Predicting the Lack of GDP Growth: A Logit Model for 40 Advanced and Developing Countries

Hamidou Diallo, Marianne Guille

***Abstract*—**This paper identifies leading triggers of deficient episodes in terms of GDP growth based on a sample of countries at different stages of development over 1994-2017. Using logit models, we build early warning systems (EWS) and our results show important differences between developing countries (DCs) and advanced economies (AEs). For AEs, the main predictors of the probability of entering in a GDP growth deficient episode are the deterioration of external imbalances and the vulnerability of fiscal position while DCs face different challenges that need to be considered. The key indicators for them are first, the low ability to pay its debts and second, their belonging or not to a common currency area. We also build homogeneous pools of countries inside AEs and DCs. For AEs, the evolution of the proportion of countries in the riskiest pool is marked first, by three distinct peaks just after the high-tech bubble burst, the global financial crisis and the European sovereign debt crisis, and second by a very low minimum level in 2006 and 2007. In contrast, the situation of DCs is characterized first by a relative stability of this proportion and then by an upward trend from 2006, that can be explained by more unfavorable socio-political environment leading to shortcomings in the fiscal consolidation.

***Keywords*—**GDP growth, early warning system, advanced economies, developing countries.

I. Introduction and Literature Review

AMONG the objectives of fiscal policymakers are ensuring the proper allocation of public spending to enhance growth and achieving economic stability with a full employment. Insufficient GDP growth episodes can undermine those objectives and contribute to asymmetries. These consequences can lead to major fiscal crises [1]. Hence, it is important to understand what could cause insufficient GDP growth and how to avoid it.

The aim of EWS is to identify economic weaknesses and vulnerabilities and ultimately anticipate such events. Thus, EWS constitute a crucial tool for policymakers to prevent or at least attenuate the impact of a turmoil. Reference [2] proposed the first EWS relying on a signaling approach. In the literature, researches focusing on EWS have been numerous in recent years. Thus, previously studies were mainly based on sovereign external debt defaults alone, while recent papers [1] focused on access to public funding and implicit domestic default (i.e., high inflation) to describe fiscal crises. More recently, due to the global financial crisis, research at the IMF [3], [4] and at the European Commission [5] used EWS to assess the leading indicators of a fiscal distress or a currency crisis. As pointed out by [6], the literature on EWS is generally restricted due to small sample sizes for advanced and emerging countries, and in some situation is limited to forecast crisis within a specific time. They show, by using the logistic models' approach, that both non-fiscal (external and internal imbalances) and fiscal variables help predict crises among advanced and emerging economies. In addition, [6] shows a dependence of financial crises' indicators on the level of development. More specifically, shifts in external aid and subsidies resulting from food prices' shocks are key drivers of financial distress in Low Income Countries. In this perspective, [6] relies only on fiscal variables while more recent work has moved away from such a limited focus. Namely, [5] uses a large set of both fiscal and macro-financial leading indicators. Their approach is European-centered, heavily influenced by the recent crises (post-2007) and demanding on data requirements. Furthermore, [6] supports more recent results that stress non-fiscal variables as crucial when assessing vulnerabilities to fiscal crises.

The purpose of this paper is to better understand the structural inadequacy causing a country to have insufficient growth compared to the area to which it belongs. Our main assumption is that there are fragilities that are systematically relevant across time and groups of countries. The goal here is to identify triggers which would be useful to signal a higher risk of future deficiencies in terms of GDP growth.

We also pay closer attention in order to distinguish drivers of AEs from those of DCs —which have been overlooked by the literature. The sample of AEs consists of the 19 Member States constituting the Euro area while that of DCs consists of the 14 countries which were members of the African Financial Community (CFA) franc zone and 7 members of West African Monetary Zone (WAMZ)[1]. The euro and CFA franc zones were linked due to the anchoring of CFA to the franc and then to the euro.

It is important to note that our analysis is based on a large and diverse sample of countries over a longer period of time (1994 - 2017, 23 years of observations), which allows to focus on a set of relevant variables for a greater number of episodes with insufficient GDP growth than similar studies. The main advantage of such a large sample is that it allows to assess which drivers are better.

We use the logit model to build EWS for deficiencies in

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[1]DCs in our sample consists of 14 countries of CFA franc currency (Benin, Burkina Faso, Cote d'Ivoire, Guinea-Bissau, Mali, Niger, Senegal and Togo forming the West African Economic and Monetary Union - WAEMU - and Cameroon, Central African Republic, Chad, Republic of Congo, Equatorial Guinea and Gabon, forming the Central African Economic and Monetary Community - CAEMC) and 6 members of WAMZ: Gambia, Ghana, Guinea, Liberia, Nigeria and Sierra Leona adding Cabo Verde.

terms of GDP growth. Using this method provides useful insights and allows us to compare predictive power and test the robustness of indicators across cut-offs. To ensure our results remain strong across samples, we used accuracy measures (type I and type II errors). In addition, the preferred models are those that have stronger area under the ROC Curve (AUC)[2]. We also build homogeneous pools of countries inside the AEs and DCs. This approach allows to identify the main indicators of vulnerabilities that can help signal a high probability of entering in an episode of deficient GDP growth. Our results show important differences in the early warning indicators between DCs and AEs.

As a reminder, the literature concerning the AEs reports mixed evidence on whether the size of public debt is a reliable leading indicator. For instance, [7] shows countries able to significantly reduce the debt-to-export ratio over a five-year horizon experience shorter default spell. While [8] highlights that a country could reintegrate the capital market at a debt level higher than that which pushes it out, [9] suggests that the level of European countries' public debt would matter insofar it captures structural and institutional characteristics, combining them with macro-competitiveness imbalances. By contrast, the DCs have been overlooked in the literature. As regards the area studied, if there is no consensus on the optimality of the CFA franc zone, it is generally accepted that it has had great success in terms of inflation control, which is still relatively low, and relatively high growth. However, the zone suffered from the deterioration of the terms of trade associated with a heavy external debt and a financial crisis caused by mismanagement of financial institutions [10].

For the AEs, the relevant indicators include the growth of exports of goods and services. The probability of entering in an episode of deficient GDP growth increases with growing macroeconomic imbalances due to large deteriorating external imbalances. The results also indicate the part played by public expenditures as a percentage of GDP and by the unemployment rate. However, we find no evidence that the amount of debt stock or financial sector or the money supply or the demography influences the probability to enter an episode of deficient GDP growth in the AEs.

AEs and DCs face different challenges that need to be considered to effectively monitor the signals of future GDP lack of growth. First, the state of public finance does appear to be a key element. For DCs, our findings are consistent with those of [10] since the probability of having an episode of GDP growth deficiency is higher in countries experimenting a heavy external debt. This raises the fundamental question of governance and management in these countries. Second, another strong predictor of the probability of entering in a deficient GDP growth episode in the DCs is their belonging or not to a common currency area. Our results reveal that the probability of going through a deficient GDP growth episode is lower in countries benefiting from a single monetary policy (CFA franc currency). In other words, it is more common to observe a deficient GDP growth in countries outside a currency area (WAMZ).

Our results distinguish, as an early warning level, a pool of countries with an average deficient probability of 2.7% in AEs while the highest deficient probability is 7.6% and a pool with an average deficient probability of 1.9% in DCs while the highest deficient probability is 7.6%. Furthermore, in AEs, the proportion of countries belonging to the riskiest pool increased year after year to reach a first peak just after the 2000-2002 high-tech bubble burst. The four years that came after seemed rather positive for economic growth so this proportion decreased to a very low minimum level in 2006 and 2007 before to increase suddenly and reach two other and higher peaks just after the global financial crisis and the European sovereign debt crisis. Finally, concerning DCs, the absence of significant abnormal rupture in the probability of having a deficient economic growth could reinforce the hypothesis that our pool assignment process appears to be relatively insensitive to macroeconomic conditions. However, we observe an upward trend in the probability of having a deficient GDP growth since 2006 that can be explained by more unfavorable economic conditions and downside risks related to shortcomings in the fiscal consolidation and the deterioration of financing conditions outside.

The paper is organized as follows. Section II proposes a definition of insufficient GDP growth episodes by tackling the determination of the optimal cut-off and examining the behavior of key economic variables around the issue. Section III describes the methodology used to build the EWS models and reports the main results obtained. Section IV presents the conclusions.

II. Definition of Sufficient GDP Growth Episodes

The aim of an EWS is to assist the detection of GDP growth changes and help identify countries with episodes at risk of further deterioration. Using an EWS would allow to take appropriate policy measures to prevent or reduce the impact of insufficient GDP growth.

We use the term insufficient GDP growth to describe a period of lack of growth, which would force a State to take exceptional measures. A country may experience GDP growth distress at time t when the value of the GDP growth is less efficient than a reference value. One of the major implications of this counter performance is the imbalances between inflows and outflows. Reference [6] highlights that if a country is unable to consistently adjust its budget, these shortcomings may contribute to a fiscal crisis. As [11] has noted, the fiscal crisis is a debt crisis, when the government is unable to proceed the interest and principal as scheduled. As such, the literature has paid particular attention to crises triggered by external default episodes, [12] or [13]. Nevertheless, fiscal crises may also include, as key drivers, domestic arrears and high inflation deteriorating the debt's value [14]-[16], [3]. In any case, to mitigate the effects of a severe financial conditions, countries

[2] The ROC (Receiving Operating Characteristics) first developed by electrical engineers and radar engineers during second world war for detecting enemy objects in battle fields, and then used in medicine, machine learning and credit scoring literature. The ROC is a tool to assess the predictive abilities

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may request the assistance of the International Monetary Fund (IMF) and thus avoid a debt's default [17].

In this section we thus propose to quantify how well an EWS discriminates the periods of lack of growth from others, by identifying the optimal cut-off. We also study the behavior of economic variables which may explain the lack of GDP growth.

A. Optimal Cut-off

The choice of criteria in determining optimal cut-off value is important in quantitative diagnostic testing. In the following, we summarize background methodologies of the cut-point before introducing the proposed evaluation criteria.

1) Cut-off Choice

EWS delivers probabilities indicating the chance for a specific crisis to occur in a certain period. The probabilities are thus a dichotomic variable. Formally, we denote:

- $Y_{i,t}$ the observed GDP growth for a country *i* at time *t*
- $I_{i,t}$ the indicator which detects the insufficient GDP growth at time *t* for a country *i*.

The indicator $I_{i,t}$ is then defined by:

$$I_{i,t} = \begin{cases} 1, Y_{i,t} < \tau_{s,t} \\ 0, \ Y_{i,t} \geq \tau_{s,t} \end{cases} \tag{1}$$

where is a cut-off (threshold) for a set s of countries at time *t*.

This is a strong hypothesis used for less granular data (annual series). It has the advantage of smoothing out underperformances within the year. In this perspective, the first step of any EWS evaluation consists of determining an optimal cut-off $\tau_{s,t}$ that discriminates between deficient and sufficient episodes. Towards a unified statistical framework for assessing financial crises forecasting methods, [18] emphasizes the strong implications of the cut-off choice for both forecasts' evaluation and economic analysis. For explanatory variable the cut-off determines type I and type II errors, i.e., the errors respectively associated to a false alarm or to a misidentified crisis[3]. The choice of the cut-off has also implications in terms of analysis of vulnerability.

A high $\tau_{s,t}$ would help assess the amplitude of deficient GDP growth and put a downward pressure on the possibility of missing a crisis (type II error), but on the other hand, would lead to weaken the EWS's validity by raising the likelihood of false alarms (type I error).

Given the importance of cut-offs, it is surprising that the methods used to determine them are often arbitrary, since it means to arbitrarily determine type I and type II nominal risks. In other cases, cut-offs are chosen in relation with the "Noise to Signal Ratio" (NSR) criterion[4] proposed by [2]. We then decide to select three different cut-offs related to the mean and standard deviation of the growth performance observed for each pool of countries. They are presented by decreasing order in Table I.

TABLE I
CUT-OFF PROPOSAL

Cut-off	Formula
1	$\tau_{s,t} = \overline{GDP\ growth}_{s,t}$
2	$\tau_{s,t} = \overline{GDP\ growth}_{s,t} - \sigma_{s,t}$
3[5]	$\tau_{s,t} = \overline{GDP\ growth}_{s,t} - 1.96\ \sigma_{s,t}$

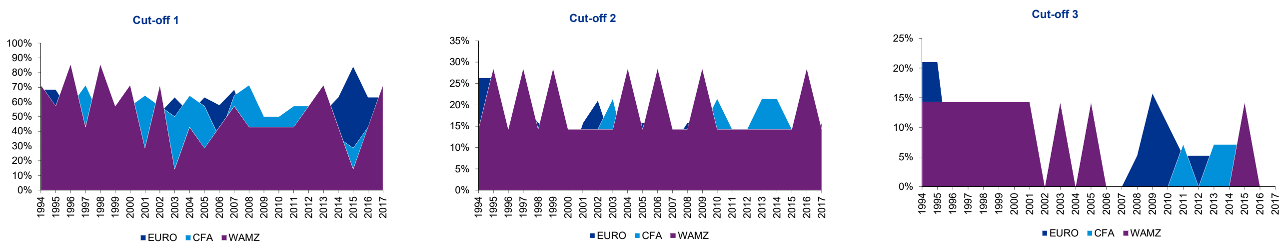

Fig. 1 Probability of GDP insufficient by cut-off; Source: [19] and authors' calculations

Depending on the selected cut-off, the database contains up to 520 GDP insufficient episodes since 1994 (Table II). They occurred most often in DCs (in number) except when using the Cut-off 3. This observation is however nuanced when we analyze insufficient rate and pay closer attention to distinguish CFA from WAMZ in the DCs. This is in line with [20], who reveals an increase of heterogeneities with countries that do not benefit from a common monetary policy.

2) Evaluation Criteria

As a reminder, [18] proposes two methods to identify the optimal cut-off by considering both types of errors. The first method is based on the traditional credit-scoring notions of sensitivity and specificity [21]. The main advantage of this credit-scoring identification method is that, in contrast to the NSR criterion, it relies on both type I and type II errors [22]-[24]. It assigns equal weight to both types of errors. However,

[3] "The type I error (or false negative) corresponds to a case in which the estimated (or forecasted) probability of crisis is smaller than the cut-off, but a crisis occurs. On the contrary, the type II error (also known as false alarm) corresponds to a situation in which the estimated (or forecasted) probability of crisis is larger than the cut-off whereas no crisis occurs. The higher the cut-off is, the more type II (respectively type I) errors are frequent (respectively infrequent)" [18].

[4] The NSR measures the false signals (size of Type II error) as a ratio of the good signals issued (1- size of Type I error) The selection rule is to pick the model that minimizes the NSR for each country.

[5] We use the central limit theorem in order to build a confidence interval (CI) for calibrated $\tau_{s,t}$. Regarding the volatility of the observed GDP, considering $z_\alpha = 1.96$ for CI = 95% will be sufficient.

this assumption should be relaxed if we assume that missing the identification of a crisis is more costly for an economy than a false alarm (or vice versa).

TABLE II
NUMBER OF IDENTIFIED DEFICIENT EPISODES (1994 – 2017)

		AEs	DCs			AEs+ DCS
			Total	CFA	WAMZ	
	Total of years	24		24		24
	Total observations	*456*	*504*	*336*	*168*	*960*
Cut-off 1	Number of identified insufficient GDP growth	255	*265*	179	86	520
	Insufficient rate	56%	*53%*	53%	51%	54%
Cut-off 2	Number of identified insufficient GDP growth	64	*75*	44	31	139
	Insufficient rate	*14%*	*15%*	*13%*	*18%*	*14%*
Cut-off 3	Number of identified insufficient GDP growth	17	*16*	5	11	33
	Insufficient rate	*4%*	*3%*	*1%*	*7%*	*3%*

The second method consists of aggregating the number of crisis and calm periods correctly identified by the EWS in an accuracy measure. The simplest measure, named total accuracy (TA), is defined as the ratio of number of episodes correctly predicted to the total number of periods. Maximizing the TA measure is thus equivalent to maximizing the number of correctly identified periods, no matter their type (crisis or calm). This measure does not arbitrate between type I and type II errors as the two types of periods are not considered separately (the denominator represents the total number of periods in the sample). Thus, [18] reports an undesirable situation in which the optimal cut-off correctly identifies all calm periods, but only a few, or none of the crisis periods. They hence propose another measure: an original evaluation criterion, the area under the curve (AUC) ROC[6]. We then choose the AUC (ROC curve) criteria in order to evaluate and identify the optimal cut-off since it is an effective tool to predict the probability of a binary outcome.

B. Examining Behavior of Key Economic Variables

The aim of this section is to observe how key economic variables change between deficient episodes and sufficient episodes. Following the literature, we analyze the behavior of key variables, by testing their relationships with insufficient GDP growth. To do this, we perform the Chi-squared test.

1) Data

We consider several variables in order to assess indicators that could assist anticipating an insufficient GDP growth.

The analysis uses annual data from world development indicators database for 40 countries—including AEs, and DCs[7] —for the period 1994-2017. The variables are categorized into several groups:

- Fiscal policy, including metrics on fiscal deficit, expenditure expansion and public debt.
- Economic activity, along with economic growth, consumption, saving, trade, unemplayment rates, credit, commercial banks activity, interest rates and inflation.
- Demography, counting the population growth, structure of population (urban, rural, age, gender…), and education.

2) Profile of Insufficient GDP Growth

As previously mentioned, we perform the Chi-squared test between our indicators $I_{i,t}$ (target variables) and key macroeconomic variables (explanatory variables). Our analysis focusses on the conditional effect of explanatory variables on indicators $I_{i,t}$.This allows us to observe the effect of a deficient GDP growth episode relative to sufficient one.

The event studies, detailed in the Appendix B, indicate that a deficient GDP growth episode tends to be linked to a difficult public debt situation (i.e., a high level of debt) and high level of expenses. In fact, we observe that the higher the insufficient GDP growth rate, the more the public debt increases. This is in line with the Keynesian view suggesting that, during periods of low growth or recession, additional government spending and reductions in some taxes degrade the public balance to bring about an "economic recovery".

Good economic activity and financial conditions fall sharply the probability of deficient economic growth episodes. At the same time, we show that countries with high money supply growth, large quantities of money, sustained food exports and trade, and low level of borrowers in commercial banks perform rather well in term of GDP growth.

Lastly, the event studies also show that an important urban population, a low population growth, a high school dropout and a high unemployment play a central role in the deficient GDP growth run-up.

III. METHODOLOGY AND RESULTS

To build EWS for deficiencies in terms of GDP growth we use a logit model. For deficient GDP growth episodes prediction, the binary response is the indicator $I_{i,t}$ previously defined. Similar to the discriminant analysis, this technique weights the independent variables and assigns a score in the form of a deficient probability to each observation in a sample.

Let us denote $x_{i,t}\ldots,x_{k,t}$ the explanatory variables for a country *i*. Then, using logistic regression, the deficient probability in terms of GDP growth for a country at time t is denoted by:

$$P\left(I_{i,t} = 1 \,\middle|\, x_{i,t}, \ldots x_{k,t}\right) = f(\, x_{i,t}, \ldots x_{k,t}) \qquad (2)$$

The model can be rewritten as

$$P\left(I_{i,t} = 1 \,\middle|\, x_{i,t}, \ldots x_{k,t}\right) = \beta_{0,t} + \sum_{i=1}^{k} \beta_{i,t}\, x_{i,t} \qquad (3)$$

The logit model can be estimated through maximum

[6] AUC - ROC curve is a performance measurement for classification problem at various thresholds settings. ROC is a probability curve and AUC represents a degree or measure of separability. It tells how much model is capable of distinguishing between classes. Higher the AUC, better the model is at predicting 0s as 0s and 1s as 1s. By analogy, higher the AUC, better the model is at distinguishing between patients with disease and no disease.

[7] See footnote 1

likelihood estimation using numerical methods assuming that the model residuals follow a normal (i.e., Gaussian) distribution.

The upside of this approach is that it is well suited for problems when the predictor variable is binary or has multiple categorical levels, or even when there are multiple independent variables in the equation. This methodology provides useful insights and allows us to compare predictive power and test the robustness of indicators across cut-offs. The preferred models are those that have stronger AUC.

A. Modelling

The database contains 960 observations for a period of 24 years. Depending on the selected cut-off, we thus have a number of deficient GDP growth episodes of 520 (54%), 139 (14%) or only 33 (3%). The objective is primarily to try to improve the overall performance of the EWS between the three cut-offs proposed.

To assess the importance of each explanatory variable, we use the stepwise regression which offers significant advantages[8]. According to this method, the choice of predictive variables is carried out by an automatic procedure that consists of considering in each step, a variable for addition to or subtraction from the set of explanatory variables based on some prespecified criterions (i.e., F-tests or t-tests, but also adjusted R-squared, Akaike information criterion, Bayesian information criterion, or false discovery rate). Then, we report the Hosmer and Lemeshow goodness-of-fit test and the AUROC measure —as well as type 1 and type 2 errors— to assess the fit and predictive power of the models[9].

1) Advanced Economies (AEs)

Table III shows results for AEs from the Eurozone logit model built using data (1994-2017).

We find that the optimal cut-off is the model 3 with an AUROC of 83.8%. The relevant indicators include annual growth of exports of goods and services and fiscal policy. The probability of entering in an episode of deficient GDP growth in the AEs increases with growing macroeconomic imbalances due to large deteriorating external imbalances. The fiscal policy, through public expenditures as a percentage of GDP, is also a significant indicator.

The odds ratio is used to figure out if a particular exposure (being in a class of a variable) is a risk factor for a particular outcome (an insufficient GDP growth). Thus, Table IV shows a relative measure of effect which allows the comparison between classes of variables. At time t, a level of public expenditure representing less than 4.5% and an annual growth of exports less than 2.5% tend to have the largest impact on the deficiency probability in terms of GDP growth for a country. All these factors can be interrelated. For example, high expenditure could contribute to a deterioration of the current account, making the fiscal position vulnerable to changes in the economic cycle.

TABLE III
AEs Logit Model

	Categorial levels	Model 1	Model 2	Model 3
Intercept		0,1381	-2,1913	-7,4775
		(0.339)	*(<.0001)*	*(0.8991)*
Adolescents out of school (% of lower secondary school age)	[0 - 1.5[	0,3603	0,6468	
		(0.002)	*(0.0023)*	
Exports of goods and services (annual % growth)	< 2.5	0,0412		1,5635
		(0.8083)		*(<.0001)*
	[2.5 - 8[	0,5007		-0,5282
		(0.0006)		*(0.2651)*
Final consumption expenditure (annual % growth)	< 1.63	0,681	0,978	
		(<.0001)	*(<.0001)*	
	[1.63 - 4.20[	0,2884	-0,4125	
		(0.0597)	*(0.106)*	
Trade (% of GDP)	< 60[	0,7727	0,3962	
		(0.0001)	*(0.0656)*	
	[60 - 100[	0,0217	0,2566	
		(0.9004)	*(0.2217)*	
Food exports (% of merchandise exports)	< 7.36		-0,31	
			(0.1577)	
	[7.36 - 17.5[		-0,4095	
			(0.0499)	
Expense (% of GDP)	< 4.5			0,8928
				(0.0136)
	[4.5 - 8[			-0,5637
				(0.2148)
Unemployment, total (% of total labor force) (modeled ILO estimate)	< 5			-7,6885
				(0.948)
	[5 - 10[			3,0699
				(0.9585)
Observations		456	456	456
Number of deficient episodes		255	64	17
% of deficient episodes		*56%*	*14%*	*4%*
Hosmer and Lemeshow test (p-value)		0.29**	0.01*	0.47**
Type error 1 (false negative)		32%	13%	4%
Type error 2 (false alarm)		30%	20%	0%
AUROC		0,7695	0,7593	0,8380

** If the p-value is below alpha (*0.1, **0.05, ***0.01), the null hypothesis that the observed and expected proportions are the same across all subgroup is rejected

We find no evidence that the level of public debt, commercial bank activity, interest rate or demography is a relevant indicator explaining an episode of deficient GDP growth in the AEs.

Finally, for the total AEs sample, the model retained can predict accurately 96% of the deficient episodes of the sample. The type 1 error (false negative) is around 4%.

[8] Advantages of stepwise regression include: (i) ability to manage large amounts of potential predictor variables, (ii) choosing the best predictor variables from the available options, (iii) selection method faster than other automatic model-selection methods, (iv) providing valuable information about the quality of the predictor variables.

[9] The Hosmer–Lemeshow test is a statistical test for goodness of fit for logistic regression models. It is used frequently in risk prediction models. The test assesses whether or not the observed event rates match expected event rates in subgroups of the model population. The Hosmer–Lemeshow test specifically identifies subgroups as the deciles of fitted risk values. Models for which expected and observed event rates in subgroups are similar are called well calibrated. When the p-value is below alpha = 0.05, so the null hypothesis that the observed and expected proportions are the same across all subgroup is rejected.

TABLE IV
ODDS RATIO WITH 95% WALD CONFIDENCE LIMITS – AES

Variable	Odds ratio
Annual growth of exports less than 2.5%	13,4
Annual growth of exports between 2.5% and 8%	1,7
Public expenditure representing less than 4.5%	3,4
Public expenditure representing between 4.5% and 8%	0,8
Unemployment rate less than 5%	0,001
Unemployment rate between 5% and 10%	0,2

TABLE V
DCS LOGIT MODEL

	Categorial levels	Model 1	Model 2	Model 3
Intercept		0,0355	-0,5451	-5,1206
		(0.785)	*(0.1467)*	*(<.0001)*
Broad money growth (annual %)	< 8	0,4446		
		(0.0014)		
	[8 - 20[	0,0976		
		(0.4726)		
External debt stocks (% of GNI)	< 38	-0,4563		
		(0.001)		
	[38 - 85[	-0,2296		
		(0.0989)		
Final consumption expenditure (annual % growth)	< 1.63	0,0448	0,4974	
		(0.748)	*(0.0096)*	
	[1.63 - 4.20[	0,4105	0,5633	
		0,0193	*(0.0165)*	
Food exports (% of merchandise exports)	< 7.36	0,3877		
		(0.01)		
	[7.36 - 17.5[	-0,4497		
		(0.0392)		
Interest payments (% of revenue)	< 4.5		-0,4116	
			(0.071)	
	[4.5 - 8[		-0,1455	
			(0.6811)	
Population growth (annual %)	< 0.5		1,385	
			(0.0222)	
	[0.5 - 2.6[		-0,5394	
			(0.1085)	
Unemployment, total (% of total labor force) (modeled ILO estimate)	< 5		0,2194	
			(0.346)	
	[5 - 10[		0,5519	
			(0.0111)	
Urban population (% of total)	< 45		-1,0285	
			(0.0001)	
	[45 - 70[		-0,3872	
			-0,1009	
Country of CFA franc (dummy)	0 or 1			-1,3695
				(<.0001)
CPIA debt policy rating (1=low to 6=high)	< 2.5			1,348
				(0.0012)
External debt stocks (% of exports of goods, services and primary income)	< 115			2,0438
				(<.0001)
	[115 - 262[			(-1.1419)
				0,1168
Observations		504	504	504
Number of deficient episodes		265	75	16
% of deficient episodes		*53%*	*15%*	*3%*
Hosmer and Lemeshow test (p-value)		0.32**	0.06**	0.01*
Type error 1 (false negative)		39%	14%	3%
Type error 2 (false alarm)		36%	29%	0%
AUROC		0,6994	0,738	0,8192

** If the p-value is below alpha (*0.1, **0.05, ***0.01), the null hypothesis that the observed and expected proportions are the same across all subgroup is rejected

2) Developing Countries (DCs)

Table V shows results for DCs logit model built using data (1994-2017).

In the case of DCs, the optimal cut-off is the model 3 with an AUROC of 81.9%. However, contrary to what we found for this group of countries, the situation of public debt (i.e., external debt level and debt policy rating) does appear to be a key element of DCs logit model. Another good predictor of the probability for DCs to enter in a GDP growth deficient episode is their belonging or not to a common currency area.

TABLE VI
ODDS RATIO WITH 95% WALD CONFIDENCE LIMITS – DCS

Variable	Odds ratio
Countries benefiting from a single monetary policy (CFA franc currency)	0,065
Debt policy rating less than 2.5	14,82
External debt stock below 115%	19,02
External debt stock above 115%	0,79

Undeniably and as confirmed by Table VI, we find that the probability of entering in a GDP growth deficiency state is much less common in countries benefiting from a single monetary policy (CFA franc currency). We also detect that the probability of having an episode of deficient GDP growth is much more common in countries experimenting a low debt policy rating and in those with an external debt stock (as a % of export of good, services and primary income) below 115%. This raises the fundamental question of governance and management in these countries.

Finally, for DCs sample, our model can predict accurately 97% of the deficient episode in the sample. The type 1 error (false negative) is 3%.

A. Model Use

TABLE VII
HOMOGENEOUS POOLS OF COUNTRY FOR AES AND DCS

Pool	Number of countries not having an episode of deficient GDP growth (goods)	Number of countries having an episode of deficient GDP growth (bads)	Total	Probability of having an episode of deficient GDP growth
AEs				
0	145	0	145	0,0%
1	146	4	150	2,7%
2	148	13	161	8,1%
Total	439	17	456	3,7%
DCs				
0	189	1	190	0,5%
1	153	3	156	1,9%
2	146	12	158	7,6%
Total	488	16	504	3,2%

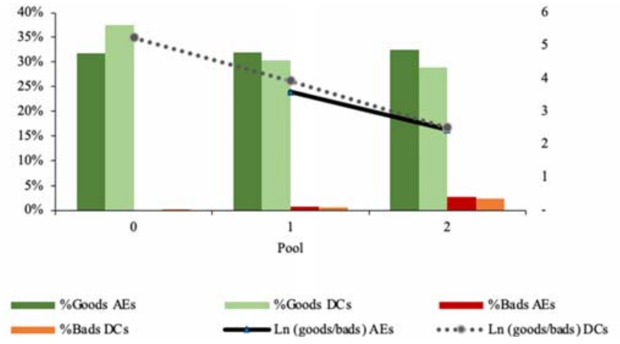

Fig. 2 Distribution across pools of country (goods/bads) for AEs and DCs

The technique of the logit model assigns a score in the form of a deficient probability to each observation from the sample. Consequently, this rating aims to capture outlooks and future evolutions suggesting the ability for a country to generate sufficient economic growth to achieve economic stability with a full employment. This rating is built based on homogeneous pools of countries.

Given the number of countries of our sample (19 for the AEs and 20 for DCs), we consider 3 pools of countries in each region. Hence, we segment the score variables obtained in the modeling section. We then obtain a fairly homogeneous distribution in 3 pools detailed in Table VII.

Regarding AEs, the riskiest group is the pool 2 with a probability of having a deficient economic growth episode of 8.1%. The pool 1 can be considered as an early warning level with a deficient probability of 2.7%. The same reasoning applied to DCs reveals an early warning level of 1.9% (pool 1) while the highest deficient probability is 7.6%. As shown in Table VII, the observations are distributed homogenously between the different pools.

The evolution of annual pooling stability from 1994 to 2017 is presented for both groups of countries in Fig. 3.

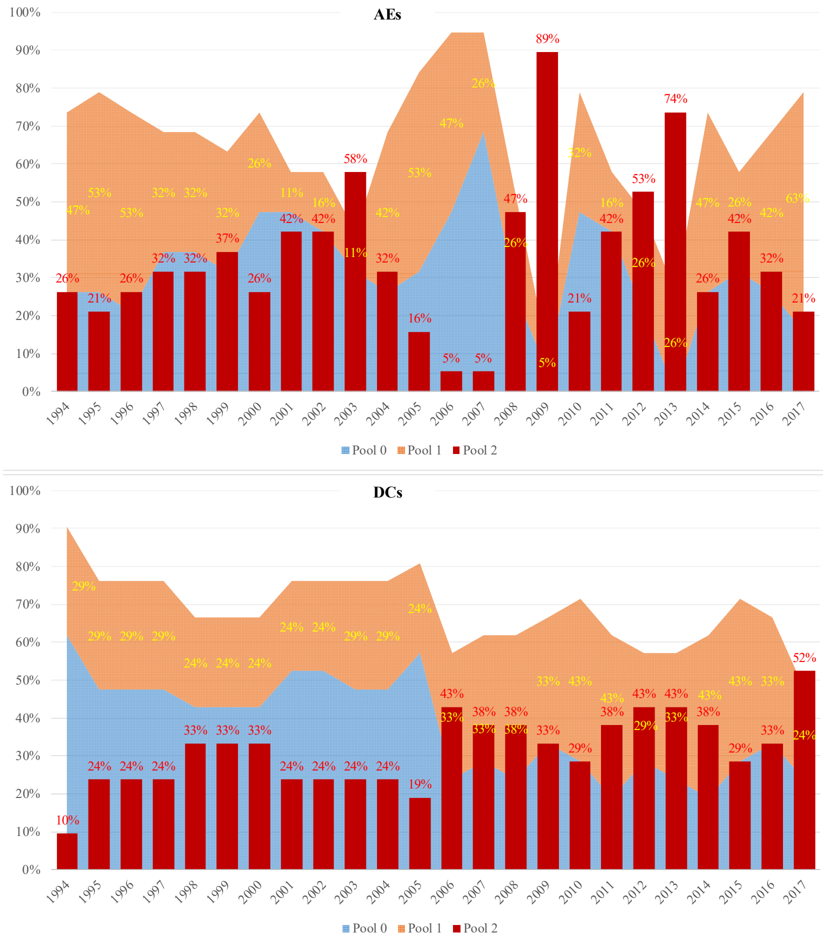

Fig. 3 Evolution of the annual pooling for AEs and DCs

Based on migrations across pools between 1994 and 2017, the instability level appears relatively high. By focusing on pools 1 and 2 (the riskier ones), we draw several lessons.

Firstly, the instability in the evolution of the countries in the pool 2 is more marked for the AEs compared to the DCs.

Secondly, the proportion of AEs in the riskiest pool 2 increased almost every year from 1995 to reach a first peak at 58% in 2003, just after the 2000-2002 stock market crash due to the Internet bubble bursting and marked by the bankruptcies or rescues in extremis of many high-tech companies[10]. Moreover, we observe that all the major countries of the euro zone (including France, Germany, Italy, and Spain) were part of this pool that year. The four succeeding years seem rather positive for economic growth, so this proportion decreased to a minimum level of 5% in 2006 and 2007 before the Eurozone knows another major breakdown due to the 2008 financial crisis. 2009 was the darkest year for AEs across the whole period of analysis. According to our results, all euro-zone countries ended up in pool 2 this year except Ireland and the Netherlands. Due to the increase in government deficits and debt that followed, these countries experienced another major crisis from 2010, often referred as the European sovereign debt crisis. The restrictive policies implemented thereafter caused another increase of the number of AEs in the riskiest pool 2, that reached a new peak at 74% in 2013 before returning at the end of the period to the low levels observed at the beginning.

Thirdly, concerning DCs, the absence of significant abnormal rupture in the probability of having a deficient economic growth could reinforce the hypothesis that our pool assignment process appears to be relatively insensitive to macroeconomic conditions including the crises discussed above. For this reason, the increasing trend of the probability of deficient growth episodes observed from 2006 can be explained by more unfavorable conditions (i.e., the delicate socio-political environment in most countries weighs heavily on business development decisions, as shown by the relatively low rate of investment). As a consequence, the downside risks related to shortcomings in fiscal consolidation and the deterioration of financing conditions have crippled growth in these DCs.

IV. Conclusion

The contributions of this paper are methodological and practical. We identify strong indicators of vulnerabilities that can help signaling a high probability for a country of entering in an episode of deficient GDP growth and show they are highly dependent of the considered economies. Our findings notably feature important differences in the early warning indicators between DCs and AEs.

For the AEs, the relevant indicators include annual growth of exports of goods and services and fiscal policy. In these countries, the probability of entering in an episode of deficient GDP growth increases with large deteriorating external imbalances. The results also indicate a clear positive impact of a vulnerable fiscal position in terms of public deficit.

We show that DCs face different challenges that need to be considered to monitor effectively for signals of future lack of GDP growth. First, the country's solvency does appear to be a key element. We clearly detect that the probability of having an episode of deficient GDP growth is much more common in DCs experimenting a low ability to fully repay their external debts. These results raise concern about management and governance in these countries since many of them have recently benefited from external debt relief under the Heavily Indebted Poor Countries Initiative (HIPC)[11]. Second, our results reveal that the lack of GDP growth is much less common in countries benefiting from a single monetary policy (CFA franc currency).

From a practical perspective, our results contribute to further analyze both groups of countries by building homogeneous pools of countries inside AEs and DCs. In AEs, the proportion of countries in the riskiest pool increased year after year to reach a first peak in 2003 just after the burst of the Internet Bubble. The 4 years that came after seemed rather positive for economic growth before this proportion increase suddenly to reach a second higher peak just after the global financial crisis and a third one just after the European sovereign debt crisis. While DCs were not affected by such abnormal ruptures, they are characterized by an increasing trend of the probability of deficient growth episodes observed from 2006. This upward trend can be explained by more unfavorable socio-political environment leading to shortcomings in the fiscal consolidation and deterioration of the ability to repay debts.

From a policy perspective, further research aimed at developing EWS models that help to reliably anticipate balance of payment (BoP) crises could become an important tool for policy-makers in DCs and allow them to obtain clear signals when and how to take preemptive measures in order to mitigate or prevent financial turmoil. Actually, many BoP crises over the past few decades had devastating social, economic and political consequences. It should be stressed that EWS can play an important role as a neutral and objective assessment of vulnerability. This consideration constitutes a focus area of analysis for policymakers in the near future.

Appendix

A. Data

We use data for 40 countries for the period 1994-2017. Countries are split into groups of AEs (19) and DCs (21). For analytical purposes, we also divide DCs into two groups: CFA franc currency zone (14), and other (7).

TABLE VIII
SAMPLE OF COUNTRIES

AEs (19)	DCs (21)		
Euro (19)	CFA currency (14)		Others (7)
Austria	Benin	Cameroon	Cabo Verde
Belgium	Burkina Faso	Central African Republic	Gambia
Cyprus	Cote d'Ivoire	Chad	Ghana
Estonia	Guinea-Bissau	Congo	Guinea
Finland	Mali	Equatorial Guinea	Liberia
France	Niger	Gabon	Nigeria
Germany	Senegal		Sierra Leone
Greece	Togo		

[10] For instance, Enron, WorldCom, Vivendi or France Telecom.

[11] The HIPC Initiative was initiated by the International Monetary Fund and the World Bank in 1996. It provides debt relief and low-interest loans to cancel or reduce external debt repayments to sustainable levels, meaning they can repay debts in a timely fashion in the future. As of January 2012, the HIPC Initiative had identified 39 countries (33 of which are in Sub-Saharan Africa) as being potentially eligible to receive debt relief. 36 countries have so far received full or partial debt relief [25]-[27].

Ireland
Italy
Latvia
Lithuania
Luxembourg
Malta
Netherlands
Portugal
Slovak Republic
Slovenia
Spain

TABLE IX
THE DATABASE VARIABLES

Categories	Variables
Demography	Adolescents out of school (% of lower secondary school age)
	Population growth (annual %)
	Unemployment, total (% of total labor force) (modeled ILO estimate)
	Urban population (% of total)
Economic activity	Borrowers from commercial banks (per 1,000 adults)
	Broad money (% of GDP)
	Broad money growth (annual %)
	Exports of goods and services (annual % growth)
	Final consumption expenditure (annual % growth)
	Food exports (% of merchandise exports)
	Trade (% of GDP)
Fiscal policy	External debt stocks (% of exports of goods, services and primary income)
	CPIA debt policy rating (1=low to 6=high)
	Expense (% of GDP)
	External debt stocks (% of GNI)
	Interest payments (% of revenue)

B. *Profile of insufficient GDP Growth*

TABLE X
GDP GROWTH PROFILE

Adolescents out of school (% of lower secondary school age)				Borrowers from commercial banks (per 1,000 adults)				Broad money (% of GDP)			
Class	N Obs	Min	Max	Class	N Obs	Min	Max	Class	N Obs	Min	Max
0	140	0,00	1,22	0	54	0,38	15,47	0	164	5,21	16,44
1	141	1,23	6,08	1	55	16,33	332,86	1	164	16,46	24,57
2	140	6,09	88,08	2	55	334,39	709,74	2	164	24,60	104,45
Broad money growth (annual %)				CPIA debt policy rating (1=low to 6=high)				Expense (% of GDP)			
Class	N Obs	Min	Max	Class	N Obs	Min	Max	Class	N Obs	Min	Max
0	165	- 88,79	8,36	0	71	1,00	2,50	0	201	3,43	28,72
1	166	8,38	19,55	1	90	3,00	3,50	1	201	28,74	40,48
2	165	19,61	701,79	2	82	4,00	4,50	2	201	40,57	98,17
Exports of goods and services (annual % growth)				External debt stocks (% of exports of goods, services and primary income)				External debt stocks (% of GNI)			
Class	N Obs	Min	Max	Class	N Obs	Min	Max	Class	N Obs	Min	Max
0	269	- 55,09	2,43	0	134	14,53	116,60	0	159	4,13	37,39
1	270	2,43	7,88	1	135	118,58	262,15	1	159	37,62	84,59
2	269	7,89	157,28	2	134	262,42	3 789,07	2	159	84,76	1 380,77
Final consumption expenditure (annual % growth)				Food exports (% of merchandise exports)				Interest payments (% of revenue)			
Class	N Obs	Min	Max	Class	N Obs	Min	Max	Class	N Obs	Min	Max
0	270	- 40,28	1,62	0	257	0,02	7,36	0	195	0,02	4,56
1	271	1,63	4,19	1	258	7,36	17,49	1	196	4,57	8,73
2	271	4,21	76,92	2	257	17,59	98,79	2	196	8,74	59,97
Population growth (annual %)				Trade (% of GDP)				Urban population (% of total)			
Class	N Obs	Min	Max	Class	N Obs	Min	Max	Class	N Obs	Min	Max
0	320	- 2,26	0,53	0	313	20,72	59,78	0	320	14,86	45,44
1	320	0,53	2,57	1	313	59,91	99,98	1	320	45,54	67,80
2	320	2,57	7,85	2	313	100,01	423,99	2	320	67,81	97,96

REFERENCES

[1] Gerling, K., P. Medas, T. Poghosyan, J. Farah-Yacoub, and Y. Xu, (2017), “Fiscal Crises,” IMF Working Paper No. 17/86 (Washington: International Monetary Fund).

[2] Kaminsky, G., S. Lizondo, and C. Reinhart, (1998), “Leading Indicators of Currency Crises,” IMF Staff Papers, Vol. 45, No. 1, pp. 1–48.

[3] Baldacci, E., I. Petrova, N. Belhocine, G. Dobrescu, and S. Mazraani, (2011), “Assessing Fiscal Stress,” IMF Working Paper No. 11/100 (International Monetary Fund).

[4] Bruns M. & Poghosyan T., 2018. "Leading indicators of fiscal distress: evidence from extreme bounds analysis," Applied Economics, Taylor & Francis Journals, vol. 50(13), pages 1454-1478, March.

[5] Berti, K., M. Salto, M. Lequien (2013) “An early-detection index of fiscal stress for EU countries”, European Economy. Economic Papers. 475. Brussels.

[6] Cerovic, S. and Gerling, K., Hodge, A. and Medas, P., (2018), “Predicting Fiscal Crises”, August 2018, IMF Working Paper No. 18/181.

[7] Kaminky, Graciela and Pablo Vega-Garcia (2016), “Systemic and Idiosyncratic Sovereign Debt Crises”, Journal of the European Economic Association, 14 (1): 80–114.

[8] Bassanetti, A., Cottarelli, C. and Presbitero, A. (2016), “Lost and found:

market access and public debt dynamics", IMF Working Paper, no. 16/256, December.
[9] Sumner, S. and Berti, K., (2017), "A Complementary Tool to Monitor Fiscal Stress in European Economies," EC Discussion Paper, 49 (June).
[10] Benassy-Quere, A. and Coupet, M., (2005), "On the Adequacy of Monetary Arrangements in Sub-Saharan Africa". The World Economy, Vol. 28, No. 3, pp. 349-373, March 2005.
[11] Bordo, M D. Meissner, C M. (2016), "Fiscal and Financial Crises", NBER Working Paper No. 22059
[12] Detragiache, E. and Spilimbergo, A., (2001), "Crises and Liquidity: Evidence and Interpretation", January 2001, IMF Working Paper No. 01/2.
[13] Chakrabarti, A., and H. Zeaiter, (2014), "The Determinants of Sovereign Default: A Sensitivity Analysis," International Review of Economics and Finance, 33, pp. 300-318.
[14] Reinhart, C. and K. Rogoff, (2009), "This time is different: Eight centuries of financial folly", Princeton, NJ: Princeton University Press.
[15] Reinhart, C. and K. Rogoff, (2011). "The Forgotten History of Domestic Debt", Economic Journal 121 (552), pp. 319-350.
[16] Bruns, M. and T. Poghosyan, (2018), "Leading Indicators of Fiscal Distress: Evidence from the Extreme Bound Analysis," Applied Economics, 50(13), pp. 1454-78.
[17] Manasse, P., N. Roubini, and A. Schimmelpfennig, (2003), "Predicting Sovereign Debt Crises," IMF Working Paper No. 03/221 (International Monetary Fund).
[18] Candelon B., Dumitrescu, E-I., Hurlin, C., (2012), "How to evaluate an Early Warning System? Towards a Unified Statistical Framework for Assessing Financial Crises Forecasting Methods", IMF Economic Review, 2012, vol. 60, issue 1, 75-113.
[19] World Bank Group, DataBank, World Development Indicators, https://databank.worldbank.org/source/world-development-indicators
[20] Diallo, Hamidou, (2018), "Regional heterogeneities and macroeconomic policies in a monetary area: the case of WAEMU", PhD thesis, Université Paris 2 Panthéon Assas, LEMMA.
[21] Basel Committee on Banking Supervision, (2005), "Studies on the Validation of Internal Rating Systems", working paper no.14, Bank for International Settlements.
[22] Engelmann, B., Hayden, E. and Tasche, D., (2003), "Testing rating accuracy?" Risk No. 16, pp. 82-86.
[23] Renault, O., and De Servigny, A., (2004), "The Standard & Poor's Guide to Measuring and Managing Credit Risk", 1st ed. McGraw-Hill, 2004.
[24] Stein, R. M., (2005), "The relationship between default prediction and lending profits: integrating ROC analysis and loan pricing", Journal of Banking & Finance, Vol. 29, pp. 1213-1236.