Mpofu, Trust R.; Nikolaidou, Eftychia

Article

Determinants of credit risk in the banking system in Sub-Saharan Africa

Review of Development Finance

HOSTED BY

ELSEVIER

CrossMark

Available online at www.sciencedirect.com

ScienceDirect

Review of Development Finance 8 (2018) 141–153

Review of DEVELOPMENT FINANCE

www.elsevier.com/locate/rdf

Determinants of credit risk in the banking system in Sub-Saharan Africa

Trust R. Mpofu *, Eftychia Nikolaidou

School of Economics, University of Cape Town, Rondebosch 7701, South Africa

Available online 20 August 2018

Abstract

This paper investigates the macroeconomic determinants of credit risk in the banking system of 22 Sub-Saharan African economies. We measure credit risk as the ratio of non-performing loans to total gross loans (NPLs) and employ dynamic panel data methods over the period 2000–2016. Using a variety of specifications, the results show that an increase in real GDP growth rate has a statistically and economically significant reducing effect on the ratio of non-performing loans to total gross loans. Furthermore, inflation rate, domestic credit to private sector by banks as a percent of GDP, trade openness, VIX as a proxy of global volatility, and the 2008/2009 global financial crisis, all have positive and significant impact on NPLs.

JEL classifications: E44; G21

Keywords: Non-performing loans; Macroeconomic factors; Banking system; Panel data; Sub-Saharan Africa

1. Introduction

The 2008/2009 global financial crisis has renewed researchers' interest on the causes of banking crises given the devastating effects they have on the entire economy. Given that credit risk is the major risk that banks face, several studies have investigated the causes of credit risk in the banking sector. In the relevant literature, credit risk is usually proxied by non-performing loans (NPLs) which are loans and advances overdue by 90 days or more from the due date. As Reinhart and Rogoff (2011) claim, NPLs are considered as a major source of bank failures and can mark the beginning of a banking crisis. Most of the studies on credit risk determinants focus on advanced economies and emerging markets probably because of data availability while there is limited number of empirical studies on the issue for Sub-Saharan African (SSA) economies. As such, this paper fills this gap by focusing on the macroeconomic determinants of credit risk measured as the ratio of non-performing loans (NPLs) to total gross loans focusing on 22 Sub-Saharan African countries over the period 2000–2016.

Studying the macroeconomic determinants of credit risk in the banking systems of SSA countries is an important issue for the following reasons: first, the assessment of credit risk in the financial sector is a vital part of macro-prudential surveillance that allows the identification of key vulnerabilities in this sector (see Beck et al., 2015). Second, according to the same authors, the stress tests conducted after the 2008/2009 global financial crisis to restore confidence in the financial sector have been based on macroeconomic assumptions. Third, the 2008/2009 global financial crisis adversely affected Africa with a lag that resulted in an abrupt stop (in 2009) of the rapid growth that the region was experiencing over 2000–2008 (Kasekende et al., 2010). Fourthly, most banks in Sub-Saharan African economies still operate in risky financial environments with weak legal institutions (see Flamini et al., 2009) while as Nikolaidou and Vogiazas (2017) claim, risks still remain in Sub-Saharan Africa because of commodity price fluctuations, reversal of capital flows and spillovers from external shocks, among other factors. Furthermore, according to IMF (2017) SSA's recovery from the 2008/2009 global financial crisis is not yet complete. Central banks in the advanced economies continue to follow easy policies to enhance their growth while at the same time, low-income economies are expanding their access to international bond markets as a result of easy financial conditions. To the best of our knowledge, there is only one study (Fofack, 2005) for Sub-Saharan Africa that

* Corresponding author.

E-mail addresses: t.mpofu@uct.ac.za (T.R. Mpofu), efi.nikolaidou@uct.ac.za (E. Nikolaidou).

Peer review under responsibility of Africagrowth Institute.

https://doi.org/10.1016/j.rdf.2018.08.001

examines the determinants of credit risk applying cross-country panel analysis over the period 1993–2002. However, this study is outdated and completely ignores dynamics in the estimation method.

As such, the present study contributes to the credit risk determinants literature by focusing on Sub-Saharan Africa, a region that has been largely neglected in the relevant literature, by covering a recent period spanning from 2000–2016, a period that includes the post 2008/2009 global financial crisis and by employing four different cross-country panel estimations (pooled-OLS, fixed effect, difference GMM and system GMM). This way this paper takes into consideration developments in recent literature that emphasizes the importance of dynamic effects in explaining the causes of credit risk and, thus, overcomes the key limitation of Fofack's (2005) study that only uses fixed effects estimation ignoring any dynamics.

The study focuses on Sub-Saharan Africa because the banking sector in this region is still at low levels of development but fast growing relative to other developing regions (Kasekende et al., 2010; EIB, 2013). Moreover, some countries in this region (for example, Kenya and Nigeria) have experienced banking crises in the past. The low levels of development of the banking sector along with its fast growth and the past experience of banking crises in some SSA countries, motivate the need for further empirical studies on the determinants of credit risk in the region, so as to come up with policies that minimise the occurrence of banking crises in the future.

Employing pooled-OLS, fixed effects, two-step difference and system GMM with robust standard errors using various specifications, the results show that an increase in real GDP growth rate has a statistically and economically significant reducing effect on the ratio of non-performing loans to total gross loans. Furthermore, inflation rate, domestic credit to private sector by banks as a percent of GDP, trade openness, VIX (Chicago Board Options Exchange Market Volatility Index) as a proxy of global volatility, and the 2008/2009 global financial crisis, all have positive and significant impact on NPLs.

The rest of the paper is organised as follows: Section 2 presents a review of the literature while Section 3 defines the data and explains the model specification and estimation techniques. Then, Section 4 presents the results and Section 5 gives the main conclusions.

2. Literature review

The empirical literature that analyses the determinants of credit risk is based on theoretical models that deal with the link between financial imperfections and the wider economy. One such theoretical framework is the financial accelerator theory discussed by Bernanke and Gertler (1989), Kiyotaki and Moore (1997) and Bernanke et al. (1999). These studies argue that the amplification and propagation of a credit shock is via information asymmetries between borrowers and lenders and a balance sheet effect. An increase in asset prices propels up the net worth of firms, households or countries and improves the capacity to borrow, which then leads to further increases in asset prices through dynamic general equilibrium effects. In this way, De Bock and Demyanets (2012) assert that strong balance sheets in boom times may lead to increased lending against inflated values of collateral. On the other hand, Diwan and Rodrick (1992) suggest that high credit risk increases the uncertainty regarding the capital position of the banks and limits their access to financing. This further increases the banks' lending rates and contributes to lower credit growth, and thus, may have implications for economic activity.

Generally, the literature suggests four measures of banks' asset quality used to proxy credit risk. These are the development of expected default frequencies (EDF), loan loss provisions (LLPs), loss given default (LGD), and non-performing loans (NPLs) as stated by Beck et al. (2015). However, the most commonly used measures/proxies of credit risk in the relevant literature are LLPs and NPLs. Due to data availability, this study uses NPLs as the proxy for credit risk. However, when it comes to the factors that determine credit risk, the literature groups them into two categories, namely, systematic and unsystematic factors (see e.g., Castro, 2013; Louzis et al., 2012).

Systematic factors are factors that have an influence on the likelihood of borrowers paying their debts. These factors include: first, macroeconomic conditions like growth in GDP, employment, stock market index, inflation rate and exchange rate, among others. Second, changes in economic policies such as changes in monetary and tax policies, economic legislation changes, import restrictions and export stimulation. Third, political changes or changes in the goals of leading political parties. Given the difficulties in incorporating the second and third type of factors in empirical analysis, most studies focus on the macroeconomic factors. On the other hand, unsystematic factors refer to specific factors that affect individuals (i.e. individuals' personality, financial solvency and capital, credit insurance) and companies (i.e. management, financial position, sources of funds and financial reporting, ability to pay the loan and industry-specific factors). Keeton and Morris (1987), Berger and DeYoung (1997), Louzis et al. (2012), Klein (2013), Nikolaidou and Vogiazas (2017), inter alia, provide more details on these factors.

Most of the empirical literature that analyses the determinants of credit risk focuses on developed and other developing countries while there is very limited work focusing on Sub-Saharan Africa. Studies that focus on other regions employ either time series analysis, like ARDL cointegration (i.e. Adebola et al. (2011) for Malaysia, Nikolaidou and Vogiazas (2014) for Bulgaria, Nikolaidou and Vogiazas (2013) for Romania) or cross-country panel analysis (i.e. Beck et al. (2015) for 75 countries,[1] Castro (2013) for Greece, Ireland, Portugal, Spain, and Italy, Klein (2013) for 16 Central, Eastern and South-eastern European countries, Nkusu (2011) for 26 advanced countries, De Bock and Demyanets (2012) for 25 emerging market countries,[2] and Espinoza and Prasad (2010) for Gulf countries). Some stud-

[1] This study includes four countries from Sub-Saharan Africa namely: Gabon, Ghana, South Africa and Uganda.

[2] This study includes one country from Sub-Saharan Africa namely: South Africa.

ies (i.e. Ekanayake and Azeez (2015) for Sri Lanka and Louzis et al. (2012) for Greece) use a single country panel analysis, that is, they analyse different commercial banks over time). Other studies analyse the feedback effects between NPLs and macroeconomic conditions using panel VAR or structural panel VAR (see Klein, 2013; De Bock and Demyanets, 2012; Nkusu, 2011; Espinoza and Prasad, 2010, inter alia).

As far as the limited number of studies that focus on Sub-Saharan Africa, we can distinguish between those that employ time series analysis (i.e. ARDL approach to cointegration by Nikolaidou and Vogiazas (2017) for Kenya, Namibia, South Africa, Uganda, and Zambia; GLS by Chimkono et al. (2016) for Malawi; OLS by Etale et al. (2016) for Nigeria, Haniifah (2015) for Uganda, and Washington (2014) for Kenya) or cross-country panel analysis by Fofack (2005) for 7 CFA and 9 non-CFA countries.[3] There are also a few studies (i.e. Warue, 2012 for Kenya; Havrylchyk, 2010 for South Africa) that employ single country panel analysis and some others that employ descriptive analysis (i.e. Viswanadham and Nahid, 2015; Ombaba, 2013; Waweru and Kalani, 2009).

Empirical findings for developed and other developing regions are as follows. Beck et al. (2015) use cross-country panel analysis over the period 2000–2010 and find that real GDP growth rate has a negative and significant relationship with NPLs while lending rates and credit growth have a positive relationship. They also find that exchange rate depreciation (appreciation) leads to a significant decline (increase) in NPLs. Using the same cross-country panel analysis, similar results for real GDP growth rate, lending rates (interest rates) and credit growth are found by Castro (2013) over the period 1997Q1–2011Q3, Nkusu (2011) over the period 1998–2009 and Espinoza and Prasad (2010) over the period 1995–2008. De Bock and Demynanets (2012) also use cross-country analysis and find a significant negative relationship between NPLs and real GDP growth rate. However, they find insignificant values for the lending interest rate and for credit growth. Castro (2013) finds a positive association between NPLs and private/public indebtedness, real exchange rate appreciation, unemployment rate, and the 2008/2009 global financial crisis but a negative relationship between NPLs and housing price index and equity prices which are similar to Nkusu's (2011) findings. Klein (2013) and Nkusu (2011) also find a positive and significant relationship between NPLs and unemployment rate. Unlike Beck et al. (2015) and Castro (2013), Klein (2013) finds that a depreciation of the exchange rate significantly leads to an increase in NPLs. This result is supported by Nkusu (2011). Furthermore, Klein (2013) finds a positive relationship between NPLs and global volatility (VIX) which is also supported by Espinoza and Prasad (2010). As far as the impact of inflation is concerned, empirical findings are ambiguous (i.e. Klein, 2013 finds a positive effect while Ekanayake and Azeez, 2015 find a negative relationship). Other studies (see e.g., Adebola et al., 2011; Louzis et al., 2012; Nikolaidou and Vogiazas, 2014; Ekanayake and Azeez, 2015) use either time series methods or single country panel analysis and find similar results as just explained above.

Using a cross-country fixed effect estimation for 16 Sub-Saharan African countries over the period 1993–2002, Fofack (2005) finds a significant negative relationship between NPLs and GDP per capita and, a positive one with real exchange rate appreciation, real interest rate and broad money (M2). Fofack's study also shows that inflation, real GDP growth rate, and domestic credit to private sector are all insignificant. Fofack's (2005) study is the only study for Sub-Saharan Africa that uses a panel analysis to investigate the determinants of credit risk in the banking sector. However, this study only employs fixed effect estimation and does not take dynamic effects into consideration. This is a key limitation of the study given that recent literature emphasises the importance of dynamic effects in explaining the causes of credit risk.

On the other hand, Warue (2012) uses a single country panel analysis for Kenya over the period 1995–2009 and finds that bank specific factors affect NPLs with higher magnitudes compared to macroeconomic factors. Warue (2012) further shows a negative and significant relationship between real GDP, GDP per capita and NPLs while the lending interest rate has a positive and significant effect only for small banks and inflation has a negative impact only for large banks and for government owned banks. Similarly, Havrylchyk (2010) uses a single country panel analysis for South Africa over the period 2001–2008 and finds that macroeconomic factors are the main drivers of credit risk (measured as loan loss provisions). This is in contrast to Warue's (2012) findings. Applying descriptive analysis, Waweru and Kalani (2009) claim that economic downturn negatively affects NPLs in Kenya over the period 1995–2003 while Ombaba (2013) and Viswanadham and Nahid (2015) studies for Kenya and Tanzania respectively, find a negative correlation between NPLs and GDP. A recent study, by Nikolaidou and Vogiazas (2017) employs the ARDL cointegration method and finds that in the long-run NPLs for all countries apart from Uganda are mainly caused by macroeconomic factors rather than bank specific factors. Haniifah (2015) employs OLS and finds that inflation, exchange rate, interest rate and GDP growth are insignificant in influencing NPLs in Uganda over the period 2000–2013. Washington (2014) applies OLS with an ECM and finds a negative and significant effect of GDP per capita growth rate, exchange rate and domestic credit to the private sector on NPLs while lending interest rates and inflation had a positive and significant effect.

Reviewing the empirical literature, it seems that NPLs are mainly driven by macroeconomic factors for both developed and developing countries. As such, this paper complements the analysis on studies that investigate the causes of credit risk by focusing on macroeconomic determinants in Sub-Saharan Africa. This study is motivated by the fact that the only study (by Fofack, 2005) that analysed the determinants of credit risk focusing on SSA using a panel estimation technique over the period 1993–2002 is outdated, ignores the recent Global financial crisis and does not consider any dynamics in the estimation. So, the present study overcomes the above limitations by using

[3] CFA countries include: Benin, Cameroon, Chad, Cote d'Ivoire, Mali, Senegal, and Togo. Non-CFA countries include: Botswana, Cape Verde, Ethiopia, Kenya, Malawi, Rwanda, South Africa, Swaziland and Zimbabwe.

a recent dataset spanning from 2000 to 2016 (a time frame that includes the post crisis period) and it uses four different panel estimation methods that incorporate dynamics. Also, the low level of development but at the same time the fast growing banking sector in Sub-Saharan Africa (relative to other developing regions) as well as the fact that some countries in the region have experienced banking crises in the past, point to the need for more empirical studies as they can come up with possible policies in minimising banking crises in the future. The findings from the empirical literature are mixed mostly for variables like exchange rate and inflation rate. These mixed findings further motivate the need for more empirical work on the macroeconomic determinants of credit risk. The next section defines the data we use, the model employed and the estimation technique.

3. Data, model specification, and estimation method

This paper uses annual data over the period 2000–2016 for a sample of 22 Sub-Saharan African economies. The data is obtained from the World Bank, IMF, and Central Banks of the focal economies. The list of the countries included in the sample appears in Table A1. This table also shows the real GDP, GDP per capita, the average growth rate and the World Bank classification per income for each of the countries included in our sample as well as for Sub-Saharan Africa region as a whole. The time period is constrained by the availability of the dependent variable (NPL). As such, our sample is an unbalanced panel. Given that panel data offers the benefit of increasing the sample size, this enables the analysis from a cross-country perspective, as it would be impossible to conduct a time series analysis for a single economy.

The variables are defined as follows: the dependent variable is non-performing loans (*NPL*) which is measured as the ratio of non-performing loans to total (gross) loans in percentages. Independent variables are as follows: GDP growth rate (*GDPGR*) is the annual percentage growth rate of real GDP based on local currency. Unemployment rate (*UNEMP*) is the total unemployment rate as a percent of total labour force based on ILO estimate. Lending interest rate (*LIR*) is the interest rate that banks offer when lending money to their clients. Inflation rate (*INFLCPI*) is the annual percentage change in the cost to the average consumer of acquiring basket of goods and services. *DCPGDP* is domestic credit to private sector by banks as percentage of GDP. *VIX* is the Chicago Board Options Exchange Market Volatility Index (CBOE) that proxies global volatility. REER is the real effective exchange rate in logarithmic form with a base year of 2010 and defined such that an increase represents an appreciation of the exchange rate. *FINCRISIS* is the dummy variable for the 2008/2009 global financial crisis which takes the value of one for 2008 and 2009 and zero otherwise. *USGDPGR* is the real GDP growth rate for the United States. Trade openness (*TRADE*) is the sum of exports and imports of goods and services measured as a share of GDP.

Table A2 provides the summary statistics of these variables. Looking at Table A2, it becomes obvious that there is a high degree of heterogeneity among the countries. The maximum NPL (74.1%) is observed in Rwanda in 2001 while the minimum (0.96%) is observed in Congo Brazzaville in 2010. GDP growth rate ranges from negative 9.69% in Equatorial Guinea in 2016 to 63.38% in the same country in 2001 while unemployment rate ranges from 0.74% in Rwanda in 2008 to 37.6% in Lesotho in 2001.

For countries with longer time periods, NPL averages during 2000–2007 exceed the averages for 2008–2009. Such economies include Gabon, Ghana, Kenya, Malawi, Mauritius, Namibia, Rwanda, Seychelles, and Uganda. For some countries (i.e. Gambia, Nigeria, Swaziland, and Zambia) the 2008–2009 averages exceed the 2000–2007 averages. On the other hand, economies like Ghana, Lesotho, Malawi, Mauritius, Seychelles, and Uganda, since 2010 have higher averages than the 2008–2009 ones. This suggests that non-performing loans for these economies have been on an upward trend since 2010. Fig. 1 below shows these averages.

To inform model specification, preliminary analysis is carried out to establish the stationarity of all the variables we use. We apply the Fisher-ADF and Fisher-PP tests to test the stationarity of the variables because the Fisher-type tests do not require a balanced panel. The results are shown in Table A3 and they indicate that all the variables are stationary in levels when using the Fisher-ADF. The Fisher-PP tests, on the other hand, indicate that, except for the lending interest rate (LIR), domestic credit to private sector by banks (DCPGDP), and TRADE, all the remaining variables are stationary in levels. In addition, we apply the Im-Pesaran-Shin (IPS) test because this test also does not require the use of a balanced panel. Results from the IPS test, show that all the variables are stationary in levels except for DCPGDP and TRADE that become stationary in their first difference. There are no results for non-performing loans (NPL) because this method does not generate the results when the time period for a single individual is less than 10 years when applying annual data. As such, we can carry on with the empirical analysis using the stationary variables in our empirical model.

In analysing the determinants of credit risk in the banking system in Sub-Saharan Africa, we follow the literature (see e.g. Nkusu, 2011; Castro, 2013; Klein, 2013, inter alia) by adopting a dynamic approach to account for the effect of possible omitted explanatory variables and the time persistence of the credit risk. Therefore, our regression equation is as follows:

$$NPL_{it} = \alpha + \sum_{k=1}^{K} \gamma_k NPL_{it-k} + X'_{it}\beta + \lambda_i + \in_{it} \quad (1)$$

where NPL denotes the ratio of non-performing loans to total (gross) loans. The subscripts i = 1,. . ., N and t = 2000, . . ., 2016 refer to the cross-sectional and time series elements of the data, respectively. X_{it} is a vector of explanatory variables, β is a vector of coefficients to be estimated, λ_i is unobserved country-specific effects, $\in_{it}$ is the error term.

To estimate Eq. (1), we use four alternative estimation techniques. First, we use the pooled-OLS. However, studies like Baltagi (2008) state that the pooled-OLS estimator is biased and inconsistent even when the $\in_{it}$ is not serially correlated while Anderson and Hsiao (1981) and Arellano and Bond (1991) show that the OLS estimator becomes biased for small val-

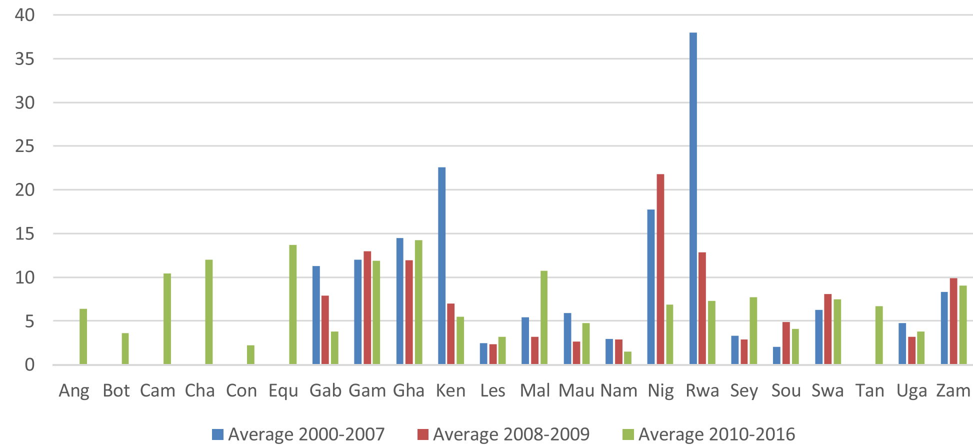

Fig. 1. Non-performing loans averages for 2000–07, 2008–09, 2010–16 for SSA countries.
Notes: Angola (Ang), Botswana (Bot), Cameroon (Cam), Chad (Cha), Congo Brazzaville (Con), Equatorial Guinea (Equ), Gabon (Gab), Gambia (Gam), Ghana (Gha), Kenya (Ken), Lesotho (Les), Malawi (Mal), Mauritius (Mau), Namibia (Nam), Nigeria (Nig), Rwanda (Rwa), Seychelles (Sey), South Africa (Sou), Swaziland (Swa), Tanzania (Tan), Uganda (Uga), Zambia (Zam).
Source: authors' own compilation and calculations using the data from the World Bank, IMF and Central Banks of the Economies.

ues of T when the lagged dependent variable is included as an explanatory variable. Second, we use the fixed effects model which allows controlling for unobserved heterogeneity across countries. On the other hand, this approach may give rise to Nickell's (1981) bias (also called dynamic panel bias) which results from the possible endogeneity of the lagged dependent variable and the fixed effects in the error term particularly in the "small T, large N" panels. In spite of that, as T gets large, the fixed effects estimator becomes consistent. Still, Judson and Owen (1999) indicate that even for T = 30 the bias can be as much as 20% of the true value of the coefficient of interest. Third, we use the Arellano and Bond (1991) two-step difference generalized method of moments (GMM). Of the two GMM methods available, the one-step and the two-step GMM, we use the two-step GMM estimator because it is asymptotically more efficient than the one-step estimator. This method transforms the data to first differences to remove the fixed effect element and uses the lagged levels of the right hand-side variables as instruments. Following the Arellano and Bond (1991) method, the differences of the strictly exogenous explanatory variables are instrumented with themselves while the dependent and predetermined or endogenous variables are instrumented with their lagged levels. Fourth, we use the system GMM because studies like Espinoza and Prasad (2010), De Bock and Demyanets (2012), and Klein (2013) among others, state that the difference GMM of Arellano and Bond (1991) has a weakness in providing estimations with low precision when the sample period has "small T" and high persistence.

4. Results

The findings from the regression analysis are in Tables A4–A8. We start our analysis by looking at the effects of the general economic environment on non-performing loans (NPLs). We do this by using real GDP growth rate and unemployment rate to proxy economic environment. Next, we add other macroeconomic variables in our regression equation applying the four different estimation techniques mentioned earlier in Section 3. In that spirit, we first present the results from the pooled ordinary least squares (OLS) and Fixed effects (FE). These results are shown in Table A4 (columns 1–6) for the impact of economic environment while on Tables A5 and A6 we present results with additional macroeconomic variables. The Arellano–Bond (AB) estimator is then employed to overcome the short-comings of the OLS estimation method (Table A4, columns 7–9; Table A7). Lastly, we use the system GMM to overcome potential drawbacks associated with the AB estimator (Table A4, columns 10–12; and Table A8).

Eq. (1) is a dynamic model. As such, we begin by interpreting the lagged dependent variable. Columns 1–6 in Table A4 include two lags of the dependent variable. Only the first lag of the dependent variable is statistically significant. The coefficient's size on the lagged NPL ranges from 0.787 to 0.801 for OLS (columns 1–3) and from 0.674 to 0.678 for FE, thus, suggesting that a shock to NPLs is likely to have a prolonging effect on the banking system. Using OLS and FE to analyse the impact of real GDP growth rate and unemployment rate, we use two lags for each variable (see columns, 1, 2, 4, and 5 in Table A4) to account for possible delay with which economic shocks affect the performance of NPL and the possibility that these two variables are closely linked. The results in Table A4 (columns 1–6) indicate that when real GDP growth rate increases, the ratio of non-performing loans to total (gross) loans decreases significantly for the second lag of real GDP. On the other hand, unemployment rate is insignificant when using OLS while it is significant but with the wrong negative sign when using FE. The dummy variable for the 2008/2009 global financial crisis is insignificant for both OLS and FE methods. The inclusion of additional macroeconomic variables leads to similar results of high persistence of NPLs, significant real GDP growth rate and insignificant unemployment rate. Some of the additional variables are significant (see Tables A5 and A6), however, we do not discuss these results in detail because of the short-comings of pooled OLS and FE methods.

As mentioned earlier, using OLS in a dynamic model leads to biased and inconsistent estimates while the use of FE may give rise to dynamic panel bias in the "small T, large N" panel which is the case with our sample. As a result, we use the Arellano–Bond (AB) estimator. We use one lag for the dependent variable and all macroeconomic variables are treated as strictly exogenous because they all enter the regression equation with at least one lag. The use of strictly exogenous variables helps with avoiding a huge number of instruments. The AR tests for serial correlation confirm that there is no serial correlation given the insignificant probabilities for AR (1) and AR (2) as shown in Table A4 (columns 7–9). The validity of the instruments is also confirmed by the insignificant p-values for the Sargan test.

The results in Table A4 (columns 7–9) reinforce the persistency of NPLs after economic shocks in the range of 0.702–0.713. Using the AB estimator, both the real GDP growth rate and the unemployment rate are insignificant. However, the positive effect of the 2008/2009 global financial crisis confirms that when the economic environment deteriorates, credit risk increases. The results presented in columns 7–9 of Table A4 indicate that NPLs increased substantially during the financial crisis. Regarding the economic significance of the findings, ceteris paribus, the results suggest that during the 2008/2009 global financial crisis, NPLs increased on average by about 1.93–1.94% points. The insignificance of real GDP growth rate and unemployment rate motivates us to run the system GMM. The results for the two-step system GMM are shown in columns 10–12 of the same table. These results also show persistency of one-lagged NPL and the increase of about 1.88% point in NPL during the financial crisis. However, the same columns indicate that a one percentage point increase in real GDP growth rate decreases the ratio of non-performing loans to total gross loans in the range of 0.13–0.16% points, holding all other things constant. The results for the unemployment rate are significant with the wrong sign. The results for GDP growth rate suggest that credit risk tends to increase when the economic environment deteriorates, which is similar to the findings by Nkusu (2011), Louzis et al. (2012), De Bock and Demynanets (2012), Castro (2013), and Beck et al. (2015) but in contrast to Fofack's (2005) finding (the only study for the same region). These findings point to the importance of implementing economic policies that promote economic growth to reduce the problems of credit risk in the banking system.

Table A7 presents the results for AB estimator when we include other macroeconomic variables. Columns 1–7 reaffirm the persistence of the one-lagged NPL in the range of 0.502–0.725 as well as the impact of the 2008/2009 global financial crisis. Now, real GDP growth rate is significant as shown in columns 1, 2, and 6. These results suggest that a one percentage point increase in real GDP growth rate leads to a decrease in NPL by about 0.15–0.23% points, ceteris paribus. However, the coefficients for unemployment rate are still insignificant in all specifications, hence they are not included in the table. Next we include domestic credit to private sector by banks (D2CPGDP (−1)).[4] We consider credit growth because the more credit expands, the higher the likelihood that the defaults will increase in the future. As such, columns 3 and 6 indicate that a one percentage point increase in domestic credit to private sector by banks as a percent of GDP increases NPL by about 0.06–0.10% points. This result is similar to Espinoza and Prasad (2010), Klein (2013), and Castro (2013) while Fofack (2005) finds an insignificant value. The positive relationship between NPLs and credit growth implies an increase in risky loans given to borrowers during credit growth periods which increases the likelihood of potential defaults in the future.

As expected, the results in Table A7 (columns 3) indicate a positive and significant impact of VIX on the ratio of non-performing loans to total gross loans. This positive relationship is in line with the financial crisis effects. Results in Column 6 indicate that a one percentage point increase in trade openness leads to a 0.05% point increase in NPL. This result implies that increasing trade openness in Sub-Saharan Africa may expose the banking system to adverse shocks. Other variables like lending interest rates, real effective exchange rate, inflation rate, and the US RGDP growth rate are insignificant in all specifications.

Given the above, we re-estimate Eq. (1) using the two-step system GMM technique with robust standard errors and adding other macroeconomic variables. The results in Table A8 support the findings from Table A4 (columns 7–12) and Table A7. The persistence of NPL continues to be statistically significant in the range of 0.492–0.662. Also, real GDP growth rate continues to have a negative and significant relationship with NPL. In terms of economic significance of the findings, a one percentage point increase in real GDP growth rate decreases NPL in the range of 0.13–0.17% points, ceteris paribus. Other variables, for example, domestic credit growth to private sector by banks and the dummy variable for the 2008/2009 global financial crisis, also have a positive and significant impact on NPL. Results in column 5 in Table A8 show the impact of inflation rate on NPL. This result indicates that a one percentage point increase in inflation rate leads to an increase in the ratio of non-performing loans to total gross loans by about 0.14% points. Our result for inflation is similar to Klein's (2013) but different to Castro's (2013) and Fofack's (2005) who find an insignificant coefficient. Such findings suggest that an increase in inflation rate weakens the borrowers' ability to service their debts by decreasing their real income, which in turn increases the likelihood of defaults by borrowers.

Furthermore, we do sensitivity analysis by replacing some of the variables with other related variables that proxy the same kind of effect. These results are shown in Table A9. We replace lending interest rate by real interest rate (RIR)[5] in columns 1 and 6 and by the SPREAD (defined as lending rate minus deposit rate) in columns 2 and 7. The coefficients for both RIR and the SPREAD are insignificant. However, looking at these same

[4] As the variable DCPGDP is not stationary, we use its first difference D2CPGDP which is equivalent to ΔDCPGDP.

[5] Real interest rate is the lending interest rate adjusted for inflation as measured by the GDP deflator.

columns (1, 2, 6 and 7), we still observe the importance of the economic environment as proxied by real GDP growth rate in affecting NPLs, as well as the dummy for the financial crisis. Next, we replace the dummy for the financial crisis (FINCRISIS) that takes the value of one for 2008 and 2009 only and zero otherwise with a dummy called CRISIS that takes the value of one from 2008 onwards and zero otherwise (see results in columns 3 and 8, Table A9). In this way, we use this dummy variable to capture a permanent effect of the financial crisis. The results for this coefficient are insignificant. Second, we use the dummy CRISIS in columns 4 and 9 that takes one for 2009 only and zero otherwise. The results on this dummy are positive and significant. Relative to the FINCRISIS dummy variable, the results for the CRISIS dummy variable in columns 4 and 9 have larger magnitudes. This suggests that the financial crisis negatively affected the Sub-Saharan African countries mostly in 2009.

As a final step, we exclude Equatorial Guinea from the sample because it is an outlier (it has the highest real GDP growth rate over the study period averaging at 63.38%[6]). The results that exclude Equatorial Guinea are shown in Table A9 columns 5 and 10 and, overall, they are not affected by this exclusion. The main conclusions regarding the importance of the real GDP growth rate as well as of the financial crisis dummy and of credit growth remain valid.

5. Conclusion

The 2008/2009 global financial crisis has revived researchers' interest on the causes of banking crises given their devastating effects on the entire economy. As such, this paper empirically examines the impact of macroeconomic factors on the ratio of non-performing loans to total gross loans in 22 Sub-Saharan African economies, a region that has been largely neglected in the relevant literature. This follows from the fact that several studies that investigate the causes of credit risk in the banking sector mostly focus on advanced economies and large emerging markets probably because of data availability.

We apply a dynamic panel data approach over the period 2000–2016 employing pooled-OLS, Fixed effects, two-step difference and system GMM estimation techniques. Using a variety of specifications, the results show that an increase in real GDP growth rate has a statistically and economically significant reducing effect on the ratio of non-performing loans to total gross loans. Specifically, a one percentage point increase in real GDP growth rate reduces NPLs in the range of 0.13–0.23% points. Furthermore, inflation rate, domestic credit to private sector by banks as a percentage of GDP, VIX as a proxy of global volatility, trade openness and the dummy variable for the 2008/2009 global financial crisis, all have positive and significant impact on NPLs. Overall, the findings of this study suggest that a deterioration in the economic environment leads to increasing credit risk in the banking sector in Sub-Saharan Africa. This implies/suggests that polices that enhance economic growth should be implemented as these could bring substantial benefits in the banking sector by reducing the likelihood of defaults on loans, and thus, minimising credit risk in the banking sector and the possibility of banking crises and the ensuing devastating effects on the entire economy.

Although panel analysis allows researchers to carry out studies when data points are not adequate for a single country using time series analysis, there is a need for more single country case studies in Sub-Saharan Africa that analyse the determinants of credit risk in the banking sector using both systematic and unsystematic factors.

Appendix A.

[6] Equatorial Guinea also has the highest mean of 11.42 and the highest median of 8.31 while the total mean of the 22 countries in our sample is 5.27 and the total median is 5.00.

Table A1
List of countries and their performance.

Country	GDP (in 2010bn US$)	GDP per capita (in 2010 US$)	GDP average growth rate	World Bank classification (per income)
Angola	103.92	3606.64	7.14	Lower middle
Botswana	16.61	7383.33	4.19	Upper middle
Cameroon	31.81	1357.07	3.99	Lower middle
Chad	12.42	859.65	7.42	Low
Congo Brazzaville	14.34	2798.07	4.28	Lower middle
Equatorial Guinea	14.69	12,028.56	11.42	Upper middle
Gabon	18.95	9569.45	2.42	Upper middle
Gambia	1.09	532.28	3.41	Low
Ghana	48.17	1707.66	6.10	Lower middle
Kenya	55.39	1143.07	4.56	Lower middle
Lesotho	3.06	1387.46	3.96	Lower middle
Malawi	8.71	481.53	4.28	Low
Mauritius	12.40	9812.55	4.33	Upper middle
Namibia	14.93	6020.90	4.70	Upper middle
Nigeria	457.13	2457.81	7.01	Lower middle
Rwanda	8.80	738.64	7.91	Low
Seychelles	1.32	13,963.59	3.24	High
South Africa	419.56	7504.30	2.96	Upper middle
Swaziland	5.25	3911.40	3.21	Lower middle
Tanzania	46.77	866.95	6.62	Low
Uganda	27.47	662.11	6.40	Low
Zambia	26.92	1622.41	6.33	Lower middle
Sub-Saharan Africa	1686.11	1632.08	4.84	All income levels

Source: authors' own compilation and calculation using the data from the World Bank.
Notes: GDP and GDP per capita values are for 2016 while GDP average growth rate is the average over the period 2000–2016.

Table A2
Descriptive statistics.

Variables	Obs	Mean	Std.Dev	Min	Max
NPL	260	8.88	8.38	0.96	74.1
GDPGR	374	5.27	5.79	−9.69	63.38
UNEMP	374	12.18	9.15	0.74	37.6
LIR	309	19.11	12.95	7.3	103.16
INFLCPI	364	9.60	20.67	−9.62	325
DCPGDP	369	20.72	20.31	1.97	106.26
TRADE	358	88.15	46.71	21.12	351.11
REER	187	4.55	0.18	3.99	5.2
VIX	374	20.18	6.98	11.56	40
USGDPGR	374	1.93	1.55	−2.78	4.09
FINCRISIS	374	0.12	0.32	0	1

Notes: the variables are defined in Section 3. Obs stands for observations. Std.Dev refers to standard deviation. Min is minimum and max is maximum.

Table A3
Panel unit root tests.

Variables	IPS	Fisher–ADF Inverse normal	Fisher–PP Inverse normal
NPL		−7.53***	−1.96**
GDPGR	−5.66***	−10.64***	−9.46***
UNEMP	−4.76***	−10.05***	−5.00***
LIR	−2.25**	−7.63***	−0.52
INFLCPI	−6.11***	−10.82***	−10.23***
DCPGDP	4.00	−2.90***	2.30
ΔDCPGDP	−4.02***	−8.96***	−10.58***
TRADE	−0.71	−6.84***	−1.2034
ΔTRADE	−12.66***	−13.37***	−15.46***
REER	−3.53***	−7.11***	−3.28***
VIX	−6.34***	−11.42***	−7.04***
USGDPGR	−3.35***	−9.32***	−9.02***

Notes: the variables are defined in Section 3. The Im-Pesaran-Shin (IPS) unit root tests do not require the use of a balanced panel and are performed over the available data considering a constant and one lag in all regressions. The null hypothesis is that "all panels contain unit-roots". The Fisher-type unit-root tests are based on augmented Dickey–Fuller (Fisher–ADF) tests with drift and one lag in all regressions and Phillips–Perron (Fisher–PP) tests with one lag in all regression. The null hypothesis is that "all panels contain unit-roots". The Fisher-type tests do not require a balanced panel because the tests are conducted for each panel individually before combining the p-values from those tests to produce the overall test. The statistics are reported and respective p-values are represented by the stars. ***, ** indicate rejection of the null hypothesis at 1% and 5% respectively. Δ refers to first difference of the variable.

Table A4
Empirical results based on the economic behaviour.

Variable	OLS (1)	OLS (2)	OLS (3)	FE (4)	FE (5)	FE (6)	AB (7)	AB (8)	AB (9)	SGMM (10)	SGMM (11)	SGMM (12)
NPL$_{-1}$	0.801***	0.797***	0.787***	0.675***	0.678***	0.674***	0.702***	0.713***	0.705***	0.644***	0.618***	0.627***
	(5.56)	(5.37)	(5.49)	(7.90)	(7.06)	(7.75)	(11.96)	(10.95)	(11.83)	(9.54)	(6.67)	(6.70)
NPL$_{-2}$	−0.042	−0.064	−0.050	−0.019	−0.025	−0.022						
	(−0.34)	(−0.50)	(−0.40)	(−0.34)	(−0.44)	(−0.40)						
GDPGR$_{-1}$	−0.059		−0.097	−0.079		−0.081	−0.071		−0.077	−0.127**		−0.140*
	(−0.87)		(−1.33)	(−1.51)		(−1.53)	(−0.81)		(−0.90)	(−2.08)		(−1.70)
GDPGR$_{-2}$	−0.124**		−0.167***	−0.169**		−0.171**	−0.141		−0.144	−0.160*		−0.179
	(−2.33)		(−3.23)	(−2.07)		(−2.07)	(−1.12)		(−1.16)	(−1.70)		(−1.56)
UNEMP$_{-1}$		−0.049	−0.066		−0.084**	−0.081***		−0.030	−0.043		−0.069*	−0.130**
		(−0.77)	(−1.07)		(2.22)	(−3.28)		(−0.68)	(−0.89)		(−1.66)	(−2.29)
UNEMP$_{-2}$		−0.005	−0.015		−0.018	−0.036		0.031	0.007		0.016	0.000
		(−0.08)	(−0.26)		(−0.23)	(−0.54)		(0.56)	(0.14)		(0.33)	(0.01)
FINCRISIS	1.480	1.307	1.624	1.574	1.280	1.543	1.926*	1.813	1.942*	1.876***	−0.193	0.992
	(1.33)	(1.16)	(1.44)	(1.64)	(1.34)	(1.59)	(1.71)	(1.60)	(1.75)	(5.64)	(−0.11)	(0.33)
C	2.679***	2.651***	4.283***	3.886***	3.937***	5.409***	3.076**	1.937	3.594**	3.915***	3.566**	6.057***
	(4.21)	(4.15)	(4.79)	(8.37)	(3.50)	(5.06)	(2.43)	(1.61)	(2.01)	(3.57)	(2.55)	(3.21)
No.Obs	216	216	216	216	216	216	211	211	211	233	233	233
R^2:overall	0.7131	0.7116	0.7238	0.7107	0.7049	0.7195						
AR(1)							0.1261	0.1368	0.1272	0.1259	0.1385	0.1343
AR(2)							0.1258	0.2517	0.1242	0.1318	0.0608	0.0972
Sargan-test							0.2513	0.2397	0.2509	0.9009	0.9587	0.9054

Notes: the models are estimated with robust standard errors. ***, **, * indicate the 1%, 5%, and 10% level of significance. Robust t-statistics are in () brackets. The model is estimated by ordinary least squares (OLS), Fixed effects (FE), two-step difference GMM of Arellano–Bond (AB), and two-step system GMM (SGMM). The variables are defined in Section 3. C stands for constant. No.Obs = the number of observations. AR (1) and AR (2) represent the p-values for the Arellano–Bond tests for 1st and 2nd order autocorrelation in first-differenced errors. Sargan-test represents the p-values for the validity of the set of instruments used for overidentifying restrictions.

Table A5
Empirical results based on additional macroeconomic variables.

Variables	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)	OLS (6)	OLS (7)	OLS (8)
NPL_{-1}	0.734*** (16.45)	0.755*** (16.57)	0.738*** (15.70)	0.775*** (9.01)	0.741*** (8.42)	0.757*** (17.91)	0.763*** (17.45)	0.763*** (17.31)
$GDPGR_{-2}$	−0.196*** (−4.05)	−0.136*** (−2.77)		−0.162** (−2.54)		−0.171*** (−3.27)	−0.160*** (−3.18)	−0.148*** (−2.99)
$UNEMP_{-1}$			−0.035* (−1.68)		−0.063* (−1.67)			
$D2CPGDP_{-1}$	0.216* (1.90)	0.218** (1.98)	0.207* (1.86)	0.317** (2.01)	0.306* (1.91)	0.244** (2.10)	0.205* (1.84)	0.212* (1.84)
LIR_{-1}	0.079** (2.52)							
FINCRISIS	1.219 (1.18)	−0.669 (−1.07)	−0.918 (−1.33)	1.861 (1.21)	1.785 (1.14)	0.789 (0.86)	1.220 (1.19)	1.030 (1.13)
VIX_{-1}		0.133** (2.53)	0.139*** (2.64)					
$REER_{-1}$				−3.736** (−1.99)	−4.691* (1.91)			
$INFLCPI_{-1}$						0.100*** (2.66)		
$DTRADE_{-1}$							0.017 (0.85)	
$USGDPGR_{-1}$								−0.096 (−0.53)
C	1.155** (2.34)	−0.100 (−0.09)	−0.291 (−0.26)	19.410** (2.24)	24.083*** (2.65)	1.702*** (3.53)	2.391*** (5.19)	2.481*** (4.99)
No.Obs	187	233	233	129	129	233	228	233
R^2	0.8056	0.7886	0.7860	0.5954	0.5923	0.7860	0.7790	0.7799

Notes: ***, **, * indicates 1%, 5%, and 10% level of significance. The models are estimated with robust standard errors. Robust t-statistics are in parentheses. See notes in Table A4 for other definitions.

Table A6
Empirical results based on additional macroeconomic variables.

Variables	FE (1)	FE (2)	FE (3)	FE (4)	FE (5)	FE (6)	FE (7)	FE (8)
NPL_{-1}	0.688*** (18.07)	0.689*** (18.26)	0.687*** (16.84)	0.547*** (6.09)	0.539*** (5.55)	0.700*** (19.06)	0.703*** (21.74)	0.701*** (19.95)
$GDPGR_{-2}$	−0.254*** (−6.13)	−0.157* (−2.03)		−0.175 (−1.62)		−0.168* (−1.95)	−0.185** (−2.35)	−0.171** (−2.17)
$UNEMP_{-1}$			−0.053 (−0.97)		−0.114 (−0.76)			
$D2CPGDP_{-1}$	0.230* (1.78)	0.227* (1.85)	0.218* (1.74)	0.277* (2.19)	0.267* (2.05)	0.241* (1.88)	0.212* (1.80)	0.220* (1.83)
LIR_{-1}	0.068 (1.64)							
FINCRISIS	1.194 (1.57)	−0.772 (−1.61)	−1.085* (−2.09)	1.848 (1.71)	1.709 (1.57)	0.926 (1.30)	1.221 (1.67)	1.069 (1.52)
VIX_{-1}		0.143** (2.46)	0.151** (2.35)					
$REER_{-1}$				−7.825** (−2.47)	−8.018** (−2.76)			
$INFLCPI_{-1}$						0.088* (1.87)		
$DTRADE_{-1}$							0.028 (1.48)	
$USGDPGR_{-1}$								−0.119 (−1.06)
C	2.023** (2.53)	0.402 (0.46)	0.170 (0.14)	40.074** (2.68)	41.664** (2.93)	2.262*** (3.99)	3.045*** (6.38)	3.173*** (5.77)
No.Obs	187	233	233	129	129	233	228	233
R^2:overall	0.8041	0.7878	0.7849	0.5754	0.5736	0.7858	0.7782	0.7793

Notes: ***, **, * indicates 1%, 5%, and 10% level of significance. The models are estimated with robust standard errors. Robust t-statistics are in parentheses. See notes in Table A4 for other definitions.

Table A7
Empirical results based on additional macroeconomic variables.

Variables	AB (1)	AB (2)	AB (3)	AB (4)	AB (5)	AB (6)	AB (7)
NPL_{-1}	0.721*** (11.22)	0.725*** (8.99)	0.654*** (9.61)	0.502*** (3.10)	0.701*** (9.48)	0.677*** (9.39)	0.672*** (8.56)
$GDPGR_{-2}$	−0.233*** (−3.11)	−0.212** (−2.41)	−0.143 (−1.31)	−0.188 (−1.20)	−0.133 (−1.27)	−0.153* (−1.65)	−0.120 (−1.28)
$D2CPGDP_{-1}$	0.072 (1.25)	0.020 (0.17)	0.095* (1.67)	0.043 (0.85)	0.082 (1.51)	0.058** (2.10)	0.073 (1.60)
LIR_{-1}	−0.104 (−0.69)						
FINCRISIS	1.584*** (3.77)	1.337** (2.25)	−0.825 (−1.33)	1.349 (0.78)	1.492 (1.63)	1.518 (1.45)	1.342 (1.51)
VIX_{-1}			0.153* (1.95)				
$REER_{-1}$				−7.071 (−0.99)			
$INFLCPI_{-1}$					0.060 (1.02)		
$DTRADE_{-1}$						0.049** (2.30)	
$USGDPGR_{-1}$							−0.124 (−0.65)
C	4.530 (1.46)	2.471* (1.89)	0.283 (0.33)	36.610 (1.13)	2.263*** (2.62)	3.027*** (3.32)	3.036*** (2.86)
No.Obs	170	170	211	118	211	206	211
AR(1)	0.1522	0.1371	0.1148	0.1851	0.1260	0.1371	0.1378
AR(2)	0.4312	0.3358	0.6797	0.0934	0.4222	0.2668	0.4217
Sargan test	0.4034	0.7306	0.4133	0.9610	0.2171	0.3235	0.2943

Notes: ***, **, * indicates 1%, 5%, and 10% level of significance. The models are estimated with robust standard errors. Robust t-statistics are in () brackets. See notes in Table A4 for other definitions.

Table A8
Empirical results based on additional macroeconomic variables.

Variables	SGMM (1)	SGMM (2)	SGMM (3)	SGMM (4)	SGMM (5)	SGMM (6)	SGMM (7)
NPL_{-1}	0.644*** (7.01)	0.662*** (10.51)	0.627*** (6.21)	0.492*** (3.25)	0.634*** (6.59)	0.652*** (6.90)	0.661*** (6.62)
$GDPGR_{-2}$	−0.166** (−2.16)	−0.155* (−1.89)	−0.132* (−1.89)	−0.188 (−1.33)	−0.159* (−1.93)	−0.151* (−1.90)	−0.137* (−1.78)
$D2CPGDP_{-1}$	0.183*** (3.00)	0.201 (1.55)	0.163*** (3.25)	0.294 (1.17)	0.206*** (3.35)	0.159*** (3.15)	0.166*** (2.92)
LIR_{-1}	−0.021 (−0.32)						
FINCRISIS	1.558 (0.96)	−0.055 (−0.02)	−0.850 (−0.57)	−9.069 (−0.34)	0.991** (2.46)	−0.082 (−0.03)	1.362** (2.05)
VIX_{-1}			0.150 (1.43)				
$REER_{-1}$				−11.199 (−1.39)			
$INFLCPI_{-1}$					0.144** (2.07)		
$DTRADE_{-1}$						0.043* (2.45)	
$USGDPGR_{-1}$							−0.171 (−1.17)
C	2.627 (1.48)	2.841*** (2.73)	0.431 (0.31)	56.933 (1.55)	2.251* (1.80)	3.285*** (2.89)	3.429** (2.37)
No.Obs	187	187	233	129	2.33	228	233
AR(1)	0.1658	0.1376	0.1258	0.2885	0.1255	0.1560	0.1239
AR(2)	0.6182	0.8564	0.8708	0.5622	0.8264	0.6675	0.9579
Sargan test	0.9757	0.9992	0.9782	1.000	0.8724	0.9603	0.8528

Notes: ***, **, * indicates 1%, 5%, and 10% level of significance. The models are estimated with robust standard errors. Robust t-statistics are in () brackets. See notes in Table A4 for other definitions.

Table A9
Sensitivity analysis.

Variables	AB (1)	AB (2)	AB (3)	AB (4)	AB (5)	SGMM (6)	SGMM (7)	SGMM (8)	SGMM (9)	SGMM (10)
NPL_{-1}	0.725***	0.698***	0.729***	0.719***	0.721***	0.662***	0.630***	0.612***	0.643***	0.644***
	(8.99)	(7.04)	(10.78)	(8.87)	(11.22)	(10.51)	(7.72)	(10.47)	(8.38)	(7.01)
$GDPGR_{-2}$	−0.212**	−0.227***	−0.212***	−0.251***	−0.233***	−0.155*	−0.165**	−0.142*	−0.193**	−0.166**
	(−2.41)	(−3.44)	(−2.80)	(−3.34)	(−3.11)	(−1.89)	(−2.20)	(−1.86)	(−2.41)	(−2.16)
$D2CPGDP_{-1}$	0.020	0.078	0.107*	0.065	0.072	0.201	0.220**	0.242***	0.188*	0.183***
	(0.17)	(1.25)	(1.91)	(1.47)	(1.25)	(1.55)	(2.45)	(3.00)	(1.86)	(3.00)
FINCRISIS	1.337**	1.482***			1.584***	−0.055	1.382			1.558
	(2.37)	(2.62)			(3.77)	(−0.02)	(0.74)			(0.96)
RIR_{-1}	0.011					−0.017				
	(0.25)					(−0.46)				
SPREAD		−0.142					0.140			
		(−0.41)					(1.09)			
CRISIS			1.053	3.686***				0.145	4.424***	
			(1.49)	(6.14)				(0.07)	(6.67)	
LIR_{-1}			−0.085	−0.136	−0.104			0.042	0.017	0.021
			(−0.60)	(−0.76)	(−0.69)			(0.52)	(0.22)	(0.32)
C	2.471*	4.277	3.554	5.211	4.530	2.841***	1.863	2.569*	2.821	2.627
	(1.89)	(1.07)	(1.41)	(1.40)	(1.46)	(2.73)	(1.05)	(1.74)	(1.52)	(1.48)
No.Obs	170	170	170	170	170	187	187	187	187	187
AR(1)	0.1371	0.1585	0.1590	0.1030	0.1522	0.1376	0.1505	0.1546	0.0877	0.1658
AR(2)	0.3358	0.6538	0.5106	0.9201	0.4312	0.8564	0.5328	0.4927	0.1916	0.6182
Sargan test	0.7306	0.3496	0.3851	0.3027	0.4034	0.9992	0.9892	0.9888	0.9858	0.9757

Notes: ***, **, * indicates 1%, 5%, and 10% level of significance. The models are estimated with robust standard errors. Robust t-statistics are in parentheses. In regressions (1)–(5), we use the two-step difference GMM of Arellano–Bond (AB) while in regressions (6)–(10), we use the two-step system GMM (SGMM). Regressions (1) and (6) uses real interest rate (RIR) defined as the lending interest rate adjusted for inflation as measured by the GDP deflator. Regressions (2) and (7) uses interest rate spread (SPREAD) defined as lending rate minus deposit rate. Regressions (3) and (8) uses CRISIS defined as a dummy variable that takes one from 2008 onwards and zero otherwise. Regressions (4) and (9) uses CRISIS defined as a dummy variable that takes one for 2009 only and zero otherwise. FINCRISIS is a dummy variable that takes one for 2008 and 2009 only and zero otherwise. In regressions (5) and (10), Equatorial Guinea is excluded from the sample. See notes in Table A4 for other definitions.

References

Adebola, S.S., Wan Yosoff, W.S.B., Dahalan, J., 2011. An ARDL approach to the determinants of non-performing loans in Islamic banking system in Malaysia. Kuwait Chapter Arab. J. Bus. Manag. Rev. 1 (2), 20–30.

Anderson, T., Hsiao, C., 1981. Estimation of dynamic models with error components. J. Am. Stat. Assoc. 76, 598–606.

Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Rev. Econ. Stud. 58, 277–297.

Baltagi, B., 2008. Econometric Analysis of Panel Data, 4th ed. John Wiley & Sons, Ltd., Chichester, UK.

Beck, R., Jakubik, P., Piloiu, A., 2015. Key determinants of non-performing loans: new evidence from a global sample. Open Econ. Rev. 26, 525–550.

Berger, A., DeYoung, R., 1997. Problem loans and cost efficiency in commercial banks. J. Bank. Finance 21, 849–870.

Bernanke, B., Gertler, M., Gilchrist, S., 1999. The financial accelerator in a quantitative business cycle framework. In: Taylor, J.B., Woodford, M. (Eds.), Handbook of Macroeconomics. Elsevier, Amsterdam.

Bernanke, B., Gertler, M., 1989. Agency costs, net worth, and business fluctuations. Am. Econ. Rev. 79, 14–31.

Castro, V., 2013. Macroeconomic determinants of the credit risk in the banking system: the case of the GIPS. Econ. Model. 31, 672–683.

Chimkono, E.E., Muturi, W., Njeru, A., 2016. Effect of non-performing loans and other factors on performance of commercial banks in Malawi. Int. J. Econ. Commer. Manag. IV (2), 549–563.

De Bock, R., Demyanets, A., 2012. Bank Asset Quality in Emerging Markets: Determinants and Spillover, IMF Working Paper 12/71.

Diwan, I., Rodrick, D., 1992. Debt Reduction, Adjustment Lending, and Burden Sharing, NBER Working Paper No. 4007, Cambridge, MA (March).

EIB, 2013. Banking in sub-Saharan Africa: Challenges and Opportunities, European Investment Bank Report.

Ekanayake, E.M.N.N., Azeez, A.A., 2015. Determinants of non-performing loans in licensed commercial banks: evidence from Sri Lank. Asian Econ. Financ. Rev. 5 (6), 868–882.

Espinoza, R., Prasad, A., 2010. Nonperforming Loans in the GCC Banking System and their macroeconomic effect, IMF Working Paper, 10/224.

Etale, L., Ayunku, P.E., Etale, E., 2016. The impact of non-performing loans and bank performance in Nigeria. Int. J. Humanit. Soc. Sci. Invent. 5 (4), 1–5.

Flamini, V., McDonald, C., Schumacher, L., 2009. The Determinants of Commercial Bank Profitability in Sub-Saharan Africa, IMF Working paper, 15.

Fofack, H., 2005. Nonperforming loans in Sub-Saharan Africa: Causal Analysis and Macroeconomic Implication, World Bank Policy Research Working Paper, 3769.

Haniifah, N., 2015. Economic determinants of non-performing loans in Ugandan commercial bank. Taylor's Bus. Rev. J. 5 (2), 137–153.

Havrylchyk, O., 2010. A macroeconomic credit risk model for stress testing the South African banking sector, South African Reserve Bank Working Paper, 10/02.

IMF, 2017. Global Financial Stability Report October: Is Growth at Risk?

Judson, R., Owen, L., 1999. Estimating dynamic panel data models: a guide for macroeconomists. Econ. Lett. 65, 9–15.

Kasekende, L., Brixova, Z., Ndikumana, L., 2010. Africa: Africa's countercyclical policy responses to the crisis. J. Glob. Dev. 1 (1).

Keeton, W.R., Morris, C.S., 1987. Why Do Banks' Loan Losses Differ, Economic Review. Federal Reserve Bank of Kansas City, pp. 3–21.

Kiyotaki, N., Moore, J., 1997. Credit cycles. J. Polit. Econ. 105, 211–248.

Klein, N., 2013. Non-Performing Loans in CESEE: Determinants and Impact on Macroeconomic Performance, IMF Working Paper 13/72.

Louzis, D.P., Vouldis, A.T., Metaxas, V.L., 2012. Macroeconomic and bank-specific determinants of non-performing loans in Greece: a comparative study of mortgage, business and consumer loan portfolio. J. Bank. Finance 36 (4), 1012–1027.

Nickell, S., 1981. Biases in dynamic models with fixed effects. Econometrica 49 (6), 1417–1426.

Nikolaidou, E., Vogiazas, S.D., 2013. Credit risk modelling in the Romanian banking system: evidence from an ARDL model. In: Karasavvoglou, A., Polychronidou, P. (Eds.), Contributions to Economics: Balkan and Eastern European Countries in the Midst of the Global Economic Crisis. Springer.

Nikolaidou, E., Vogiazas, S.D., 2014. Credit risk determinants for the Bulgarian banking system. Int. Adv. Econ. Res. 20 (1), 87–102.

Nikolaidou, E., Vogiazas, S., 2017. Credit risk determinants in Sub-Saharan banking systems: evidence from five countries and lessons learnt from Central East and South East European countries. Rev. Dev. Finance 7, 52–63.

Nkusu, M., 2011. Nonperforming Loans and macrofinancial Vulnerabilities in Advanced Economies, IMF Working Paper 11/161.

Ombaba, M.K.B., 2013. Assessing the factors contributing to NPLs in Kenyan bank. Eur. J. Bus. Manag. 5 (32), 155–163.

Reinhart, C.M., Rogoff, K.S., 2011. From financial crash to debt crisis. Am. Econ. Rev. 101 (5), 1676–1706.

Viswanadham, N., Nahid, B., 2015. Determinants of NPLs in commercial banks: a study of NBC bank Dodoma Tanzania. Int. J. Finance Bank. Stud. 4 (1), 70–94.

Warue, B.N., 2012. The effects of bank specific and macroeconomic factors on nonperforming loans in commercial banks in Kenya: a comparative panel data analysis. Adv. Manag. Appl. Econ. 3 (2), 135–164.

Washington, G.K., 2014. Effects of macroeconomic variables on credit risk in the Kenyan banking system. Int. J. Bus. Commer. 3 (9), 1–26.

Waweru, N.M., Kalani, V.M., 2009. Commercial banking crises in Kenya: causes and remedies. Afr. J. Account. Econ. Finance Bank. Res. 4 (4), 12–33.