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# Early Warning Systems and Systemic Banking Crises in Low Income Countries: A Multinomial Logit Approach

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AFRICAN DEVELOPMENT BANK GROUP

# Early warning systems and systemic banking crises in low income countries: A multinomial logit approach[1]


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## Abstract

This paper estimates an early warning system for predicting systemic banking crises in a sample of low income countries in Sub-Saharan Africa. Since the average duration of crises in this sample of countries is longer than one year, the predictive performance of standard binomial logit models is likely to be hampered by the so-called crisis duration bias. The bias arises from the decision to either treat crisis years after the onset of a crisis as non-crisis years or remove them altogether from the model. To overcome this potential drawback, we propose a multinomial logit approach, which is shown to improve the predictive power compared to the binomial logit model. Our results suggest that crisis events in low income countries are associated with low economic growth, drying up of banking system liquidity and widening of foreign exchange net open positions.
JEL Classification: C52, G21, G28, E58.
Keywords: Banking crises, Systemic risk, Early warning systems, Low income countries, Sub-Saharan Africa, Logit estimation, Financial regulation.

Keywords: Monetary policy, Taylor curve, inflation targeting
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## 1. Introduction

The recent global financial crisis has stimulated new interest among academics and policy makers in models aimed at providing alerts about the risk of the onset of a systemic banking crisis based on systematic theoretical and empirical analysis, the so-called early warning systems (EWSs). While most of the focus has been on advanced economies (Barrell et al, 2010; Babecký et al; 2013), which have been at the epicenter of the recent turmoil, the relevant empirical literature has devoted scant attention to low income countries (LICs). This is surprising as LICs experienced a number of costly banking crises, especially during the 80s and 90s, which took longer to resolve than in other groups of economies.

This paper aims at filling this gap and builds a EWS for predicting systemic banking crises in LICs. Our contribution to the literature is twofold. The first is related to the policy relevance of the sample examined, i.e. LICs in Sub-Saharan Africa (SSA), which has surprisingly been under-studied in the literature on banking crises. The second contribution is methodological and refers to the use of the multinomial logit model, which is shown to improve upon the widely-used binomial model in terms of number of crises correctly called and number of false alarms produced.

From a policy perspective, LICs in SSA represent an interesting sample for the analysis of banking crises. Despite a large number of long-lasting crises experienced during the 1980s and 1990s, banking systems in these countries have on average proved resilient to the recent episodes of global financial stress. This is primarily the result of the structural reforms implemented by many countries over the past decade within a context of sound macroeconomic policies. Most countries have improved the regulatory framework for supervision, bolstering prudential requirements and supervisory rules (IMF, 2012a). However, relevant macroeconomic and banking system vulnerabilities are still in place and others are likely to emerge as financial deepening increases and financial transactions become more sophisticated. In this respect, EWSs can represent a valuable tool for policymakers and regulators in the region.

In spite of the above, LICs in SSA have received no specific attention in the context of building EWSs. Banking crises in SSA LICs have been either the subject of surveys based on qualitative analysis (Honohan, 1993; Brownsbridge and Harvey, 1998; Daumont et al, 2004) or have been studied in cross-country panels, pooled together with advanced economies and emerging markets (Demirgüç-Kunt and Detragiache, 1998; Kaminsky and Reinhart, 1999; and Davis and Karim, 2008). The latter approach builds on the argument of efficiency and relies on the assumptions that (i) the same set of variables are likely to explain the occurrence of crises in different contexts and (ii) that parameters are constant and homogenous in the sample. However, these hypotheses are unlikely to hold. Indeed, a preliminary analysis of optimal country clusters tends to improve the quality of the prediction. Van den Berg et al (2008) show that a EWS built by aggregating countries on a regional basis outperforms that where all countries are pooled. The evidence that the ability of the EWS to predict crises improves when the sample of economies under analysis includes homogenous countries can be taken as an accepted result. In this respect, our paper adds to the many examples of studies analyzing homogeneous economies, which include, among others, Barrell et al (2010) and Alessi and Detken (2011), who focus on OECD economies; Wong et al (2010), who study EMEAP economies; and Babecký et al (2013), who focus on EU and OECD countries.

We develop our EWS for LICs in SSA by adopting the multinomial logit approach. The empirical literature on EWSs for systemic banking crises has generally adopted either the signals approach or the binomial logit framework. The former considers the impact of covariates in isolation and benchmarked against specific threshold values (Kaminsky and Reinhart, 1998; Borio and Drehmann, 2009), whereas the latter relates a binary banking crisis dummy to a vector of explanatory variables to provide estimates of the probability of an incoming crisis (Demirgüç-Kunt and Detragiache, 1998; Beck et al, 2006; Davis and Karim, 2008; Barrell et al 2010). In spite of recent attempts to integrate the two approaches through the use of the binary classification tree technique (Duttagupta and Cashin, 2008), the literature suggests that the empirical strategy based on the estimation of the binomial multivariate logit outperforms the signals approach. Demirgüç-Kunt and Detragiache (2000) and Davis and Karim (2008) show that crisis probabilities estimated through the binomial logit exhibit lower type I (missed crises) and type II (false alarms) errors than the signals approach and therefore provide a more accurate basis for building a EWS.

Although being an interesting step forward in the prediction of banking crises, in cases where the crisis is longer than one year the use of the binomial logit model forces the researcher either to treat crisis years other than the first as non-crisis observations (Eichengreen and Arteta, 2000; Barell et al, 2010) or to exclude them from the sample (Demirgüç-Kunt and Detriagiache, 1998; Beck et al, 2006). However, in the years after the onset of the crisis the variables that are correlated to this event are likely to be affected by the crisis itself. Therefore, the need to treat years after the crisis as tranquil periods or remove them from the sample forces the researcher to ignore information that is potentially valuable, for example about the fact that the crisis is still ongoing or which variables, if any, are associated with the protraction of the crisis rather than with its arrival. If this is the case, the EWS may be deceptive in delivering crisis signals and especially false alarms, thus providing misleading policy implications. We define this effect as the *crisis duration bias*, and aim at controlling its impact on the predictive power of the model by extracting valuable information from the appropriate classification of the periods subsequent to the onset of a crisis. The point we raise is general yet it assumes greater relevance in samples like ours where banking crises tend to last longer than one year.

We borrow from the literature on currency crises and, to account for the information provided by the explanatory variables during the crisis years subsequent to the onset of the crisis, we allow for three outcomes in the dependent variable: (i) the first year crisis regime when the crisis occurs; (ii) the crisis regime for crisis years subsequent to the first year of the crisis; and (iii) the tranquil regime for remaining observations (Bussiere and Fratzscher, 2006). To the best of our knowledge, ours represents the first attempt to adapt the multinomial logit approach in the context of forecasting systemic banking crises.

Our results suggest that a decline in GDP growth, banking system illiquidity and large foreign exchange net open positions are positively correlated with the probability of a systemic banking crisis in SSA LICs. These results confirm the importance for financial stability of the structural features of SSA LICs' banking systems, characterized by low asset diversification and high exposure to liquidity and foreign exchange risk. Our conclusions have relevant policy implications for regulators in the region, underlining the importance of building an effective macroprudential framework to address the vulnerabilities of concentrated and dollarized environments.

The results are robust to alternative definitions of systemic banking crisis and to the sample composition. Most importantly, we find that the multinomial logit with three outcomes outperforms the binomial logit. In particular, the multinomial logit model reduces the number of both false alarms and missed crises compared to the binomial logit model, regardless of how crisis years after the onset of the crisis are treated and of the empirical specification adopted.

The paper is organized as follows. Section 2 presents the dataset and the empirical methodology. Section 3 presents the empirical results of the multinomial model. Section 4 presents robustness checks and provides a comparison between the multinomial approach and the binomial logit model. Section 5 concludes and draws some policy implications.

## 2. Data description and methodology

### 2.1. Data

We select our sample of LICs according to the World Bank classification, which is based on Gross National Income (GNI) per capita. LICs are defined as economies with a 2011 GNI per capita below $1,025. Seventy-five percent of these economies are located in SSA. To take account of countries which changed their status between 1980 and 2008, we also consider in our sample lower middle income countries (LMICs), which are economies with a GNI per capita between $1,026 and $4,035. For example, in 1994 Cameroon and Republic of Congo moved from LMIC status to LIC status and back again to LMIC status in 2005. Côte d'Ivoire lost its LMIC status in 1993 to gain it back in 2008. Finally, Nigeria became LMIC in 2008.

Our final dataset comprises annual observations from 35 LICs in SSA over the period 1980 to 2008, namely: Benin, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Chad, Comoros, Congo, Rep., Côte d'Ivoire, Eritrea, Ethiopia, Gambia, The, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Madagascar, Malawi, Mali, Mauritania, Mozambique, Niger, Nigeria, Rwanda, Sao Tome and Principe, Senegal, Sierra Leone, Sudan, Swaziland, Tanzania, Togo, Uganda and Zambia. We exclude Liberia because of its offshore status and Somalia because of data availability. We also leave out Angola, Congo DRC and Zimbabwe which, because of the hyperinflation experienced for much of the period under consideration, are outliers with respect to two of the regressors we use (inflation and currency depreciation).

We draw evidence about systemic banking crises from Reinhart and Rogoff (2009). Using information from Caprio et al (2005) and a variety of other sources of qualitative and quantitative information, Reinhart and Rogoff (2009) define a crisis as systemic if either of the following occurs: (i) bank runs which lead to the liquidation or the restructuring of one or more financial institutions, or (ii) in the absence of bank runs, the closure, restructuring or large-scale government assistance of one or more institutions which marks the beginning of similar outcomes for other financial institutions. This classification provides us with 160 annual crisis observations, comprising 31 systemic crisis episodes in 26 countries, with average crisis duration of 5.2 years as opposed to 2.1 years for G-10 countries.

The choice of the explanatory variables is based on both the relevant literature (Demirgüç-Kunt and Detragiache, 1998; and Kaminsky and Reinhart, 1999) and on the structural features of the banking system of the sample of economies at hand. Balance sheet variables are typically embedded in prudential regulatory frameworks, and therefore their inclusion in the design of EWSs is likely to offer useful insights to financial regulators as to their relevance for financial stability. There is evidence that balance sheet variables are leading indicators of banking crises along with macroeconomic and financial variables in a number of economies (Männasoo and Mayes, 2009; Barrell et al, 2010; and Wong et al, 2010).

According to the above criteria, and given data availability, we use three groups of explanatory variables to estimate our EWS:

a) Macroeconomic fundamentals: real GDP growth, inflation and nominal exchange rate depreciation. Economic growth is expected to affect the credit quality of the banking system by impacting the ability of borrowers to pay back their debt. This is especially the case for LICs, as the relatively low economic diversification leads to a concentration of banks' exposures such that a shock to the dominant sector of the economy may become of systemic importance (Narain et al, 2003). On the other hand, high inflation is associated with macroeconomic instability and impacts the real return on assets, discouraging savings and incentivizing borrowing, increasing this way the likelihood of experiencing a crisis. This is also the case for nominal depreciation, as a drop in the exchange rate is likely to destabilize the banking sector if the latter is heavily exposed to foreign exchange (FX) risk.

b) Monetary conditions: broad money (M2) cover of international reserves and growth of the credit-to-GDP ratio. The ratio of M2 to official reserves captures the ability of the economy to withstand a reversal in capital flows, especially in the presence of a currency peg. Therefore, the higher the value for this variable, the higher the vulnerability to capital outflows, and hence the probability of incurring a banking crisis. Similarly, excessive credit growth can trigger bank problems through a generalized deterioration in asset quality and/or a reduction in liquidity, especially in the context of volatile funding sources. Accordingly, the probability of a crisis is expected to increase when credit grows too fast. We use growth of the credit-to-GDP ratio instead of growth of real credit due to data availability and practical implications. The credit-to-GDP ratio was adopted as a common reference point under Basel III to guide the build-up of countercyclical capital buffers (BCBS, 2010).

c) Banking system characteristics: FX net open position, liquidity position and leverage. A negative FX net open position is a signal of currency mismatch between the value of banks' assets and liabilities, which exposes banks to potentially substantial losses in the event the domestic currency depreciates. This channel is very relevant for LICs, whose operating environment is characterized by shallow financial markets and a high degree of dollarization, exposing banks to considerable FX risk (IMF, 2012b). The liquidity position of the banking system is proxied by the ratio of private credit to deposits. The higher the ratio, the lower the capacity of the banking system to withstand deposit withdrawals, hence a positive relation with the likelihood of a crisis is expected. As in the case of the FX net open position, the liquidity position of the banking system is very relevant for our sample, which is characterized by a high turnover of deposits and limited alternative sources of funding (IMF, 2012b). Finally, the leverage of the banking system, which we proxy through the ratio of aggregate equity to total assets, indicates the banks' ability to face unexpected losses. A deteriorating capital position exposes banks to solvency risk, and increases the probability of incurring a banking crisis.

The Appendix reports sources and definitions of the variables. We exclude variables such as changes in the terms of trade, real interest rate and government deficit due to data availability. However, these variables are found to be statistically insignificant in sub-samples where data are available. We also exclude some institutional indicators that have previously been associated with banking crises, such as the lack of independence of the central bank and the strength of the regulatory and supervisory framework because of lack of observations or variability in the sample under analysis. We finally exclude GDP per capita, which is comparable across our sample economies. In order to reduce the impact of extreme observations and measurement errors on empirical results, the independent variables have been winsorized using the 2.5 and 97.5 percentiles.

Given that the focus of our study is on building a EWS, we lag all variables by one year, apart from real GDP growth, which has two lags. This is because a shock to the economy may lead to widespread defaults and therefore systemic problems which are recognized with a relatively long lag (Bordo et al, 2011). It is worth noting that the use of a set of lagged explanatory variables also helps deal with potential endogeneity of regressors. Table 1 presents some descriptive statistics of the variables included in the dataset.

### 2.2. Methodology

We build our EWS for predicting systemic banking crises by adopting the multinomial logit model, previously employed by Bussiere and Fratzscher (2006) in the context of currency crises. The estimated model returns a predicted measure of fragility of the banking sector, i.e. the estimated probability of a crisis, as a function of a vector of potential explanatory variables.

More formally, we assume that each economy *i=1,…,n* can be in one of the following *j+1=3* states: tranquil period (*j=0*), first year of crisis (*j=1*), or crisis years other than the first (*j=2*). The probability that an economy is in state *j* is given by

$$(1) \quad Pr\left(Y_t = j|\boldsymbol{X_{i,t}}\right) = \frac{e^{\beta_j' X_{i,t}}}{1+\sum_{l=1}^{J} e^{\beta_l' X_{i,t}}}, \boldsymbol{\beta_0} = \mathbf{0}, J = 2$$

where $\boldsymbol{X_{i,t}}$ is the vector of regressors of dimension *k* and **β** is the vector of parameters to be estimated. The log-likelihood function to be maximized is

$$(2) \quad Ln(L) = \sum_{i=1}^{n} \sum_{j=0}^{J} d_{i,j} lnPr(Y_i = j)$$

where $d_{ij}=1$ if the economy *i* is in state *j*.

We set the tranquil regime as the base outcome in order to provide identification for the multinomial logit model, which gives the following *J=2* log-odds ratio:

$$(3) \quad \frac{Pr(Y_{i,t}=1)}{Pr(Y_{i,t}=0)} = e^{\boldsymbol{\beta}_1' \boldsymbol{X}_{i,t}} \text{ and}$$

$$(4) \quad \frac{Pr(Y_{i,t}=2)}{Pr(Y_{i,t}=0)} = e^{\boldsymbol{\beta}_2' \boldsymbol{X}_{i,t}}.$$

The vector of parameters $\boldsymbol{\beta_1}$ measures the effect of a change in the independent variables $\boldsymbol{X}_{i,t}$ on the probability of entering a systemic banking crisis relative to the probability of being in tranquil times. Accordingly, $\boldsymbol{\beta_2}$ measures the effect of a change in the independent variable $\boldsymbol{X}_{i,t}$ on the probability of remaining in a state of crisis relative to the probability of being in tranquil times.

Eq. (2) is a generalization of the log-likelihood for the binomial logit model, where only two states are allowed, i.e. $Pr(Y_t=2)=0$. The binomial model has the advantage of estimating a lower number of parameters, with a significant gain in the number of degrees of freedom. However, empirical results might be biased if the assumption that crisis years other than first can be treated as non-crisis years or dropped from the model is not valid. In the former case, crisis years are treated as tranquil periods. In the latter, any data in crisis years other than the first are discarded. In either cases, potentially valuable information is not taken into account. In the context of currency crises this phenomenon is known as the *post-crisis bias*: after the onset of the crisis, economic variables do not go back immediately to a “tranquil” steady-state but take time to converge to equilibrium. To account for it, transition periods where the economy recovers from the crisis are explicitly modeled (Bussiere and Fratzscher, 2006).

In the context of systemic banking crisis, the existence of some kind of *post-crisis bias* is even more likely to be present. On the one hand, banking crises are more persistent than currency crises as they tend to last longer (Babecký et al, 2013). On the other hand, due to the credit crunch and the generalized loss of confidence that typically accompany a banking crisis, economic recovery takes longer than after a currency crisis (Frydl, 1999). Put differently, since banking crises are typically long-lasting, in the period after the onset of the crisis the economy is *still* in a state of crisis, and hence relevant economic variables behave differently from both "equilibrium" periods *and* the outbreak of a crisis. This phenomenon is what we call the *crisis duration bias*.

The existence of three scenarios – "tranquil" times, the first year of crisis, and the crisis years after the first – that are likely to be significantly different from each other in our sample of economies is strongly supported by the preliminary evidence we report in Table 2. The Table presents the average values of our independent variables when the crisis occurs (column 2), in the combined tranquil periods and crisis years (column 3), in tranquil times (column 4) and in crisis years other than the first (column 5). Comparison of columns (4) and (5) suggests that, if the economy is still experiencing the crisis, its behavior is different than in tranquil times. More formally, the null hypothesis of equality of means is rejected for all the variables, in line with the hypothesis that these periods should be treated differently when building the EWS – to save space, results are not reported, but are available upon request from the authors. The descriptive evidence reported in Table 2 suggests that mixing information on tranquil times and post-crisis periods (as in column 3) is likely to be misleading and that therefore there exists a potential *crisis duration bias*.

We take the descriptive evidence of Table 2 as a rationale for the use of the multinomial logit model. However, one final remark must be made. Although the multinomial logit model allows us to account for the existence of a *crisis duration bias*, it nonetheless rests on a questionable assumption, i.e. the independence of irrelevant alternatives holds. In the next section, we provide evidence for its validity using the Hausman-McFadden test.

## 3. Empirical results

We begin by estimating our multinomial logit by including all selected regressors and, as in Barrell et al (2010), we adopt the general-to-specific approach to obtain the final specification of the empirical model. At each step we omit the variable that is least significant in both the first year crisis regime and the crisis regime. However, we obtain the same final specification if at each step we drop the variable least significant in the arrival-of-the-crisis regime only.

Table 3, which lists the specific variable deletions and their corresponding *t*-statistics, summarizes the results. The first panel, which refers to the probability of entering a crisis compared to being in a tranquil time, shows that a decline in real output, banking system illiquidity and excessive direct FX risk are all positively correlated with the probability of experiencing a systemic banking crisis. Our results confirm the importance for financial stability of the structural features of SSA LICs' banking systems, characterized by high loan concentration risk and significant exposure to liquidity risk and currency risk.

Our findings show that banking systems in SSA LICs are more likely to collapse when economic growth declines two years prior to the crisis. Undiversified economies contribute to a build-up of banks' exposures to a few sectors and customers so that credit risk is magnified during an economic downturn. Sectoral concentration of loans ranges from 50-70 percent in SSA LICs, with the majority of loans being provided to just one or two economic sectors (Beck et al, 2011). Banking systems whose assets are not well-diversified at the sectoral level are more vulnerable to sector-specific shocks, which exert pressure on bank profitability and solvency with a time lag due to the provisioning rules that tend to delay recognition of losses.

Our results also indicate that banking systems which one year prior to the crisis engage in excessive credit activity relative to the deposit base are more likely to experience a systemic crisis. Banks in SSA LICs tend to rely heavily on volatile customer deposits for funding. In particular, checking accounts, which are typically perceived as the most unstable category of deposits, represent the bulk of total deposits in many countries (IMF, 2012b). On the other hand, savings accounts, which are normally a stable source of funding for banks in advanced economies, exhibit a relatively high turnover in SSA LICs due to the low income of most depositors. Liquidity risk in SSA LICs' banking system is exacerbated by the high degree of dollarization which characterizes these economies.

In addition to liquidity risk, financial dollarization exposes banks to substantial direct FX risk. Our findings show that banking systems which one year prior to the crisis are characterized by excessive direct FX risk through currency mismatches between the value of their assets and liabilities are more likely to experience a distress. In SSA LICs, rapid fluctuations of the exchange rate, which often reflect thin FX markets, expose commercial banks to potentially sizeable losses, threatening the soundness and the stability of the banking system. Exposure to direct FX risk is intensified by the absence of derivatives markets, which limit hedging opportunities.

The second panel of Table 3, which refers to the probability of remaining in a crisis compared to being in a tranquil time, confirms the relevance of what we call the *crisis duration bias*, i.e. that econometric results of binomial logit models are partly explained by variable behavior during crisis years other than the first. Here the coefficients for our explanatory variables are different and their marginal effects greater. These findings are intuitive and in line with expectations. Both the liquidity position and the currency mismatch of the banking system deteriorate once a crisis occurs due to a generalized loss of confidence and pressures on the exchange rate. This is confirmed by the behavioral pattern of the independent variables reported in column (5) of Table 2, as discussed above. Moreover, we find that negative credit growth and high banking system capitalization are associated with the crisis regime relative to tranquil times. Again, these results are in line with expectations: on the one hand, a negative and significant coefficient for credit growth indicates that a credit crunch increases the likelihood of remaining in a state of crisis; on the other hand, a positive and significant coefficient for leverage is a sign that the recapitalization of banks lowers the probability of remaining in a crisis.

Table 3 provides also information about the performance of our multinomial logit model in terms of predictive power of our EWS. It is customary to assess the goodness-of-fit of a EWS by looking at the percentage of observations and crises correctly called and the percentage of false alarms. In line with other studies (Demirgüç-Kunt and Detragiache, 1998; Barrell et al, 2010), we use the in-sample probability as a cut-off threshold to identify which crises are called, which for our sample is 3.5 percent. Based on this threshold, our model correctly calls 64.5 percent of crises, with an overall share of observations correctly called of 72.3 percent and false alarms, or the probability of sending a distress signal conditional on no distress taking place (type II errors), of 27.4 percent. In the absence of information about the policymaker’s loss function, Borio and Drehmann (2009) suggest that a two-thirds level of accuracy represents an acceptable trade-off between the cost of missing a crisis and that of issuing a false alarm. Based on these results, we contend that a EWS built on GDP growth, liquidity ratios and currency mismatches can help policymakers and regulators in SSA LICs to anticipate banking crises.

## 4. Robustness checks

We run a number of robustness exercises for our multinomial model. We first examine the possibility that our results are driven by the specific classification of systemic banking crisis adopted. A variety of classifications of banking crises has been employed in the empirical literature, which identify crisis beginning dates, ending dates and whether the crisis was systemic or not (Von Hagen and Ho, 2007). Different classification schemes employ different criteria, and therefore crisis dating *and* crisis duration may differ. We therefore test our results based on two alternative and widely used classifications of systemic banking crisis: the Laeven and Valencia (2012) classification and the Demirgüç-Kunt and Detriagiache (2002, 2005) classification.

Laeven and Valencia (2012) classify systemic crisis based on either of the following measures: (i) deposit runs proxied by a monthly percentage decline in deposits in excess of 5 percent; or (ii) the introduction if deposit freezes or blanket guarantees; or (iii) liquidity support defined as monetary authorities' claims on banks of at least 5 percent of total deposits. Demirgüç-Kunt and Detriagiache (2002, 2005) identify an event of systemic distress when at least one of the following occurs: (i) large scale nationalizations; (ii) emergency measures to support the banking system such as bank holidays, guarantees etc.; (iii) the cost of rescue operations of at least 2 percent of GDP; or (iv) nonperforming loans as a fraction of total loans are at least 10 percent. In Table 4, panels (1) and (2) show that the estimated parameters remain broadly stable when using different dependent variables compared to our baseline specification, confirming that low economic growth, banking system illiquidity and large FX net open positions are solid predictors of banking crises in our sample.

Next we test whether our results hold if we drop from our sample countries that never experienced a systemic banking crisis. These are: Comoros, Gambia, Lesotho, Malawi, Rwanda and Sudan. Our results remain robust to the exclusion (Table 4, panel 3) and do not yield significant changes in the parameter estimates.

We then compare our EWS based on the multinomial logit with the EWS based upon the binomial logit model to check whether there is any evidence in favor of what we call the *crisis duration bias*. First, we estimate a binomial logit model where we assume one year crisis duration (as in Eichengreen and Arteta, 2000, and Barrell et al, 2010). In other words, our binary banking crisis dummy $d_{ij}$ takes on value one when the country enters a systemic banking crisis and zero otherwise, including when the country is still experiencing a crisis. To align the empirical strategy with the one used for the multinomial logit model, we obtain the final specification by using a general-to-specific approach. Results are presented in Table 5. The final specification is different from that obtained with the multinomial logit model, with only two variables, namely liquidity and output growth, found to be statistically significant. As expected, the predictive power of this model is lower than that of the multinomial logit model. The number of crises correctly called is 58.1 percent compared with 64.5 percent of the multinomial logit model, while type II errors are 31.6 percent as opposed to 27.4 percent for the multinomial logit model.

A related robustness test is to compare the multinomial logit model with the binomial logit in which all observations in years classified as crisis after the initial year of the crisis are dropped (as in Demirgüç-Kunt and Detriagiache, 1998, and and Beck et al, 2006). Accordingly, we estimate a second binomial logit model in which the banking crisis dummy still takes the value of one when the country enters a crisis and zero otherwise but the variable excludes all crisis years after the first (see results in Table 6). The predictive power of the binomial logit is again lower than that of the multinomial logit, although it improves relative to the previous binomial model. The number of crisis correctly called is 61.3 percent vs. 64.5 percent of the multinomial, while type II errors are 29.5 percent vs. 27.4 percent of the multinomial logit model.

It is important to notice that, as expected, the estimates of the latter model are similar to the multinomial logit. This result is in line with the Independence from Irrelevant Alternatives (IIA) hypothesis that is implicitly assumed at the outset of the estimating model. For completeness, we formally check whether the IIA assumption holds by running the Hausman-McFadden test for the equality of the parameters in the two alternative models. The associated test-statistic, which under the null hypothesis that the IIA holds is distributed as a $\chi^2$, is negative. Following Hausman and MacFadden (1984), we take this as evidence in favor of the null hypothesis of equality of parameters, suggesting that the IIA holds and, ultimately, that the multinomial logit model is unbiased.

Overall, there is evidence in favor of the multinomial logit as a superior empirical framework relative to the binomial model in predicting banking crises in countries where historically the duration of crises has been long lasting. The rationale is that the multinomial model allows accounting for the information content provided by the explanatory variables during the crisis years subsequent to the beginning of a crisis, which represents a promising way to solve what we call the *crisis duration bias*.

Admittedly, a limitation to this claim is the lack of out-of-sample forecasting. However, in our case an out-of-sample forecasting exercise would result in a severe loss of observations and degrees of freedom, since the latest episode of a systemic banking crisis in our sample dates back to 1995. On the other hand, one should not be excessively concerned with out-of-sample testing to assess the goodness-of-fit of EWSs. As Inoue and Kilian (2006) show, in-sample and out-of-sample performance are strongly related and therefore to assess the performance of a EWS it is sufficient to focus on in-sample accuracy.

## 5. Conclusions

This paper develops a EWS for predicting systemic banking crises in LICs based on the multinomial logit model. We build our EWS using a panel data set of 35 SSA LICs, which despite having been hit by a number of severe and long-lasting banking crisis episodes have received no attention in the relevant empirical literature. In particular, this paper adopts the multinomial logit approach to address the concern that the econometric results of traditional binomial logit models may be affected by variable behavior during crisis years other than the first, which we define as the *crisis duration bias*.

Our EWS suggests that a decline in economic growth, banking system illiquidity and widening currency mismatches in banks' balance sheets are the main predictors of systemic banking crises in SSA LICs. These results confirm the importance of banking sector characteristics for financial stability. Overall, the predictive power of our EWS as measured by in-sample performance is reasonably satisfactory. Our EWS predicts well most of the systemic banking crises experienced by SSA LICs during 1980-2008. Most importantly, our results show that moving from a binomial logit model to a multinomial logit model improves the predictive power of the EWS. We believe that an interesting and relevant related issue would be the systematic analysis of the relative performance of multinomial vs. binomial logit models when the sample size and the average duration of crises change: we leave this issue to future research.

Our results have important policy implications at a time when financial regulators and central banks in SSA LICs are reassessing their financial regulatory agenda in the context of recent reforms spurred by the global financial crisis. In particular, our findings underscore the importance of implementing an effective macroprudential framework for monitoring systemic risk arising from credit concentration risk as well as from maturity and currency mismatches. Many LICs in SSA already use a number of tools which are now considered of macroprudential nature such as reserve requirements, caps on FX positions and limits on loan concentration. With a history of recurrent banking crises arising from specificities of their economies and financial markets, several SSA LICs have adopted financial regulations beyond traditional capital adequacy rules. However, most countries do not have a macroprudential framework in place and often regulators have no explicit objective to prevent the build-up of systemic risk. Therefore, countries might benefit from an explicit legal and institutional framework for financial stability. At the same time, it is important that financial regulators in the region, with the assistance of international financial institutions, continue efforts to strengthen supervisory capacity. Ultimately, EWSs are useful tools for policymaking but should never substitute the judgment of financial regulators.

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## Table 1: Summary statistics

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| GDP growth | 944 | 3.4 | 4.8 | -8.0 | 14.6 |
| Inflation | 978 | 14.0 | 18.3 | -5.1 | 82.0 |
| Depreciation | 1,029 | 12.8 | 26.5 | -16.6 | 103.0 |
| M2 / reserves | 959 | 10.9 | 21.8 | 0.9 | 104.5 |
| Credit-to-GDP growth | 936 | 1.9 | 17.6 | -37.2 | 45.6 |
| Leverage | 947 | 18.9 | 11.4 | 4.2 | 54.7 |
| Liquidity | 965 | 90.9 | 54.0 | 19.1 | 236.4 |
| Net open position | 945 | 1.7 | 17.0 | -46.6 | 35.2 |

## Table 2: Averages of independent variables

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | **All times** | **First year of crisis** | **Tranquil times AND crisis years after the first** | **Tranquil times** | **Crisis years after the first** |
| GDP growth (-2) | 3.4 | 1.1 | 3.5 | 3.8 | 1.7 |
| Inflation (-1) | 14.1 | 16.0 | 14.0 | 13.7 | 15.8 |
| Depreciation (-1) | 13.3 | 15.8 | 13.2 | 12.6 | 17.0 |
| M2 / reserves (-1) | 10.9 | 19.8 | 10.6 | 10.1 | 13.0 |
| Credit-to-GDP growth (-1) | 1.6 | 4.9 | 1.5 | 2.1 | -1.7 |
| Leverage (-1) | 19.1 | 15.3 | 19.2 | 19.4 | 18.4 |
| Liquidity (-1) | 90.0 | 114.6 | 89.1 | 84.8 | 111.7 |
| Net open position (-1) | 1.8 | -4.1 | 2.0 | 3.4 | -5.7 |

### Table 3: Results of the multinomial logit model

| | | | | |
|---|---|---|---|---|
| *Initial year of crisis* | | | | |
| Liquidity (-1) | 0.008*** | 0.008*** | 0.010*** | 0.010*** |
| | (2.82) | (2.64) | (3.27) | (3.41) |
| Net open position (-1) | -0.018* | -0.017 | -0.010 | -0.010 |
| | (-1.79) | (-1.58) | (-0.82) | (-0.78) |
| GDP growth (-2) | -0.103*** | -0.102*** | -0.098*** | -0.097*** |
| | (-3.20) | (-3.15) | (-3.02) | (-3.14) |
| Leverage (-1) | -0.019 | -0.018 | -0.018 | -0.018 |
| | (-0.85) | (-0.81) | (-0.84) | (-0.84) |
| Credit-to-GDP growth (-1) | 0.015 | 0.016 | 0.017 | 0.017 |
| | (1.52) | (1.55) | (1.71) | (1.73) |
| M2 / reserves (-1) | | 0.003 | 0.004 | 0.004 |
| | | (0.42) | (0.54) | (0.54) |
| Inflation (-1) | | | 0.012 | 0.010 |
| | | | (1.19) | (0.50) |
| Depreciation (-1) | | | | 0.002 |
| | | | | (0.16) |
| *Crisis years following initial year of crisis* | | | | |
| Liquidity (-1) | 0.009*** | 0.010*** | 0.010*** | 0.010*** |
| | (5.08) | (5.25) | (5.02) | (5.00) |
| Net open position (-1) | -0.026*** | -0.028*** | -0.027*** | -0.027*** |
| | (-4.87) | (-4.92) | (-4.32) | (-4.27) |
| GDP growth (-2) | -0.065*** | -0.066*** | -0.066*** | -0.066*** |
| | (-3.02) | (-3.10) | (-3.10) | (-3.13) |
| Leverage (-1) | 0.014* | 0.013 | 0.013 | 0.013 |
| | (1.65) | (1.53) | (1.52) | (1.52) |
| Credit-to-GDP growth (-1) | -0.010* | -0.010* | -0.010 | -0.010 |
| | (-1.69) | (-1.76) | (-1.61) | (-1.62) |
| M2 / reserves (-1) | | -0.005 | -0.005 | -0.005 |
| | | (-0.98) | (-0.98) | (-0.99) |
| Inflation (-1) | | | 0.001 | 0.002 |
| | | | (0.20) | (0.35) |
| Depreciation (-1) | | | | -0.001 |
| | | | | (-0.30) |
| No. of crisis | 31 | | | |
| No. of observations | 889 | | | |
| % Correct | 72.3 | | | |
| % Crisis correct | 64.5 | | | |
| % Type I error | 35.5 | | | |
| % Type II error | 27.4 | | | |
| Wald chi2 | 91.5*** | | | |
| % Pseudo R2 | 9.0 | | | |

Notes:
All the explanatory variables have been winsorized at the 5% level to reduce the impact of outliers. We present the coefficients of the logit regressions; t statistics are given in parentheses. ***, ** and * indicate that the coefficient is significant at the 1%, 5% and 10% level, respectively. Cut-off threshold of 3.5 percent (in-sample probability).

## Table 4: Robustness tests of the multinomial logit

| | (1) | (2) | (3) |
|---|---|---|---|
| *Initial year of crisis* | | | |
| Liquidity (-1) | 0.008*** | 0.008** | 0.008** |
| | (2.63) | (2.44) | (3.24) |
| Net open position (-1) | -0.018* | -0.022** | -0.019* |
| | (-1.67) | (-2.35) | (-1.79) |
| GDP growth (-2) | -0.090*** | -0.079** | -0.108*** |
| | (-2.81) | (-2.13) | (-3.24) |
| Leverage (-1) | -0.030 | -0.017 | -0.013 |
| | (-1.35) | (-0.59) | (-0.63) |
| Credit-to-GDP growth (-1) | 0.018** | 0.016 | 0.017 |
| | (2.04) | (1.64) | (1.62) |
| *Crisis years following initial year of crisis* | | | |
| Liquidity (-1) | 0.005** | 0.008*** | 0.009*** |
| | (2.19) | (4.36) | (4.42) |
| Net open position (-1) | -0.023*** | -0.022*** | -0.026*** |
| | (-3.14) | (-3.82) | (-4.40) |
| GDP growth (-2) | -0.067** | -0.068*** | -0.064*** |
| | (-2.06) | (-3.07) | (-2.83) |
| Leverage (-1) | -0.023* | 0.004 | 0.018** |
| | (-1.83) | (0.41) | (2.21) |
| Credit-to-GDP growth (-1) | -0.018** | -0.008 | -0.010 |
| | (-2.27) | (-1.12) | (-1.60) |

Notes:
The table presents robustness tests based on the multinomial logit model. We present the coefficients of the logit regressions; t statistics are given in parentheses; ***, ** and * indicate that the coefficient is significant at the 1%, 5% and 10% level, respectively. In panel (1) the dependent variable is based on Laeven and Valencia (2012). In panel (2) the dependent variable is based on Demirgüç-Kunt and Detriagiache (2002, 2005). Panel (3) excludes countries which never experienced a systemic banking crisis: Comoros, Gambia, Lesotho, Malawi, Rwanda and Sudan. Panel (4) reports the coefficients of our independent variables when controlling for country fixed effects.

## Table 5: Results of the binomial logit – Panel assuming one year crisis duration (1)

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Liquidity (-1) | 0.007** | 0.007** | 0.009*** | 0.008*** | 0.008*** | 0.007*** | 0.007*** |
| | (2.45) | (2.49) | (3.24) | (2.90) | (2.65) | (2.57) | (2.70) |
| GDP growth (-2) | -0.088*** | -0.098*** | -0.090*** | -0.087*** | -0.084*** | -0.083*** | -0.082*** |
| | (-2.68) | (-2.97) | (-2.77) | (-2.71) | (-2.61) | (-2.59) | (-2.70) |
| Credit-to-GDP growth (-1) | | 0.016 | 0.018* | 0.019* | 0.020* | 0.019* | 0.019* |
| | | (1.59) | (1.85) | (1.90) | (1.95) | (1.93) | (1.94) |
| Inflation (-1) | | | 0.015 | 0.015 | 0.014 | 0.012 | 0.010 |
| | | | (1.69) | (1.60) | (1.57) | (1.19) | (0.50) |
| Leverage (-1) | | | | -0.024 | -0.022 | -0.021 | -0.021 |
| | | | | (-1.09) | (-0.99) | (-0.94) | (-0.95) |
| M2 / reserves (-1) | | | | | 0.006 | 0.005 | 0.005 |
| | | | | | (0.83) | (0.72) | (0.72) |
| Net open position (-1) | | | | | | -0.005 | -0.004 |
| | | | | | | (-0.39) | (-0.36) |
| Depreciation (-1) | | | | | | | 0.002 |
| | | | | | | | (0.16) |
| No. of crisis | 31 | | | | | | |
| No. of observations | 911 | | | | | | |
| % Correct | 68.1 | | | | | | |
| % Crisis correct | 58.1 | | | | | | |
| % Type I error | 41.9 | | | | | | |
| % Type II error | 31.6 | | | | | | |
| Wald chi2 | 19.5*** | | | | | | |
| % Pseudo R2 | 4.6 | | | | | | |

Notes:
All the explanatory variables have been winsorized at the 1% level to reduce the impact of outliers. We present the coefficients of the logit regressions; t statistics are given in parentheses. ***, ** and * indicate that the coefficient is significant at the 1%, 5% and 10% level, respectively. Cut-off threshold of 3.4 percent (in-sample probability).

**Table 6: Results of the binomial logit – Panel excluding years after first year crisis**

| | | | | | | |
|---|---|---|---|---|---|---|
| Liquidity (-1) | 0.008*** | 0.008*** | 0.009*** | 0.009*** | 0.009*** | 0.009*** |
| | (2.80) | (2.89) | (3.56) | (3.21) | (3.01) | (3.16) |
| Net open position (-1) | -0.017* | -0.018* | -0.013 | -0.009 | -0.008 | -0.007 |
| | (-1.78) | (-1.91) | (-1.20) | (-0.83) | (-0.70) | (-0.66) |
| GDP growth (-2) | -0.095*** | -0.104*** | -0.100*** | -0.098*** | -0.096*** | -0.095*** |
| | (-2.76) | (-3.02) | (-2.90) | (-2.87) | (-2.81) | (-2.92) |
| Credit-to-GDP growth (-1) | | 0.014 | 0.016 | 0.017 | 0.017 | 0.017 |
| | | (1.42) | (1.56) | (1.67) | (1.70) | (1.71) |
| Inflation (-1) | | | 0.011 | 0.013 | 0.013 | 0.011 |
| | | | (1.05) | (1.17) | (1.20) | (0.56) |
| Leverage (-1) | | | | -0.016 | -0.016 | -0.015 |
| | | | | (-0.79) | (-0.75) | (-0.75) |
| M2 / reserves (-1) | | | | | 0.003 | 0.003 |
| | | | | | (0.38) | (0.39) |
| Depreciation (-1) | | | | | | 0.002 |
| | | | | | | (0.16) |
| No. of crisis | 31 | | | | | |
| No. of observations | 767 | | | | | |
| % Correct | 70.3 | | | | | |
| % Crisis correct | 61.3 | | | | | |
| % Type I error | 38.7 | | | | | |
| % Type II error | 29.4 | | | | | |
| Wald chi2 | 27.5*** | | | | | |
| % Pseudo R2 | 7.5 | | | | | |

Notes:
All the explanatory variables have been winsorized at the 1% level to reduce the impact of outliers. We present the coefficients of the logit regressions; t statistics are given in parentheses. ***, ** and * indicate that the coefficient is significant at the 1%, 5% and 10% level, respectively. Cut-off threshold of 4.0 percent (in-sample probability).

**Appendix: Description and sources of data**

| Variable | Data definition | Source |
|---|---|---|
| Banking crisis | A dummy variable which in the binomial logit takes on value of 1 if banking distress occurs and 0 otherwise.<br><br>In the multinomial logit model, the variable takes on the value of 1 on the first year of the crisis, the value of 2 on crisis years other than the first, and 0 for all other times. | Reinhart and Rogoff (2009)<br><br>Laeven and Valencia (2012)<br><br>Demirgüç-Kunt and Detragiache (2002, 2005) |
| GDP growth | Annual percentage change of real GDP. | Africa Development Indicators (World Bank) |
| Inflation | Annual percentage change of the GDP deflator. | Africa Development Indicators (World Bank) |
| Depreciation | Rate of change of the nominal exchange rate vs. the US dollar. An increase indicates a depreciation of the domestic currency. | Africa Development Indicators (World Bank) |
| Terms of trade change | Rate of change in the terms of trade of goods and services. | Africa Development Indicators (World Bank) |
| M2 / Reserves | Ratio of M2 to foreign exchange reserves of the Central Bank. | Africa Development Indicators (World Bank) |
| Real interest rate | Lending interest rate adjusted for inflation as measured by the GDP deflator. | Africa Development Indicators (World Bank) |
| Credit-to-GDP growth | Rate of growth of the ratio of real domestic private credit to GDP. | Global Financial Development Database (World Bank) |
| Net open FX position | Ratio of net foreign assets to GDP. | IMF IFS: line 31N divided by GDP |

| | | |
|---|---|---|
| Leverage [5] | Ratio of baking system capital to assets. | IMF IFS: line 27a divided by lines 22a-22d |
| Liquidity | Ratio of banking system private credit to deposits. | IMF IFS: 22d divided by lines 24 + 25 |

[5] We use aggregate data to determine capital and liquidity ratios. The resulting ratios are essentially the average ratios of the system. However, simple aggregation of balance sheets data can disguise important structural information. If ratios are symmetrically distributed, the average would also convey information about the median and the mode. If ratios are not symmetrically distributed, focusing on the mean only can be affected by the value of outliers. For example, one very strongly capitalized bank could be more than offsetting many other undercapitalized banks. In our sample, however, this problem is minimized by the high concentration of the banking systems, where the three largest banks represent typically more than 75 percent of the market (Beck et al, 2011).

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