018) report that "no other gap outperforms the baseline (HP filter) credit-to-GDP gap while credit gaps based on linear projections in real-time perform poorly.

The HP filter has been defined as "a data-smoothing technique". To forecast the long-term trend of an economic or financial data, it is necessary to weed the data of short-term innovations that business cycles are known for. Thus, the HP filter has occupied a central role in decomposing data into its trend and cycle components during analysis. The argument against the HP filter actually did not start with Hamilton (2017) and Drehmann and Yetman, (2018). Back in 1995, Cogley and Nason (1995) had observed that when Hodrick-Prescott filter is used to generate gaps, it "can generate business cycle dynamics" that may not exist in the original data. According to some scholars, "the Hodrick–Prescott filter will only be optimal when: Data exists in a I(2) trend, or when noise in the data is approximately normally distributed or analysis is purely historical and static". The weaknesses of the HP filter led to the use of other filter methods such as the state-space (Sspace) model-based Kalman (1960, 1963) and Kalman and Bucy (1961) filter among others. The whole issue here bothers on decomposing a time series into its trend and cycle components as well as other disturbances.

2.6 Empirical Review

A number of empirical studies have continued the search for early warning indicators.

Du (2021) set out to predict financial crisis in China using "stock price index change rate, industrial added value growth rate, domestic and foreign real deposit interest rate differential, and foreign direct investment as a percentage of GDP". The forecast result show that the probability of a systemic financial crisis in China in 2020 was extremely low, almost zero. Du (2021) used the traditional static Logit line to compare with the dynamic Logit models where the lagging binary variables were constructed. The actual dynamic fitting effect was better than the static logit model. The early warning status of systemic financial crisis in 2020 was predicted using the dynamic logit model and the forecast of various early warning indicators realized by the Auto-Regressive Integrated Moving Average (ARIMA) model.

Sally and Katsiaryna (2021) predicted upcoming financial crisis using different financial variables which can serve as early warning indicators of banking crises. Sally and Katsiaryna (2021) employed data from 59 economies (advanced and emerging) and their results show that financial overheating can be detected in real-time using Equity prices and output gap in advanced markets. For emerging markets, Sally and Katsiaryna (2021) suggest equity and property prices and credit gap. In another study, Ihejirika (2020) used the signal approach, the area under the receiver operating characteristic (AU-ROC) curve and some graphical presentations employing annual data for the period 1981 to 2019 to analyze the power of credit to GDP gap as an early warning indicator of financial crisis in Nigeria. The area under the receiver operating characteristic (AU-ROC) curve was 63.68% which shows that Credit-to-GDP Gap performs poorly in Nigeria.

Drehmann and Yetman's (2020) horse race and expanded samples on quarterly data from 1970 to 2017 for 41 economies show that credit gaps based on linear projections in original time perform poorly when based on country-by-country estimation, and are subject to their own end-point problem. But when they estimated as a panel, and impose the same coefficients on all economies, "linear projections perform marginally better than the baseline credit-to-GDP gap, with somehow larger improvements concentrated in the post-2000 period and for emerging market economies".

Kehinde and Davi (2020b) estimates "an Early Warning Signal (EWS) Model for Predicting Financial Crisis in Emerging African Economies" over a 37 years period ending December 2017. They used the Multinomial Logit model to analyze their data. Their findings suggest that rising debts, liquidity and currency risk exposure increases the likelihood of the economies experiencing crisis.

3.0 Methodology

3.1 State space model and Kalman filter

Data series y_t, can be decomposed into a finite set of unobserved – underlying components modeled in state-space form and estimated using the Kalman filter (Rummel, 2015).

Take for instance, the values of non-performing loans (NPL) ratio (y_t) observed for a number of years can be decomposed into:

$$y_t = \tau_t + c_t + \gamma_t + v_t + \varepsilon_t \ldots\ldots\ldots\ldots\ldots..1$$

Where

y_t = dependent time − series variable (say NPL Ratio);
τ_t = a slowly − changing unobserved component (trend);
c_t = a periodically − recurring unobserved component(cycle);
γ_t = a periodic unobserved component (seasonal);
v_t = an unobserved autoregressive component and
ε_t = an unobserved irregular component (disturbance)

The recommended state-space model for managing heavily trending data series is the local linear trend model, "which allows the trend level and slope to vary over time" (Rummel, 2015).

The general form of the local linear trend model is as follows:

$y_t = \tau_t + \varepsilon_t$ $\quad$ $\varepsilon_t \sim$ iid $N(0, \sigma_\varepsilon^2)$ ……………………………..(2)

$\tau_t = \tau_{t-1} + \beta_{t-1} + \eta_t$ $\quad$ $\eta_t \sim$ iid $N(0, \sigma_\eta^2)$ …………………………….(3)

$\beta_t = \beta_{t-1} + \zeta_t$ $\quad$ $\zeta_t \sim$ iid $N(0, \sigma_\zeta^2)$ ……………………… (4)

In equations 2 to 4 above, η_t represent the measurement error or shock process, β_t is the stochastic slope and ζ_t stands for the slope disturbances. It is assumed that η_t, β_t and ζ_t are independent and identically distributed random numbers (~ iid N(0, σ^2)).

However, according to Rummel (2015), "smoother trends can be obtained by formulating higher-order random walks. Harvey (1985) and Clark (1987) considered the local linear trend model with the stochastic cycle following an ARIMA (2,0,0) model:

$y_t = \tau_t + c_t$ …………………………………………………… ….(5)

$\tau_t = \tau_{t-1} + \beta_{t-1} + \eta_t$ $\quad \eta_t \sim$ iid N(0, σ_η^2) ……………...(6)

$\beta_t = \beta_{t-1} + \omega_t$ $\quad \omega_t \sim$ iid N(0, σ_ω^2)……………..(7)

$c_t = \phi_1 c_{t-1} + \phi_2 c_{t-2} + \zeta_t$ $\quad \zeta_t \sim$ iid N(0, σ_ζ^2) ……………..(8)

Equation (8) models the stationary cyclical component as a finite autoregression rather than a more general ARMA process. However, we follow the steps of Rummel (2015) and set both the variance of η_t and ω_t equal to zero, which is similar to removing the error terms from the equation and specify the state space equation in e-views as follows:

```
param c(1) 0.9 c(2) 0.2 c(3) -10 c(4) -10 c(5) -10
@ename v1
@ename v2
@ename v3
@evar var(v1) = 0
@evar var(v2) = 0
@evar var(v3) = exp(c(5))
@signal y_t = trend + cycle
@state  trend =  trend(-1) + beta(-1) + v1
@state  beta =  beta(-1) + v2
@state  cycle = c(1)*cycle(-1) + c(2)*sv1(-1) + v3
@state  sv1 = cycle(-1)
```

The highlighted text represents the respective ratios used in the study. For example, for the decomposition of cpsgdp ratio using Kalman filter, the line (signal equation) will read:

@signal cpsgdp = trend + cycle

On the other hand, the HP filter is expressed in e-views 10 as:

minimize $trend_t$:

$$\left\{\sum_{t=1}^{T}(ratio_t - trend_t)^2 + \lambda \sum_{t=2}^{T-1}\left((trend_{t+1} - trend_t) - (trend_t - trend_{t-1})\right)^2\right\} \ldots\ldots. 5$$

Where,

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

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

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

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

In this study, we use both the HP filter and the Kalman filter to decompose credit-to-GDP ratio, asset prices (we use the all-share index), non-performing loans ratio and loan to deposit ratio into their trend τ_t and cycle (gap) c_t components. We then use the generated gaps to predict financial fragility in Nigeria. The decomposition of these time series is represented by the following trend-cycle decomposition equation:

$y_t = \tau_t + c_t$ …………………………………..9

$c_t = y_t - \tau_t$ ……………………………….10

where

y_t = the dependent variable (credit-to-GDP ratio or asset prices or Non-Performing Loans or Loan to Deposit Ratio)
τ_t = trend component.

3.3 Data

A combination of sources provides us with data especially on financial crisis. These include Laeven and Valencia's (2012) **"**Systemic Banking Crises Database: An Update", Laeven and Valencia's (2018) "Systemic Banking Crises Revisited" as well as 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". Further, financial crisis data for the years1998, 2000, 2006, 2017 and 2018 were taken from Ihejirika, (2020). Data on the early warning indicator variables (credit-to-GDP ratio, asset prices, non-performing loans and loan to deposit ratio) were sourced from the Central Bank of Nigeria (CBN) statistical bulletin 2020 and Nigeria deposit insurance corporation annual reports several issues.

3.4 Prediction evaluation and comparison of HP and Kalman Filters' results

The area under the receiver operating characteristic curve (AU-ROC curve)

The AU-ROC curve was used to evaluate the predictive ability of the variables and secondly compare the performance of HP and Kalman filter generated gaps. "The ROC curve is a visual index of the accuracy of the evaluation. As observed in Ihejirika, (2020), the AU-ROC curve is "a popular measure of the accuracy of a warning indicator. Comparably, higher AUC values indicate better performance" (see Drehmann & Juselius, 2014). Furthermore, characterization of AUC values by Mandrekar, (2010) indicate that an AUC of 0.5 indicate no prediction ability, 0.7 - 0.8 acceptable, 0.81 – 0.9 excellent and above 0.9 is considered outstanding.

4.0 Analysis and Results

First is presented in figure 1 below the ROC Curve based on gaps generated using the Kalman filter. From figure 1 below, cpsgdp gap is clearly far above the reference line and has the closest distance to corner (i.e., the uppermost left-hand side labeled 1.0). The cpsgdp gap is followed by nplrkmgap, ldrkmgap and asset prices in that order.

Next is the ROC Curve showing the predictive ability of early warning indicators gaps derived from the Hodrick-Prescott filter. This is shown in figure 2 below.

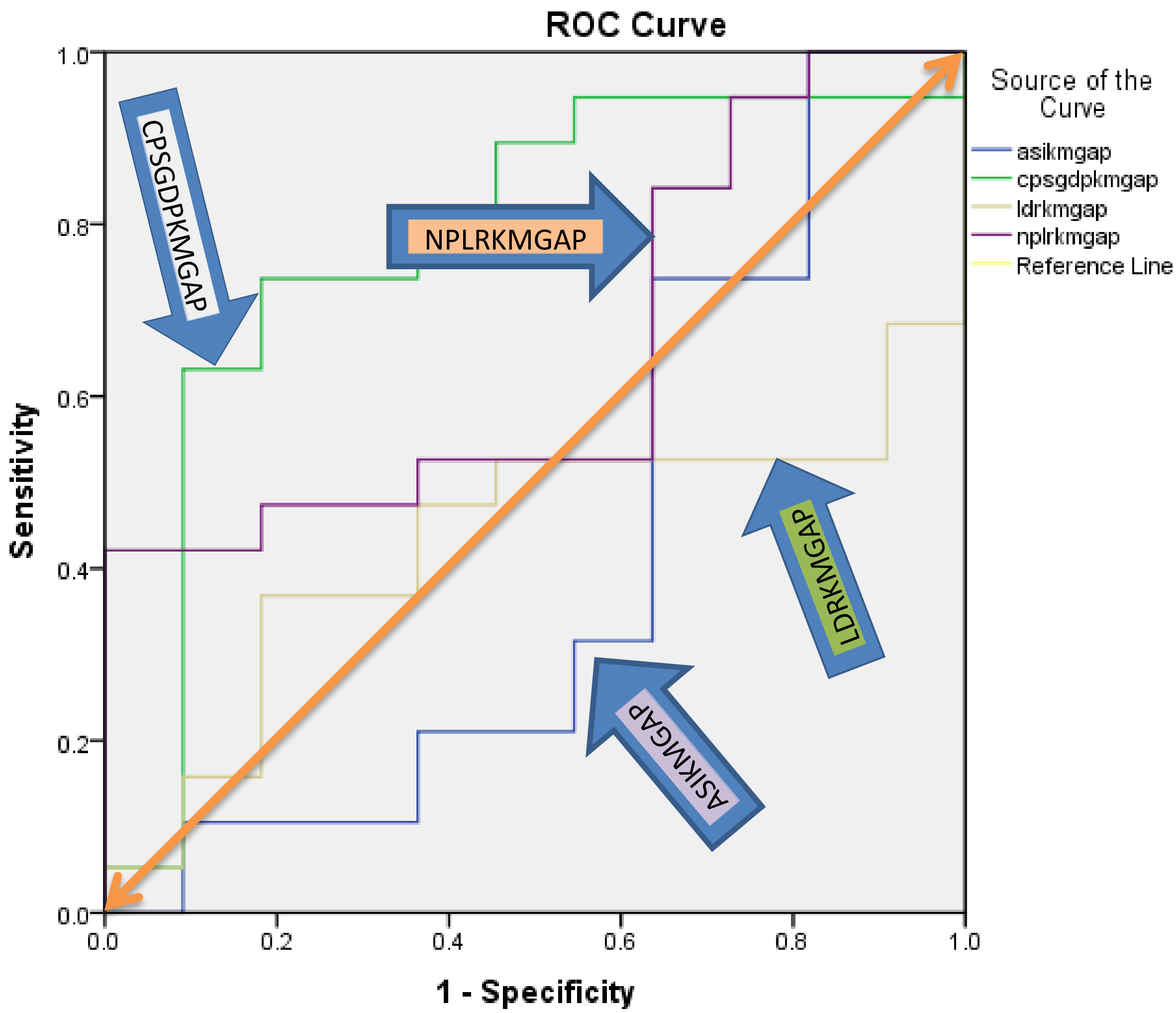

Figure 1: ROC Curve generated by Kalman Filter gaps - asikmgap, cpsgdpkmgap, ldrkmgap and nplrkmgap

Definitions: asikmgap indicates that the gap was generated using Kalman filter while asigapHP indicate that the gap came from Hodrick-Prescott filter. This applies to other gaps used in the study.

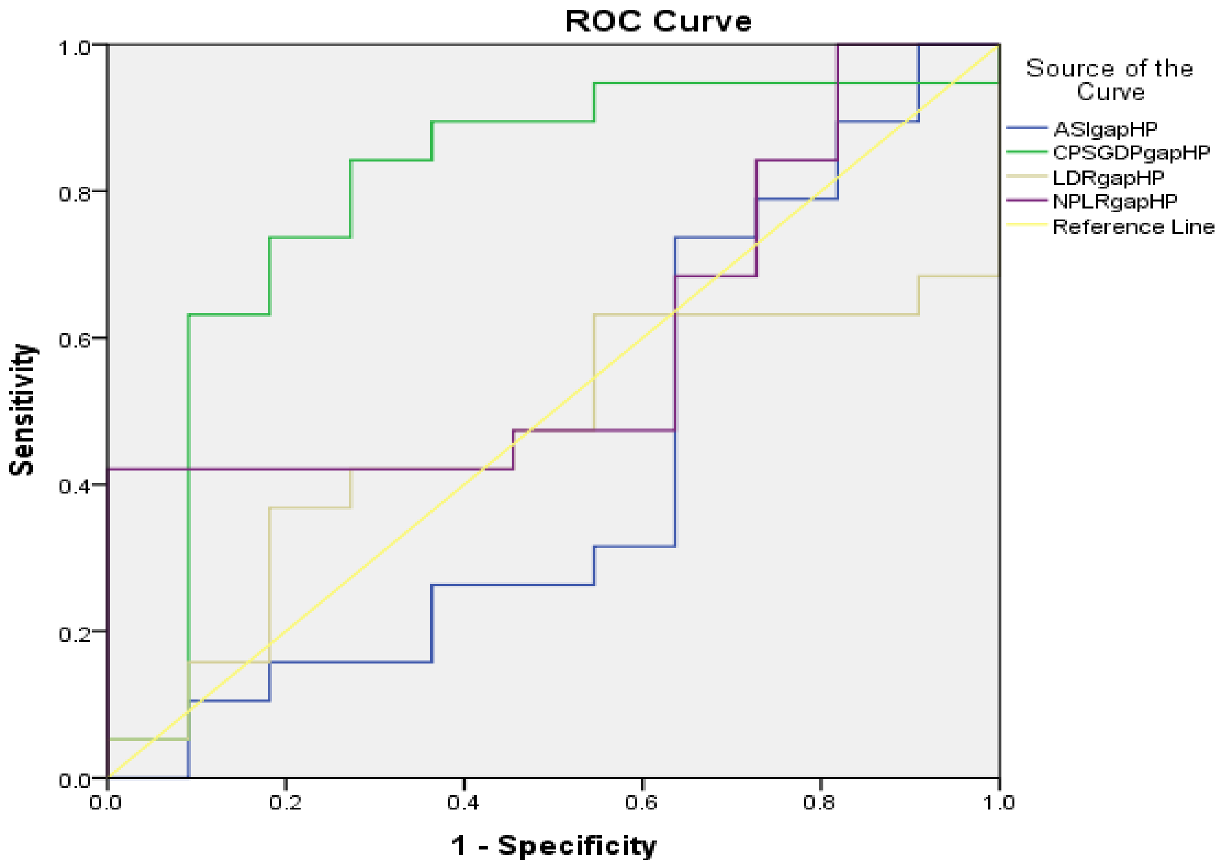

Figure 2: ROC Curve generated by Hodrick - Prescott Filter gaps - asigapHP, cpsgdpgapHP, ldrgapHP and nplrgapHP

Again, figure 2 above show that cpsgdp gap outperformed the other gaps in the same order. Therefore, the Empirical ROC Curve employing the distance to corner statistic, indicates that credit-to-GDP gap (whether HP or Kalman filter is used) outperforms non-performing loans, asset prices and loan-to-deposit ratio as a predictor of financial crisis in Nigeria.

To evaluate the ability of these gaps to signal financial crisis, we turn to the area under the receiver operating characteristics curve shown below in table 1.

From table 1 below, credit to GDP gap generated from Kalman filter has an AU-ROC curve of 0.799 and 0.799 when HP filter was used. Following the AUC criteria above, the credit-to-GDP gap AUC of 0.780 and 0.799 respectively falls in the acceptable category and thus is cable of predicting financial crisis in Nigeria. On the other hand, Non-performing loans ratio, Loan to deposit ratio and asset prices with AUC's 0.651 or 0.598, 0.431or 0.464 and 0.411or 0.426 respectively fall in the category of EWIs with no prediction ability. The two filter methods ranked the gaps in the same other though HP filter AU-ROC curve gave higher values except NPLRgap where the Kalman filter figure 0.651 was higher than 0.598 recorded by the HP filter.

Table 1: Area Under the ROC Curve

Test Result Variable(s)	Area (Kalman filter)	Asymptotic Sig.	Area (HP filter)	Asymptotic Sig.
ASI gap	.411	0.425931	.426	.505
CPSGD gap	.780	0.011815	.799	.007
LDR gap	.431	0.532609	.464	.747
NPLR gap	.651	0.175211	.598	.378

Source: Researchers' Desk, SPSS 23 output 2022

Table 2: Logistic regression results

Further investigation using Logit regression analysis show the extent nonperforming loans, asset prices, credit-to-GDP and loan-to-deposit ratio can predict financial crisis in Nigeria. From the results in table 2 below, none of the EWIs showed enough strength at 5% level of significance to be able to predict financial crisis. However, credit-to-GDP out performs other EWIs with the likelihood of predicting financial crisis at the 10% level of significance whether gaps are gerated from HP or Kalman filters. However, a serious problem here is the level of standard error and explosive coefficients observed in the estimated models.

Table 2: Logistic regression results

Dependent Variable: CRISIS

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-179.4986	100.3097	-1.789443	0.0735
CPSGDPKMGAP	29.14328	16.52731	1.763340	0.0778
ASIKMGAP	-3.08E-05	6.26E-05	-0.492330	0.6225
LDRKMGAP	-1.874734	3.668654	-0.511014	0.6093
NPLRKMGAP	5.361513	6.524214	0.821787	0.4112
C	0.740636	0.460573	1.608077	0.1078
CPSGDPGAPHP	34.97068	20.68954	1.690259	0.0910
ASIGAPHP	-2.63E-05	6.08E-05	-0.432858	0.6651
LDRGAPHP	-0.958660	3.689288	-0.259849	0.7950
NPLRGAPHP	5.829461	7.486084	0.778706	0.4362

Turning to the model accuracy, the Expectation-Prediction (Classification) Table presented in tables 3 and 4 below indicates that out of nineteen crisis episodes, 17 using Kalman filter generated gaps and 18 HP were correctly predicted while six/five out of eleven non-crises periods were correctly classified. This gives a sensitivity of 89.47% Kalman filter and 94.74% HP filter and specificity of 54.555% and 45.45% respectively. Overall, the estimated models correctly predicts 76.67% (which ever filter was used) of the observations. We report that the estimated equation is better than the constant probability model with 13.33 percentage points as indicated by the total gain and represents a 36.36% improvement over the 63.33 percent correct prediction of the default model shown in table 3 and 4 below.

Table 3: Expectation-Prediction Evaluation for Binary Specification (Kalman gaps)
Success cutoff: C = 0.5 (Kalman)

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	6	2	8	0	0	0
P(Dep=1)>C	5	17	22	11	19	30
Total	11	19	30	11	19	30
Correct	6	17	23	0	19	19
% Correct	54.55	89.47	76.67	0.00	100.00	63.33
% Incorrect	45.45	10.53	23.33	100.00	0.00	36.67
Total Gain*	54.55	-10.53	13.33			
Percent Gain**	54.55	NA	36.36			

H-L Statistic 3.0805 Prob. Chi-Sq(8) 0.9292
Andrews Statistic 11.6300 Prob. Chi-Sq(10) 0.3106

Table 4: Expectation-Prediction Evaluation for Binary Specification (HP gaps) HP
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	5	1	6	0	0	0
P(Dep=1)>C	6	18	24	11	19	30
Total	11	19	30	11	19	30
Correct	5	18	23	0	19	19
% Correct	45.45	94.74	76.67	0.00	100.00	63.33
% Incorrect	54.55	5.26	23.33	100.00	0.00	36.67
Total Gain*	45.45	-5.26	13.33			
Percent Gain**	45.45	NA	36.36			

H-L Statistic 6.5766 Prob. Chi-Sq(8) 0.5829
Andrews Statistic 13.6746 Prob. Chi-Sq(10) 0.1884

To test the validity of the estimated Logit regression models, the Goodness-of-Fit Evaluation for Binary Specification Andrews and Hosmer-Lemeshow Tests was used. The H-L Statistic value of 3.0805 and 6.5766 with prob. Chi-Sq(8) 0.9292 and Prob. Chi-Sq(8) 0.5829 as well as the Andrews Statistic value of 11.6300 and 13.6746 with Prob. Chi-Sq(10) 0.3106 and Prob. Chi-

Sq(10) 0.1884 show p-values for both the HL and Andrews test statistics that are larger than 0.05, implying that the models have good fit.

4.2 Discussion of findings

Using the AUC and distance to corner, the results indicate that credit-to-GDP gap is a predictor of financial crisis in Nigeria. Comparably, the AUC and distance to corner also show that credit-to-GDP gap outperforms Non-performing loans, loan to deposit ratio and asset prices as EWIs of financial crisis no matter which filter was used. This result supports several earlier studies including Du (2021), Sally and Katsiaryna (2021) for advanced economies, Drehmann and Yetman (2020), Beutel, List and Schweinitz (2019), Giordani and Simon (2019), Geršl, and Jašová (2018) among others. However, the result of the present study is at variant with Sally and Katsiaryna (2021) whose study indicated that asset prices do better for emerging economies and Ihejirika (2020) whose findings show that Credit-to-GDP Gap performs poorly in Nigeria. Similarly, the results from the Logit regression show that none of the EWIs tested (Credit-to-GDP gap, Nonperforming loans, Loan-to-Deposit ratio and asset prices) could predict financial crisis at the 5% level of significance although credit-to-GDP gap could at 10%. Furthermore, several studies argue that the method and specifications adopted by researchers affect the results (see Du, 2021; Drehmann & Yetman, 2020; Bakhuashvili 2017; Hamilton 2017). Going by the results of the AU-ROC curve and the Logistic regression, we do not find any significant difference whether gaps are from HP filter or Kalman filter.

5.0 Conclusion

This study has applied two distinct methods of analysis to evaluate and compare the predictive ability of certain EWIs of financial crisis when gaps are generated using two filter methods – the Hodrick – Prescott and Kalman Filters. First, the receiver operating characteristics curve where the AU-ROC curve and distance to corner were the basis of evaluation and 2, the logistic regression encompassing the estimates for individual indicator parameters, the model Expectation-Prediction Evaluation and the Hosmer-Lemeshow (HL) and Andrews Tests for goodness-of-fit. On the basis of the AUC and Distance to Corner, the study concludes that credit-to-GDP gap is a predictor of financial crisis in Nigeria. On the other hand, the Logit regression leads to the conclusion that none of the EWIs tested (Credit-to-GDP gap, Nonperforming loans, Loan-to-Deposit ratio and asset prices) could predict financial crisis at the

5% level of significance although credit-to-GDP gap could at 10%. Nevertheless, both the AUC and Logit regression, suggest that credit-to-GDP gap outperforms Non-performing loans, Loan to deposit ratio and asset prices as EWIs of financial crisis in Nigeria. It is hoped that regulatory authorities apply the EWIs of financial crisis with caution, explore the different methodologies available and identify which EWI, filter method as well as the analytical model suitable for their jurisdiction.

References

Aiyar , S., Wolfgang B., Garrido, J. M., Anna I., Andreas J., Kang, K., Dmitriy K., Yan L., Monaghan, D. and Moretti , M. (2015). A Strategy for Resolving Europe's Problem *Loans IMF staff discussion notes DN/15/19*

Aldasoro, I., Borio, C. E., & Drehmann, M. (2018) Early warning indicators of banking crises: Expanding the family *BIS Quarterly Review, March, 29-45.*

Anne V (2000) Asset price crises and banking crises: some empirical evidence. *BIS Conference Papers Vol. 8 – March*

Bakhuashvili, S. (2017, June 27). *Credit-to-GDP Gap as an Indicator for Upcoming Financial Crisis* (Paper presentation). 32nd International Academic Conference, Geneva, DOI: 10.20472/IAC.2017.032.007

BCBS, (2010a) "Guidance for national authorities operating the countercyclical capital buffer", *Bank for International Settlements*, December.

Basel Committee on Banking Supervision, (2010) Basel III: A global regulatory framework for more resilient banks and banking systems". *Bank for International Settlements,* Dec.

Beutel J, List S & Von S (2019) "An evaluation of early warning models for systemic banking crises: Does machine learning improve predictions?," *IWH Discussion Papers 2/2019, Halle Institute for Economic Research (IWH).*

Bordo, M. C. & O. Jeanne (2002) "Monetary Policy And Asset Prices: Does 'Benign Neglect' Make Sense?," *International Finance, , 5(2,Summer), 139-164.*

Borio, C & P Lowe (2002): "Asset prices, financial and monetary stability: exploring the nexus," *BIS Working Papers no 114.*

Borio, C., Drehmann M., & Xia, D. (2018) Financial cycle and recession risk. *BIS Quarterly Review,* December

Caggiano, G., Calice, P., & Leonida, L. (2013) Early Warning Systems and Systemic Banking Crises in Low Income Countries: A Multinomial Logit Approach. *Working Paper Series N° **190** African Development Bank, Tunis, Tunisia*;

CBN (2010) Financial Stability Report Maiden Edition. CBN, Abuja. http://www.cbn.gov.ng/.

Clark, P.K (1987), 'The cyclical component of US economic activity', *Quarterly Journal of*

Economics, Vol. 102, No. 4, pages 797-814.

Cogley, T & Nason, J.M., (1995) "Effects of the Hodrick-Prescott filter on trend and difference stationary time series Implications for business cycle research," *Journal of Economic Dynamics and Control, Elsevier, vol. 19(1-2), 253-278.*

Dieter G., Gavin, M,. Oet, M.V,. & Ong, S.J (2010) Early Warning Systems for Systemic Banking Risk: Critical Review and Modeling Implications Banks and Bank Systems 5(2) 199-211, Available at SSRN: https://ssrn.com/abstract=2244422

Drehmann, M & M Juselius (2014): "Evaluating early warning indicators of banking crises: satisfying policy requirements", *International Journal of Forecasting, 30(3) 759–80. Also published as BIS Working Papers, no 421, August 2013*

Drehmann, M., & Yetman, J. (2020) Which credit gap is better at predicting financial crises? A comparison of univariate filters. *BIS Working Papers No 878*.

Drehmann, M. & J. Yetman (2018). "Why you should use the Hodrick-Prescott filter – at least to generate credit gaps," *BIS Working Papers* no 744.

Drehmann, M., Borio, C., Gambacorta, L., Jiménez, G. & C Trucharte (2010). "Countercyclical capital buffers: exploring options." *BIS Working Papers* no 317.

Du, Q. (2021) financial crisis early warning based on panel data and dynamic dual choice model. *Hindawi complexity 1 – 10 HTTPS://DOI.org/10.1155/2021/5596384*

European Commission (2017) European Semester Thematic Factsheet Banking Sector and Financial Stability

Fadare S.O. (2011) Banking Sector Liquidity and Financial Crisis in Nigeria www.ccsenet.org/ijef International Journal of Economics and Finance Vol. 3, No. 5 doi:10.5539/ijef.v3n5p3

Geršl, A & Jašová, M, (2018) "Credit-based early warning indicators of banking crises in emerging markets," Economic Systems, Elsevier, vol. 42(1), 18-31.

Giordani, P., & Simon, K. (2019) Tracking financial fragility. *Federal Reserve Bank of San Francisco Working Paper 2019-06.*

Goetzmann, W.N (2015). "Bubble Investing: Learning from History," NBER Working Papers 21693, National Bureau of Economic Research, Inc.

Guender, A. (2018). “Credit prices vs. credit quantities as predictors of economic activity in Europe: Which tell a better story?”, *Journal of Macroeconomics*, 57, 380-99.

Hamilton, J.D. (2017). Why You Should Never Use the Hodrick-Prescott Filter. *National Bureau of Economic Research Working Paper 23429 http://www.nber.org/papers/w23429*

HBS (2019) Harvard Business School’s Global Crises Data bank.by Country - Behavioral Finance & Financial Stability web page.

Harvey, A C (1985), ‘Trends and cycles in macroeconomic time series’, *Journal of Business & Economic Statistics*, Vol. 3, No. 3, pages 216-27.

Heung, T. T. (2017). "Asset Price Booms, Busts and Financial Crises," *Joseph Wharton Scholars. Available at https://repository.upenn.edu/joseph_wharton_scholars/28*

Hodrick, R J & Prescott, E C (1997), ‘Postwar US business cycles: an empirical investigation’, *Journal of Money, Credit and Banking*, Vol. 29, No. 1, pages 1-16.

Ihejirika, P. O (2020).Does the credit-to-GDP gap predict financial crisis in Nigeria? *International Journal of social and administrative Sciences. Vol. 5, No. 2, 109-126. DOI: 10.18488/journal.136.2020.52.109.126*.

Kalemli-Ozcan, S., Laeven, L., Moreno, D., 2015. Debt overhang in europe: Evidence from ¨ firm-bank-sovereign linkages. University of Mariland Working Paper mimeo

Kalman, R E (1960), ‘A new approach to linear filtering and prediction problems’, *Journal of Basic Engineering, Transactions ASME, Series D*, Vol. 82, pages 35-45.

Kalman, R E (1963), ‘New methods in Wiener filtering theory’, in Bogdanoff, J L and Kozin, F (eds), *Proceedings of the first symposium on engineering applications of random function theory and probability*, New York, Wiley, pages 270-388.

Kalman, R E and Bucy, R S (1961), ‘New results in linear filtering and prediction theory’, *Journal of Basic Engineering, Transactions ASME, Series D*, Vol. 83, pages 95-108.

Kehinde, D. I, & Devi D. T (2020). An Early Warning Signal (EWS) Model for Predicting

Financial Crisis in Emerging African Economies. *International Journal of Financial Research. Vol. 12, No. 1, pp 101-110.*

Laeven L & F. Valencia (2012). Systemic Banking Crises Database: An Update. *International Monetary Fund WP/12/163 June*

Laeven, L., & Valencia, F. (2018). Systemic banking crises revisited. *International Monetary Fund WP/18/206 September.*

Liu, W. & E. Moench (2016). "What predicts US recessions?". *International Journal of Forecasting*, 32(4), 1138-50.

Mandrekar, J. N. (2010). Receiver operating characteristic curve in diagnostic test assessment. *Journal of Thoracic Oncology, 5(9), 1315 – 1316.*

Muhammad, S.S (2014) Using Loan-to-Deposit Ratio to Avert Liquidity Risk: A Case of 2008 Liquidity Crisis *Research Journal of Finance and Accounting* 5(3), 2014 www.iiste.org ISSN 2222-1697 (Paper) ISSN 2222-2847 (Online)

Murphy**,** C.B. (2020) Loan-to-Deposit Ratio (LDR): Corporate Finance & Accounting Financial Ratios Dotdash Meredith publishing

Ponka, H (2017). "The role of credit in predicting US recessions". *Journal of Forecasting*, 36(5), 469-82.

Reinhart, C. M., & K. S. Rogoff. (2009). *This Time is Different: Eight Centuries of Financial Folly.* Princeton: Princeton University Press.

Reinhart, C., & K. Rogoff. (2011). From financial crash to debt crisis. *American Economic Review 101 (5):1676–706. doi:10.1257/aer.101.5.1676.*

Rummel, O. (2015). Estimating the output gap for Kenya: a practical guide to some state-space and Kalman filter trend-cycle decompositions. Bank of England Centre for Central Banking Studies Economic Modelling and Forecasting

Sally C & Katsiaryna S (2021). Financial Cycles – Early Warning Indicators of Banking Crises? *IMF Working Paper. Strategy, Policy, and Review Department. Pp 1-78*

Sorge, M, (2004), Stress-Testing Financial Systems: An Overview of Current Methodologies. *BIS Working Paper No. 165*, *Available* at SSRN: https://ssrn.com/abstract=759585 or http://dx.doi.org/10.2139/ssrn.759585