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Fiscal Affairs Department

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Abstract

This paper identifies leading indicators of fiscal crises based on a large sample of countries at different stages of development over 1970-2015. Our results are robust to different methodologies and sample periods. Previous literature on early warning sistems (EWS) for fiscal crises is scarce and based on small samples of advanced and emerging markets, raising doubts about the robustness of the results. Using a larger sample, our analysis shows that both nonfiscal (external and internal imbalances) and fiscal variables help predict crises among advanced and emerging economies. Our models performed well in out-of-sample forecasting and in predicting the most recent crises, a weakness of EWS in general. We also build EWS for low income countries, which had been overlooked in the literature.

JEL Classification Numbers: H63; E62; E65; E66; F47; G01

Keywords: Fiscal crises, Early Warning System, Low income countries

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I. Introduction

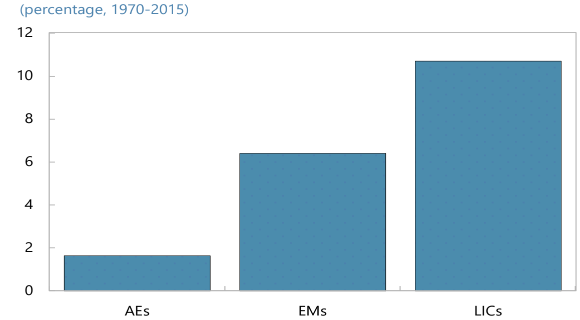
Two core objectives of fiscal policy are to promote economic stability and ensure provision of public services. Periods of fiscal distress, and ultimately fiscal crises, can undermine those objectives contributing to economic volatility and disruptions in essential public services. Avoiding fiscal crises is also important because it has implications for economic growth and the development agenda. Fatas and Mihov (2013) showed that volatile fiscal policy lowers economic growth, and work by Gerling et al. (2017) suggests fiscal crises can have long-term implications for GDP per capita. As such, it is important to understand what may be causing the crises and how to avoid them.

The literature on fiscal crises and on early warning indicators is limited, although it has expanded in recent years. Most of the past literature focused on sovereign external debt defaults alone, although more recent papers (Gerling et al., 2017) have looked at more comprehensive definitions of fiscal crises, including access to official financing and implicit domestic default (high inflation). There is also a growing interest in leading indicators of fiscal crises (or fiscal distress), partly motivated by the global financial crises. For example, IMF staff has produced some research (e.g., Baldacci et al., 2011, and Bruns and Poghosyan, 2018) and the European Commission developed an early warning system (Berti, Salto, and Lequien, 2013). One limitation of the literature on early warning systems in general is that it relies on relatively small samples of advanced and emerging markets, and, in some cases, is heavily focused on predicting crises during a specific period.

The objective of this paper is to better understand the structural weaknesses that make countries prone to entering a fiscal crisis. Our assumption is that there are vulnerabilities that are systematically relevant across time and groups of countries. The objective is to identify them as they would be useful to signal when there is a higher risk of future crises. Past studies, by focusing on small samples, may be able to explain specific crises better, but their results may not be as useful to detect (and prevent) potential future crises. We take advantage of a new large sample of fiscal crises built by Gerling et al. (2017) to identify more robust macro-fiscal vulnerabilities and triggers that have been important across different fiscal crises.

We also pay closer attention to the drivers of fiscal crises in low income countries (LICs)—which have been largely overlooked in the literature. This is surprising as fiscal crises are most frequent in LICs. They are six times more likely to enter a crisis than an advanced economy and almost twice as likely as an emerging market. Not surprisingly, there have been several initiatives to provide debt relief to LICs to help alleviate the effects of the

Figure 1.1. Probability of Starting a Fiscal Crisis
(percentage, 1970-2015)



Sources: Gerling and others (2017) and authors' calculations

crises (e.g., IMF, 2011a). However, efforts to reduce the frequency of crises have not been successful. As these countries have unique characteristics, we investigate separately the potential leading indicators of crises and whether they are different from advanced and emerging economies.

We use two of the more common approaches to build early warning systems (EWS) for fiscal crises: the signal approach and logit model. Using two methodologies provides useful insights and allows us to compare predictive power and test the robustness of indicators across methodologies. As Berg et al. (2005) stressed, a key focus should be on the ability to forecast future crises. The preferred models are those that have stronger out-of-sample performance than models that may explain well past crises (overfitting), but are poor at predicting future ones.

Our results show that there is a small set of robust leading indicators (both fiscal and non-fiscal) that help assess the probability of a fiscal crisis. This is especially the case for advanced and emerging markets. For these countries, we find that domestic imbalances (large output or credit gaps), external imbalances (current account deficit), and rising public expenditures increase the probability of a crisis. We also tested how the early warning systems would perform out of sample, especially how well they would have predicated the fiscal distress episodes during the latest global financial crisis (2007-15). Importantly, the models would be able to predict accurately around 75 percent of the crises for these countries.

We find that the leading indicators of fiscal crises vary depending on the level of development. While there are some common drivers among all economies, some vulnerabilities are specific to LICs. These countries are highly vulnerable to changes in external aid, reflecting the high budget dependence on these flows, and food prices (increases pressure for subsidies).

The remainder of the paper is organized as follows. Section II presents a literature review of past work. The next section describes the definition of fiscal crises and examines the behavior of key macro-fiscal variables around crises, using event studies. Section IV presents the methodology used to build the EWS models. This is followed by a section with the main results of the early warning exercise. Section VI presents the conclusions.

II. Previous Literature on Early Warning Systems

There is ample empirical literature on Early Warning System (EWS) models, analyzing currency, banking, and sovereign debt crises. These studies differ not only by the type of crises, but also by the methodology and set of indicators used. In most cases, the data coverage tends to be limited, focusing on samples of advanced and emerging markets. In the fiscal area, attention has been mainly on sovereign debt crises (e.g., Detragiache and Spilimbergo, 2001; Chakrabarti and

Zeaiter, 2014),[2] but there is a nascent literature on identifying early warning indicators for episodes of fiscal distress more broadly defined. These include Baldacci et al. (2011) and Bruns and Poghosyan (2018), which identify variables that help predict periods of fiscal stress for advanced economies and emerging markets. There has also been recent work focused on European countries (e.g., Sumner and Berti, 2017).

One of the most used methodologies is the *signals* approach popularized by Kaminsky, Lizondo, and Reinhart (1998) for currency crises.[3] This approach selects a number of variables as leading indicators of crises and determines threshold values for each variable beyond which signals are issued indicating that a crisis is likely to happen in the near future. This approach has been used in the context of fiscal crises more recently. For example, Baldacci et al (2011) looked at a sample of emerging and advanced economies. They focused on a parsimonious set of fiscal leading indicators (e.g., fiscal balances and debt (size, composition, and maturity)) to help signal possibility of fiscal distress. Berti, Salto, and Lequien (2013) estimated a EWS focused on European Union countries. They find that macro-financial variables seem to be more relevant than fiscal variables to assess countries' vulnerabilities to fiscal distress.

The other frequently used approach draws on limited dependent variable techniques (multivariate logit or probit). The most common tool is a panel regression with a binary dependent variable equal to one if a crisis occurs and zero otherwise. The impact of a set of determinants on the crisis probability is then derived by estimating the model and testing the significance of various leading indicators. Literature using this methodology to analyze sovereign debt crises includes Manasse et al. (2003), Gourinchas and Obstfeld (2012), and Dawood, Horsewood, and Strobel (2017). Sumner and Berti (2017) proposed a logit model to complement the signal approach used by the European Commission to identify periods of fiscal distress. They confirm the importance of macro-financial indicators and find some evidence that increases in public debt can be a predictor of distress periods. Bruns and Poghosyan (2018) use extreme bound analysis to identify leading indicators for crises. They find that both fiscal and non-fiscal leading indicators (e.g., output gap and current account balance) should be considered when assessing a country's vulnerability to fiscal distress.

III. Fiscal Crises Episodes

We start by defining fiscal crises and analyzing the behavior of fiscal and macro variables around them. This will help identify potential candidates for early warning indicators.

[2] Others, in addition to external debt defaults, also looked at large-scale official financing (e.g., Manasse, Roubini, and Schimmelpfennig, 2003) and, to a limited degree, evidence on domestic public default, namely Reinhart and Rogoff (2009 and 2011) and Gourinchas and Obstfeld (2012).

[3] See Abiad (2003) for a survey, including other methodologies.

A. Definition of Fiscal Crises

We use the term fiscal crisis to describe a period of heightened budgetary distress, resulting in the sovereign taking exceptional measures. A country may experience fiscal distress when large imbalances emerge between inflows and outflows. These imbalances may lead to a fiscal crisis if the country is not able to respond by sufficiently adjusting its fiscal position. As Bordo and Meissner (2016) note, the canonical fiscal crisis is a debt crisis, when the government is unable to service the interest and or principle as scheduled. Indeed, there has been significant attention in the literature to crises triggered by external default episodes (e.g., Detragiache and Spilimbergo, 2001; Chakrabarti and Zeaiter, 2014). It is important to note, however, that fiscal crises may not necessarily be associated with external debt defaults. They can be associated with other forms of expropriation, including domestic arrears and high inflation that erodes the value of some types of debt (Reinhart and Rogoff[4], 2009 and 2011). In addition, countries that face severe financial conditions may opt to ask for official creditors' assistance (e.g., the IMF) instead of defaulting (Manasse and others, 2003).

Our analysis is based on the fiscal crisis episodes identified by Gerling et al. (2017). One key advantage of this database is that is covers a large sample of countries (188), including low income countries, from 1970 to 2015. Another advantage is that it includes episodes of broadly defined budgetary distress and not only outright debt default. Specifically, a fiscal crisis is identified when one or more of the following distinct criteria are satisfied:

- Credit events associated with sovereign debt (e.g., outright defaults and restructuring).
- Recourse to large-scale IMF financial support. Countries under distress may opt to request support from international institutions instead of defaulting. This criterion captures any year under an IMF financial arrangement with access above 100 percent of quota and fiscal adjustment as a program objective.
- Implicit domestic public default (e.g., via high inflation rates). This reflects periods where governments have difficulty meeting their obligations and resort either to running domestic payment arrears or printing money to finance the budget. These episodes are identified by looking at periods of very high inflation and/or accumulation of domestic arrears when data are available.
- Loss of market confidence in the sovereign. This criterion captures any year with extreme market pressures. One sub-criterion is *loss of market access*: when sovereigns default or stop issuing bonds, controlling for financing needs and previous patterns of issuance. The second sub-criterion is *price of market access*: there is a threshold for spreads (1,000 basis points).

[4] Baldacci et al. (2011) and Bruns and Poghosyan (2018) also have broadly similar fiscal crisis definitions.

The database contains 439 fiscal crisis episodes, implying that countries faced on average two crises since 1970 (Table 3.1). They occurred most often in low income developing countries (LICs, an average of about 3 crises per country) and least often in AMs.

Table 3.1. Number of Identified Fiscal Crisis Episodes (1970–2015)

	Total	AM	EM	LIC
Total number of start years	**439**	25	188	226
Average per country	**2.3**	0.7	2.3	3.2
Average duration per episode	**5.6**	3.8	5.6	5.8

B. Examining Behavior of Key Economic Variables Around Fiscal Crises

We now turn to study the behavior of fiscal and macro variables around fiscal crises. The aim is to observe how these variables change between crisis periods and *tranquil* (non-crisis) periods. Following the literature, we apply an event study to analyze the behavior of key variables during an 11-year window around the start of the crisis, by comparing the dynamics of variables within this window with that of an out-of-window tranquil period. Following closely Gourinchas and Obstfeld (2012), we specify fixed-effects panel regressions for each variable:

$$y_{i,t} = \alpha_i + \sum_{j=-5}^{5} \beta_j D_{t+j} + \varepsilon_{i,t}$$

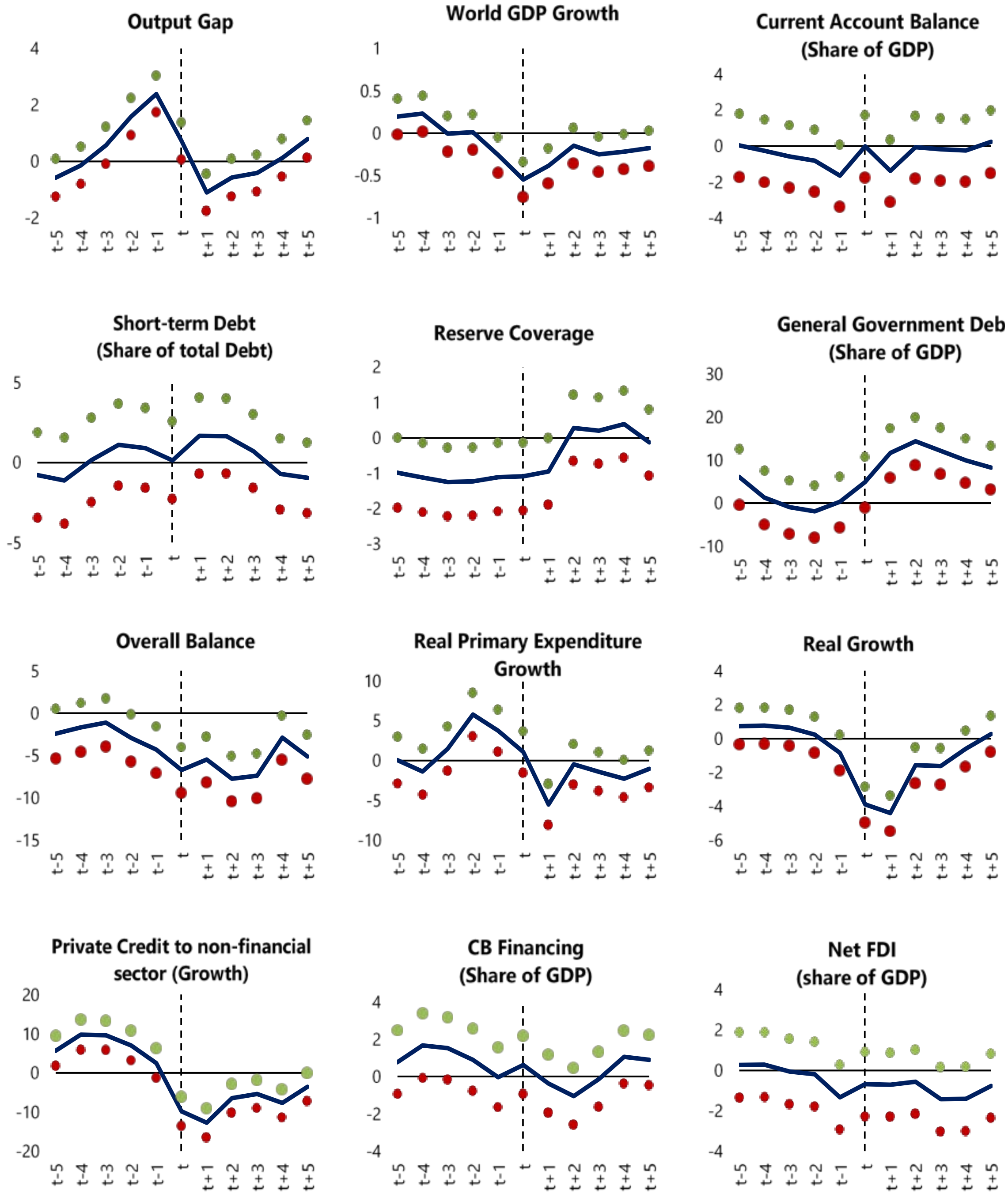
where y is a variable of interest, α_i the fixed-effect, D_{t+j} the 11 dummy variables taking the value of 1 in period $t+j$ (if period t is a crisis start year), and β_j the conditional effect of a crisis in period t+j of the crisis window relative to tranquil times. We set the event window around crisis episodes to 11 years to observe the buildup of imbalances before the crisis and time for adjustment once the crisis starts. The error term ε captures all the remaining variation in the realization of the variable under study.

Our analysis will focus on the conditional effect of a crisis, β_j, on the key fiscal and macro variables. This allows us to observe the effect of the crisis relative to tranquil times. For example, if the output gap tends to be higher (or lower) than normal times in the years before the crisis starts and the years immediately after.

C. Advanced and Emerging Economies

The event studies indicate that a fiscal crisis tends to be preceded by loose fiscal policy (Figure 3.1). In the run-up to a crisis, there is robust real expenditure growth. The overall balance also tends to deteriorate sharply before the crisis. Once the crisis begins, governments contain expenditure growth aggressively, suggesting fiscal policy is procyclical as economic conditions are weaker during this period. At the crisis onset, public debt ratios rise substantially, especially in AMs and EMs, and only fall very gradually several years after.

Figure 3.1. Event Studies. Advanced and Emerging Economies



Note: The Figure plots the estimates of β_j for each variable during the 11-year time window (solid line), together with the 95 percent confidence interval (dotted lines). This is the event study approach in Gourinchas and Obstfeld (2012) and measures the difference between values during the 11-year time window and "normal" period average. The x-axis is the time distance to the start of fiscal crises.

Economic growth falls sharply at the onset of the crisis. In the crisis run-up, economic growth is generally higher than in normal times. As the crisis starts, it declines sharply. AMs and EMs experience the largest fall in real growth in the first two years of the crisis. Private credit growth, robust before the crisis, tends to decelerate just before the crisis and fall sharply in the first two years.

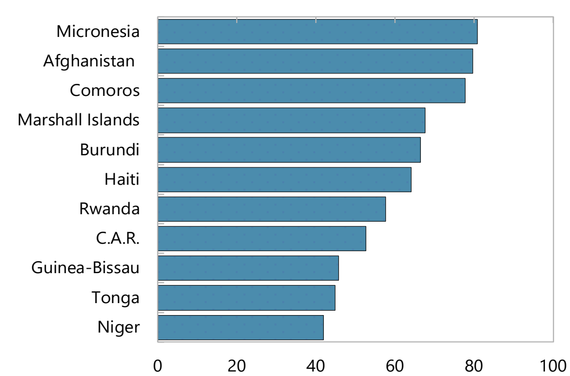
The event studies also show a worsening of the twin deficits, fiscal balance and external current account, in the crisis run-up. More generally, the evidence suggests fiscal crises start when there are several domestic and external imbalances, it does not appear to be driven only by "fiscal" factors.

D. Low Income Countries

External Variables

The event studies suggest external factors play a significant role in understanding fiscal crises in low income countries (Figure 3.3). Crises on average are preceded by periods of sharply rising food prices which can have a large direct impact on households, but also the governments' budgets. In many cases, governments have large food subsidies or take measures to counteract rises in food prices, including other safety net expenditure measures as well as tax breaks.[5] Not surprisingly, LICs also seem vulnerable to slower world economic growth. Declining foreign direct investment (FDI) and lower FX reserve coverage before fiscal crises also suggest external vulnerabilities may be a driver of the crises.

Figure 3.2. Ratio of Budget Grants to Current Expenditure (average 2010–16, in percent)



Sources: Authors' calculations

Data also indicate that official aid (grants and concessional loans) tends to fall around the start of the crisis. This is important as aid is a key source of fiscal revenue in many cases (IMF, 2009). For example, in about one third of LIC countries, the ratio of grants to current spending exceeds 20 percent, and in 8 countries, this proportion surpasses 50 percent (Figure 3.2).

[5] See for example IMF 2011b. In particular, in response to food price increases in 2007/08 and 2011/12, many LICs reduced taxes or increased explicit subsidies. For example, in 2007/08, 17 low income countries reduced food taxes, and 9 countries increased direct subsidies, while many introduced other safety net expenditure measures (food stamps, school feeding programs, food-for work programs, fertilizer subsidies).

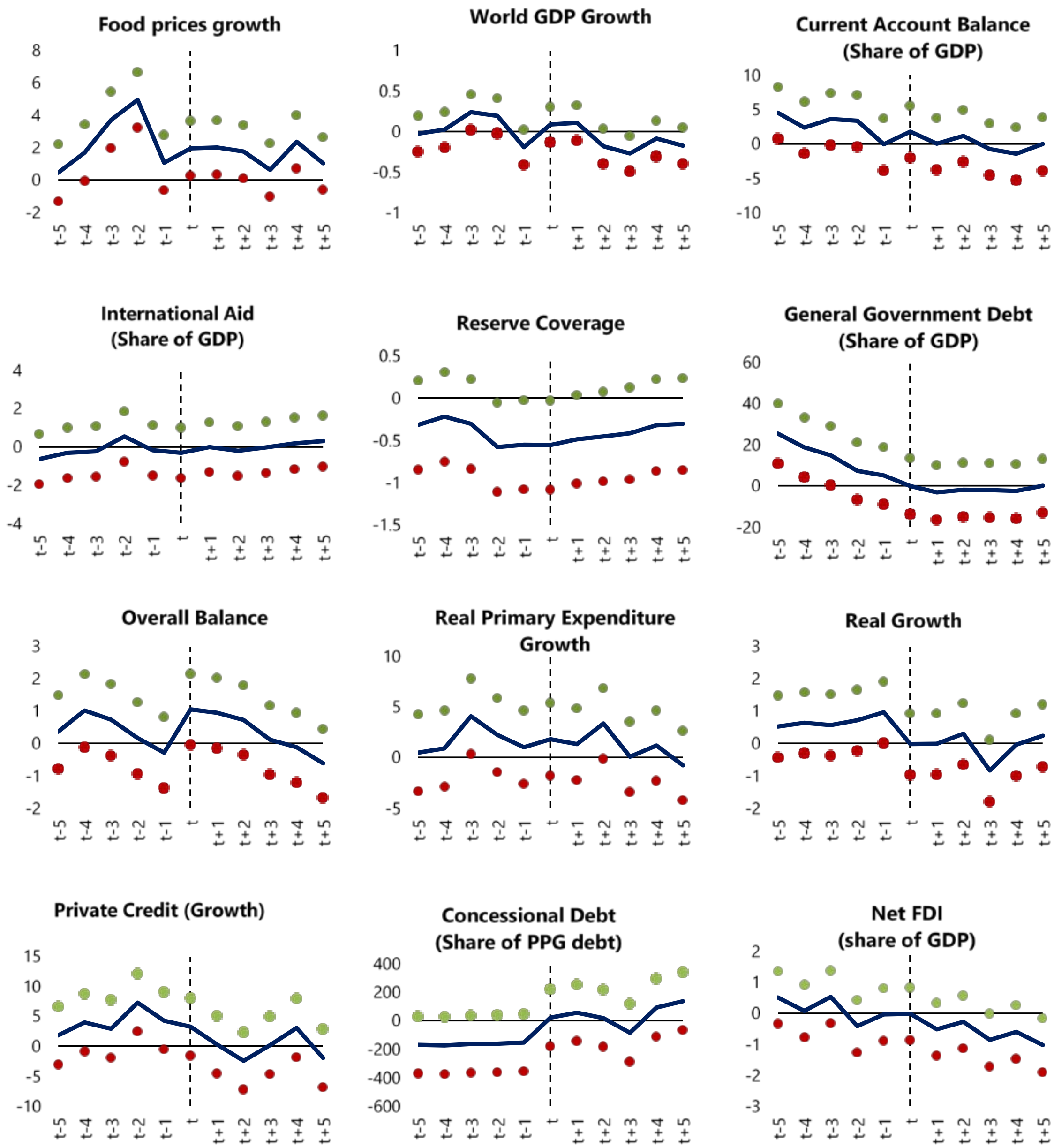
Domestic Macro-Fiscal Variables

The domestic economy tends to "overheat" before fiscal crises. Economic growth peaks just before the onset, falling afterwards and remaining below the average of tranquil times for some time. This finding is consistent with Gerling et al. (2017). A similar pattern is observed in growth of private sector credit.

Fiscal and debt indicators show a mixed picture around crises. Public debt tends to be significantly higher than in normal times, but is on a downward trend even before the onset of the fiscal crises. Decomposing debt prior to crises reveals that the share of concessional debt in total external debt is lower than normal times, implying that countries have shifted towards non-concessional sources of financing prior to crises. The composition of external debt shifts back towards concessional sources once the crisis begins.

The overall fiscal balance does deteriorate somewhat just before the crisis, but remains close to its level in tranquil times and quickly recovers as the crisis starts. Because the dynamics of the fiscal balance can be influenced by many factors it does not give a clear view of the policy stance. However, real expenditure dynamics suggest countries start tightening a few years before the onset of the crisis—possibly reflecting mounting vulnerabilities—as real primary expenditure growth declines significantly.

Figure 3.3. Event Studies. Low Income Countries



Note: The Figure plots the estimates of β_j for each variable during the 11-year time window (solid line), together with the 95 percent confidence interval (dotted lines). This is the event study approach in Gourinchas and Obstfeld (2012) and measures the difference between values during the 11-year time window and "normal" period average. The x-axis is the time distance to the start of fiscal crises.

IV. ESTIMATION STRATEGY AND DATA

A. Alternative Approaches to Predict Crises

In order to construct early warning systems for fiscal crises, we adopt two alternative approaches that have been used in the literature. We first use the signal approach, followed by multivariate logit models. Past studies have compared the performance of the different methods to predict crises, without definitive conclusions (Berg and Pattillo, 1999; Berg et al., 2005; and Baldacci et al., 2011). Using both methods will allow greater insight into the different drivers of fiscal crises and prevent our conclusions being driven by the limitations of one approach.

Signal approach

The signals approach involves monitoring the developments of economic variables that tend to behave differently prior to a crisis. Once they cross a specific threshold this gives a warning signal for a possible fiscal crisis in the next 1-2 years. These thresholds, as discussed below, are derived to balance between the risk of having many false signals and the risk of missing the crisis altogether. An advantage of this approach is that it assesses the relative power of individual variables as predictors of fiscal crisis. This is useful as it increases understanding of the sources of vulnerabilities and policy actions that contribute to a crisis. Another advantage is that it is easier to use with an unbalanced panel. If some data are missing for a variable, but there are observations around crisis periods, this will just make the estimation of the threshold less precise. In addition, this will not affect the estimation of thresholds for other variables where more data are available.

For each explanatory variable x_i, we define an indicator variable

$$d_t^i = \begin{cases} 1 & if\ x_i > crit^i \\ 0 & if\ otherwise \end{cases}$$

where $crit^i$ is an *indicator variable threshold*. There is a 'signal' of an approaching crisis if $d_t^i = 1$.

The threshold $crit^i$ for an explanatory variable will be a value specific to each country, corresponding to a *percentile* of values (e.g., 10th percentile) taken by the explanatory variable over the sample period for that country.[6] The percentile will be common across countries in the sample. For example, the $crit^i$ for the exchange rate can be the 10th percentile observed over the sample period for each country. The use of percentiles to define thresholds, instead of absolute values, takes into consideration structural differences across countries (e.g., quality of institutions). For example, some countries may be able to withstand higher debt levels than others without risk of distress.

[6] Observations more than 1½ standard deviations from the country-specific sample mean of each variable are omitted, to remove the effect of outliers.

For each explanatory variable, there are the following possibilities in each year:

Table 4.1. Occurrence of Crisis—True versus Predicted

		State of the World	
		Crisis next year	*no crisis next year*
Predicted result	*signal*	**true positive**	**false alarm** (type I error)
	no signal	**miss** (type II error)	**true negative**

A low *crit*^{i} would help detect the largest number of crises and reduce the probability of missing a crisis (type II error). While this is the main objective, setting the threshold too low would undermine the credibility of the EWS as it would increase the probability of false alarms (type I error). Following the literature, the *crit*^{i} is chosen to balance these two considerations. Specifically, the value of *crit*^{i} used to compute the indicator variable d_t^i for each country is the value corresponding to the percentile that maximizes the signal-to noise-ratio (SNR). The SNR is defined as the ratio of correct signals (as a percentage of crises in sample) to false alarms (as a percentage of tranquil periods in sample).

While individual variables contain important information on vulnerabilities, a crisis is more likely to happen if several of these indicators are producing signals. As such, in addition to examining individual variables, we construct a composite early warning indicator:

$$CI_t = \sum_i w_i \, d_t^i$$

which is a weighted average of the indicator variables. For each indicator variable d_t^i, the corresponding weight w_i is given by the measure of signaling power (1 – TME) for the relevant explanatory variable.[7]

Logit model

The early warning systems under this approach draw on standard panel regression (multivariate probit or logit models) with a binary dependent variable equal to one when a crisis begins (or when there is a crisis). The impact of a set of explanatory variables on the crisis probability is derived by estimating the model, through maximum likelihood estimation (e.g., 2016, Catao et al., 2013, and Gourinchas and Obstfeld, 2012). The main advantage of this approach is that it allows testing for the statistical significance of the different leading indicators and takes into account their correlation.

[7] Total Misclassified Errors (TME), that is the ratio of misses (type II) plus the ratio of false alarms (type I error).

We estimate a pooled logit model. Once a crisis starts, the next two years (if still crisis years) are removed from the sample to avoid a bias. The years after the onset of the crisis tend to have different behavior than other years and could bias the results. The probability of a positive outcome is assumed to be determined by the logistic cumulative distribution function.

$$p(start\ fiscal\ crisis_{it} = 1) = F(X_{i,t-h}\beta)$$

For each regression specification, we calculate fitted values (probabilities of crisis for each sample observation). We then search over potential cut-off probabilities (from 1% to 35%) and select the optimal cut-off probability that minimizes the TME. The optimal cut-off probability can be used to generate early warning signals for each regression model.

B. Data

The analysis uses annual data for 188 countries—including advanced, emerging, and low income—for the period 1970-2015. However, the availability and quality of data varies significantly (see Annex I for more details). To test for indicators that could help predict crises we looked at a variety of variables following the literature on fiscal and sovereign debt crises. We also included data that are particularly relevant for low income countries, such as aid flows and concessional debt. Variables fall into the following categories:

- *Fiscal and public debt*. These include primary and overall balances, expenditure growth, gross financing needs, and measures of public (domestic and external) debt.
- *Economic activity and financial*. These include economic growth, real time output gap, unemployment rates, credit growth and credit gap, interest rates. [8]
- *External*. These include variables such as the current account, foreign aid flows (which also have a fiscal impact), exchange rates, terms of trade, international prices of key commodities (food, oil), global growth, and remittances.

V. Early Warning Systems

A. Advanced and Emerging Economies

The choice of variables

We first estimate early warning systems for advanced economies and emerging markets. This relies on a sample of 118 countries. The advantage of merging the two groups of countries is that we have a larger set of crises, which is a significant limitation when only analyzing advanced economies. In addition, the classification of some countries has changed during the period of the

[8] The real-time output gap is based on the different vintages of the IMF's World Economic Outlook. The credit gap is the percentage deviation of private sector credit from its trend, which is estimated using a one-sided filtering approach based on data available at each time period, analogous to when forecasting in real time.

sample—this is especially the case for emerging markets that become advanced economies (under the IMF's World Economic Outlook classification). Furthermore, the event studies indicate that economic variables tended to behave in a similar fashion around crises for EMs and AEs.

The selection of variables needs to consider that we want to test the robustness of the EWS across different sample periods. One concern in the literature is the risk of overfitting a specific sample, at the cost of reduced ability to predict future crises. As Berg et al. (2005) stressed, the real test is whether the EWS can predict future crises (out of sample forecasts). As such, we build our EWS using a parsimonious set of variables to reduce the risk that by trying to achieve a strong performance in sample, we end up undermining out of sample forecasts. In addition, we select potential leading indicators based on their individual signal power for the "in sample" period using data up to 2006. We then test the robustness of the EWS in the "out of sample" period, that is 2007-15 period. This provides a test of how well the EWS would have helped detect fiscal crises during the turbulent years around the global financial crises. As noted by Christofides, Eicher, and Papageorgiou (2016), EWS have in general performed badly in predicting the 2008 global crisis.

Signal Approach

We first assess a large set of possible leading indicators individually. As discussed in the previous section, we derive the "optimal" threshold for each individual indicator. Appendix Tables A.2–A.3 show the results for the 1- and 2-years lag approaches for both the in-sample and full sample.[9] The tables show the threshold percentile, the signaling power, and type I and II errors for the best performing indicators. For example, the 1-year lag exercise indicates that the threshold for the current account surplus is the 38th percentile for the 1970-2006 sample. If the current account balance is below, there is a higher risk of a fiscal crisis. This indicator alone would have signaled correctly 55 percent of the crises (or 1- type II error) over the next year within the 1970-2006 sample. The results in Tables A.2-A.3 show the individual indicators with stronger signaling power remained broadly the same across the two samples (1970-2006 and 1970-2015)—suggesting the drivers of fiscal crises are similar across samples.

The best individual performers in-sample (1970-2006) are chosen based on the tables and then used to build the composite indicators, with 1- and 2-year lags, to assess the probability of starting a crisis. The strategy is to be parsimonious, so we focus on a small set of indicators that have the strongest signaling power. Also, we use only indicators for which a significant number of observations are available. This implies some of the best individual indicators are not used due to data limitations—this is particularly the case for gross financing needs, some debt indicators, and a measure of budget rigidities (size of the wage bill). Table 5.1 shows the performance and weights on individual indicators for the composite indicator constructed using data in-sample

[9] The 'one-year lag approach' means that early warning signals have been produced by studying the behavior of indicator variables one year before a crisis. The 'two-years lag approach' has an analogous definition.

(1970-2006). We also present the weights and results for the composite indicator constructed with the same variables but using the full sample (1970-2015), where we have considerably more observations. Using as much data as are available over the full sample (1970-2015), the compositor indicator constructed covers a period containing up to 112 crises.

Table 5.1. Early Warning System for AEs and EMs: Signals Approach

	1 year ahead	2 years ahead	1 year ahead	2 years ahead
	In-Sample[1]		**Full Sample[1]**	
Number of Crises[2]	70	43	112	82
Number of Non-Crisis Years[3]	1330	824	2369	1798
Number of Countries[4]	69	69	105	103
Type I Error[5]	0.34	0.31	0.33	0.42
Type II Error	0.44	0.49	0.41	0.33
Signal to Noise Ratio	1.63	1.64	1.78	1.60
Variable weights for the composite indicator				
Private credit gap (one sided) (% potential credit)	0.09		0.06	
Real time output gap (% of potential GDP)		0.14		0.14
Current Account (% GDP)	0.23	0.17	0.26	0.24
Real GDP per capita (% Ch.)	0.10		0.08	
Openness (Exports and Imports as % of GDP)	0.10	0.14	0.07	0.16
Reserve Coverage (months of imports)	0.09		0.08	
Central Bank Claims on Government (% GDP, 1st diff.)	0.12		0.19	
Central Bank Claims on Government (% GDP)		0.11		0.09
Overall Balance (% GDP, 1st diff.)	0.16		0.11	
Primary Balance (% GDP, 1st diff.)		0.22		0.14
Expenditure (% GDP, 1st diff.)	0.12		0.15	
Real Primary Expenditure (% Ch.)		0.23		0.22

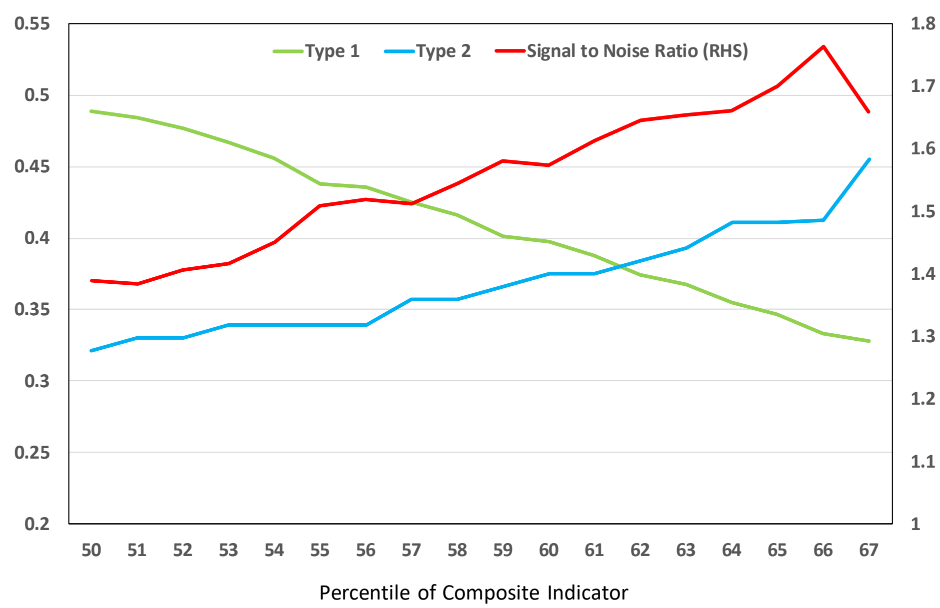
[1]Early Warning System estimated using an unbalanced panel 1970-2006 for the in-sample and 1970-2015 for the full sample.
[2]Number of crises in the period for which data are available on variables used to predict crises.
[3]Number of non-crisis years in the period for which data are available, plus crisis years if 3 or more years from the beginning of a crisis.
[4]Number of countries for which data are available on all variables used to predict crisis.
[5]Type I error, type II error and the signal to noise ratio describe performance over the period of the sample.

The results show that variables linked to domestic economic activity, fiscal policy, and external imbalances matter (Table 5.1). Some of the key indicators are relevant at both one- or two-year lags—suggesting there may be a buildup of vulnerabilities over time. This is the case for the current account deficit, degree of openness, use of central bank credit to finance the deficit, size of the fiscal (overall or primary) deficit and pace of expansion in public expenditures—all these increase the probability of a future crisis. The relevance of the current account deficit as a leading indicator confirms that twin deficits arise before the crises, as shown by the event studies. The 1-year lag approach also suggests a few other indicators could be relevant, including economic

growth, and reserve coverage. A large output gap is an important signal 2-years ahead. Credit gaps also matter (1-year ahead), which likely reflects imbalances in the real economy.[10]

The performance of the composite indicators is similar for both the in sample and out-of-sample forecasts—suggesting our choice of indicators is robust. The models can identify half of the crises (Table A.4.) either one or two years ahead. However, in the out of sample—we estimate the weights for the composite indicator using the data up to 2006 and use it to predict crises in the 2007-15 period—predictive power is somewhat superior for the two-years lag. This reflects a lower proportion of false alarms. We can also see the tradeoff between false alarms and missed crises in Figure 5.1. Our strategy is to maximize the signal to noise ratio, which leads to a lower type 1 error. Trying to get a lower type 2 error would require a large number of false alarms—especially as non-crisis years are by far the most common—undermining the credibility of the early warning system.

Figure 5.1. Signals Composite Indicator: Setting the Cut-off Threshold
Tradeoff between false alarms (type 1 error) and missed crises (type 2 error)



Logit Approach

We now turn to the logit approach. Despite data constraints, the number of crises covered (up to 94 in the full sample) is still relatively large, although smaller than for the signals approach. The

[10] Borio et al. (2013) show that information about the financial cycle and the credit gap, can yield proxy measures of potential output and output gaps that are estimated more precisely and more robustly in real time than those using real GDP data.

focus is primarily on trying to improve the overall performance of the EWS relative to the signal approach. To assess the importance of each explanatory variable, we focus on the average marginal effects, which take into account that the impact of a given variable will depend on the values taken by other variables. We also report the pseudo r-square and the AUROC measure—as well as type 1 and type 2 errors—to assess the fit and predictive power of the models.[11] The type I and II errors are computed based on the early warning signals generated by fitted values exceeding the optimal cutoff fitted value (chosen to minimize the TME). As for the signal approach, we selected the variables based on the in sample (up to 2006) performance of the model, but we also show the results for the full sample.

Table 5.2. Advanced and Emerging Economies Logit Model

	In-Sample			**Full sample**		
Dependent variable: first year of crisis	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
L2. Growth (%)	-0.000785	-0.000864	-0.000871	-0.00133**	-0.00143**	-0.00144**
	(0.236)	(0.212)	(0.236)	(0.017)	(0.014)	(0.012)
L1. Current Account (% of GDP)	-0.00104**	-0.00111**	-0.000838**	-0.00174***	-0.00183***	-0.00171***
	(0.019)	(0.018)	(0.043)	(0.000)	(0.000)	(0.000)
L2. Real Primary Expenditures (%Ch.)	0.000291*	0.000301*	0.000274*	0.000433***	0.000450***	0.000446***
	(0.067)	(0.064)	(0.094)	(0.005)	(0.005)	(0.005)
L1. World GDP growth	-0.00776	-0.00808	-0.00413	-0.00518	-0.00542	-0.00387
	(0.193)	(0.183)	(0.458)	(0.125)	(0.112)	(0.257)
L1. Output gap	0.00345*	0.00380*	0.00298	0.00631***	0.00677***	0.00630***
	(0.085)	(0.078)	(0.116)	(0.000)	(0.000)	(0.001)
L1. Interest expenses (% of revenue)	0.000892**	0.000877**		0.000600*	0.000583*	
	(0.022)	(0.027)		(0.083)	(0.099)	
L3. Credit Gap		0.00000405			0.00000806*	
		(0.416)			(0.077)	
Debt (% of revenue)			0.0000964***			0.0000476*
			(0.002)			(0.071)
Observations	1331	1306	1206	2304	2259	2167
pseudo R sq.	0.04	0.04	0.05	0.05	0.05	0.05
No. crises	56	56	47	94	94	85
Type 1 error (%)	34	33	38	39	41	29
Type 2 error (%)	38	39	28	29	27	36
Threshold prob.(%)	4.3	4.4	3.5	3.9	3.9	4.1
AUROC	0.66	0.66	0.69	0.71	0.71	0.72

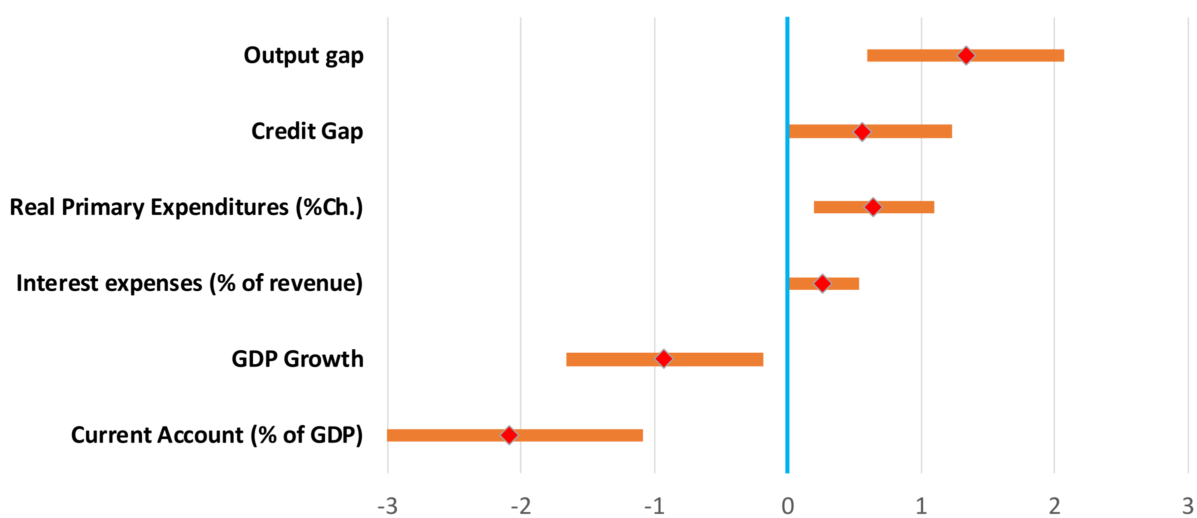
Note: Reported are marginal effects, p-values in parentheses (*p<0.1, **p<0.05,***p<0.01). The dependent variable is binary (1 for the first year of fiscal crisis; 0 otherwise). The type 2 error corresponds to the portion of missed crises and the type 1 error to the portion of false alarms. The sample covers the period 1970-2015. The in-sample is 1970-2006.

[11] The AUROC measure gives the size of the area under the ROC curve, the closer to 1 the better. Note also the pseudo r-square is based on the default STATA version and could have significantly lower values than the typical r-square for OLS even with relatively high predictive power (see Louviere et al., 2000).

The results, by and large, highlight similar leading indicators as the signals approach (Table 5.2). The probability of entering a crisis increases with growing macroeconomic imbalances due to large output gaps and deteriorating external imbalances. The results also indicate a role for fiscal policy, via public expenditures growth. Figure 5.2 shows the marginal effects for the key indicators (scaled by standard deviation). Current account deficits, high output gaps, and declines in growth tend to have the largest impact on the probability of a crisis. All these factors can be interrelated. For example, high expenditure growth could contribute to a deterioration in the current account and a large output gap, making the fiscal position vulnerable to changes in the economic cycle. The models also show some evidence that the degree of indebtedness and cost of debt matters, as the probability of a crisis increases if interest expenses and debt (both as a share of revenue) rise. Finally, the results for the full sample are similar with the variables showing even higher statistical significance. [12]

Figure 5.2. Average Marginal Effects for AMs and EMs

(mean and 95 percent confidence interval)



*Marginal effects are scaled by the sample standard deviation of the explanatory variable. The marginal effects show the percentage point change in the probability of crisis given a one standard deviation change in the explanatory variable, on average across all possible values of other explanatory variables.

The logit model exhibits stronger performance in predicting fiscal crises. This likely reflects higher degrees of freedom: using different lags for different explanatory variables and taking into

[12] We also estimate models with fixed effects as a robustness check. However, under this approach we lose from the sample all countries that never had a crisis during the sample period. This has a large impact on the sample of advanced economies, where crises are rare. The potential loss of crucial information is a reason why fixed effects are usually not used. The results from the fixed effects suggest the same leading indicators with the exception that the level of FX reserves (as share of GDP) also seems to be a relevant indicator, similar to the signals approach.

account the joint impact of all variables. In some of the specifications (Table A.5.), the models can predict around 70 percent of the crises in sample, with the type 1 error (false alarms) around 34-38 percent in the pooled regressions. The predictive power is marginally better for the out of sample forecasts (predicting crises for 2007-15). The model accurately predicts around 75 percent of these crises, with similar type I errors. These results indicate our choice of indicators is robust to different samples.

Comparison with other studies

Our analysis relies on a larger sample of countries and longer time span than most past studies. When comparing results across studies, it is important to note that our models focus on a set of variables that are relevant across a larger number of crises—while other papers can get better fit in-sample for a smaller number of crises. The advantage of the large sample is that it allows us to assess which leading indicators are more robust. In addition, to ensure our results are robust across samples, we only use early warning indicators that we find relevant in the early years (in sample 1970-2006) and then test predictive power on the out of sample period. Several of the past papers used all the information available to select indicators, which prevents a meaningful test of whether their models are robust out of sample. Furthermore, to estimate the output and credit gaps at any point in time, we used the information available at the time. This is particularly relevant for the output gap, as the "real time" output gap can vary significantly from ex-post calculations.

The predictive power in sample of our models is similar to those in past studies, but our results are also robust out of sample. We predict the onset of a crisis in sample with about the same accuracy as in other papers on average (Table A.6). However, our parsimonious approach, based on a relatively small set of variables and the pooled logit, also produces reasonably accurate out of sample forecasts.[13] Importantly, some of the out of sample forecasts generated in past studies are not robust tests as the leading indicators in their EWS are chosen based on information from the entire sample.[14] The type I errors from our EWS tend to be somewhat higher than in other studies with smaller samples. For policymakers, it may be preferable to have a somewhat higher type I error as the cost of missing a crisis is much larger than the cost of a false signal.

Our results confirm more recent research that stresses non-fiscal variables as crucial when assessing vulnerabilities to fiscal crises. Baldacci and others (2011) relied only on fiscal variables. More recent work has moved away from such a limited focus. Namely, the European Commission (EC) EWS (Berti and el., 2012), which uses a large set of both fiscal and macro-financial leading

[13] Fuertes and Kalotychou (2006) had already argued that simple models tend to perform better (in their case a parsimonious logit model) out of sample.

[14] This is the case for all the papers in Table A.6 that had out of sample predictions. In addition, in some cases the out-of-sample period is very short.

indicators.[15] Their approach is European-centered, heavily influenced by the recent crises (post-2007), and demanding on data requirements. Other papers, like us, focus on a smaller set of non-fiscal variables including external current account, and credit and output gaps.[16]

Our analysis also sheds some light on the debate about whether fiscal and debt variables are robust leading indicators.[17] Our results suggest that indeed fiscal variables matter. Strong expenditure growth and financing pressures (e.g., need for central bank financing) can help predict crises. For debt, there is mixed evidence in the literature on whether the size of public debt is a reliable leading indicator. Some past studies found that the size of FX debt and short-term debt can be good predictors for sovereign debt crises. Sumner and Berti (2017) find that the change in public debt may be a useful indicator for a group of European countries. We found evidence that the size and cost of debt appear to be good leading indicators.

B. Low Income Countries

Contrary to advanced and emerging economies, there is no literature on EWS for LICs that we can build on. We analyze a sample of 70 low income countries. We start by testing the same set of variables for advanced and emerging economies and add others that may be more relevant for LICs. For example, LICs rely much less on market financing and much more on international support via grants and concessional loans. The high dependence on aid makes LICs more vulnerable to volatile aid flows—which impact both the external current account and public finances. Other possible factors include commodity prices and the global environment in general.

The Signals Approach

As for AEs and EMs, we estimated the "optimal" threshold for each individual indicator (Appendix Tables A.7–A.8). Again, we did not use some of the best individual indicators to construct the composite indicator due to data limitations—this is particularly the case for gross financing needs.

Global factors and external vulnerabilities appear among the main determinants of fiscal crises, but fiscal variables and credit conditions are also important leading indicators (Table 5.3). For the 1-year lag, the main indicators signaling a crisis are: the current account deficit, deteriorating

[15] The EC uses a set of 25 variables, comprising 12 fiscal variables (including: primary balance, cyclically adjusted balance, level and change in public debt, short-term public debt, gross financing needs, interest – growth rate differential, change in government expenditures), and 13 financial-competitiveness variables (including: yield curve, real GDP growth, GDP per capita, net international investment position, private credit, short-term debt of non-financial corporations and households, value added in construction, current account balance, change in real effective exchange rate, and change in nominal unit labor costs).

[16] For example, Sumner and Berti (2017), Bruns and Poghosyan (2018), and Ciarlone and Trebeschi (2005).

[17] Burns and Poghosyan (2018) find that fiscal balances help predict crises. Others find weak or no evidence that fiscal variables play a role (e.g., Manasse et al., 2003; or the new indicator proposed by Sumner and Berti, 2017).

fiscal balance, falling world GDP per capita growth, and high private credit gap. The role of the credit gap could be indirect—signaling an overheating in the economy that eventually leads to economic deterioration—or direct, if problems in banks eventually require government support. For the 2-years lag approach, the most significant variables were also external, namely rising world food prices, declining terms of trade, and low reserve coverage. The composition and maturity of debt are also among the more relevant indicators, as a higher share of concessional debt (in total external debt) and longer maturity of new external debt reduce the probability of entering a crisis.

Table 5.3. Early Warning System for LICs (all countries): Signals Approach

	1 year ahead	2 years ahead	1 year ahead	2 years ahead
	In-Sample[1]		**Full-Sample**[1]	
Number of Crises[2]	84	115	142	161
Number of Non-Crisis Years[3]	679	916	1167	1268
Number of Countries[4]	40	57	62	61
Type I Error[5]	0.27	0.29	0.27	0.29
Type II Error	0.54	0.54	0.57	0.53
Signal to Noise Ratio	1.69	1.56	1.61	1.63
Variable weights for the composite indicator				
Private Credit (Gap %)	0.17		0.19	
Overall Balance (% Change)	0.36		0.31	
Current Account (% GDP)	0.35		0.28	
World Real GDP per capita (% Change)	0.13		0.22	
Avge. Maturity on New PPG External Debt Disbursements (%, 1st diff.)		0.20		0.19
Concessional Debt (% of PPG External Debt, 1st diff.)		0.03		0.12
Reserve Coverage (months of imports, 1st diff.)		0.17		0.23
World Food Prices (% Change)		0.40		0.23
Terms of Trade (% Change)		0.20		0.23

[1]Early Warning System estimated using an unbalanced panel 1970-2006 for the in-sample and 1970-2015 for the full sample.

[2]Number of crises in the period for which data are available on variables used to predict crises.

[3]Number of non-crisis years in the period for which data are available, plus crisis years if 3 or more years from the beginning of a crisis.

[4]Number of countries for which data are available on all variables used to predict crisis.

[5]Type I error, type II error and the signal to noise ratio describe performance over the period of the sample.

The performance of the composite indicators varies somewhat between the in sample and out-of-sample forecasts.[18] The composite indicator can identify slightly less than half of the crises in sample (Table A.9). The 1-year lag has a higher signal to noise ratio largely reflecting the lower percentage of false alarms. The 2-year lag version can predict crises better out of sample, identifying 55 percent of the crises, but the type I error is higher (false alarms) than for the 1-year lag version. The performance may be different when we analyze separate groups of LICs—we explore this further below.

[18] As before, to obtain the out of sample forecasts, we estimate the weights for the composite indicator using the data up to 2006 and use it to predict crises in the 2007–15 period.

We analyze separately commodity versus diversified exporters (see Appendix I). In principle, these two groups of countries may face very different vulnerabilities. For example, commodity exporters will be more exposed to falls in commodity prices (oil, metals), while the opposite will be true for diversified exporters.

The performance of the composite indicator, for the commodity exporters, is better than for all LICs (Appendix Tables A.10 and A.11). Based on the results in sample, the composite indicator is able to identify around 60-65 percent of the crises. The performance of out-of-sample forecasting is similar, as we can predict 60-70 percent of the crises. In terms of individual leading indicators, the results suggest that external imbalances and fiscal variables are important. Among the external variables are world real growth, the external current account, volatility in foreign aid, FDI (reduces risk of crisis) and world food prices. A large credit gap (to a lesser degree), also provides a significant signal—indicating that the risk of a crisis increases the more the economy is overheating. Fiscal variables matter too, especially large expenditures or a deteriorating primary balance.

The in-sample performance for diversified exporters is only marginally worse, with the model being able to predict close to 60 percent of crises with the 1-year lag. The performance out-of-sample is stronger for the 2-year lags, as the model can predict a larger share of the crises, almost 70 percent, but with a high type I error. External, financial, and fiscal variables matter (Appendix Table A.10). For the 1-year lag, the most significant indicators are the fiscal balance, current account, and oil prices (higher increases risk). For the 2-years lag, the most significant variables were related to domestic imbalances, size of private credit and fast economic growth (relative to average of past 5 years). Other relevant indicators, include composition of the debt (the more multilateral debt the better) and terms of trade.

Logit Approach

The logit-based EWS performs significantly better than the signal approach both in and out of sample. This suggests that the interaction of several indicators is important in trying to predict crises. For the total LICs sample, the models can predict accurately almost 75 percent of the crises in sample (Tables 5.4 and A.12). The type 1 error (false alarms) is around 35-40 percent. The out-of-sample forecasts show a somewhat weaker performance.

Table 5.4. Low Income Countries Logit Model

Dependent variable: first year of crisis	In-sample			Full sample		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
L1. Current Account (% of GDP)	0.000255	0.000226		0.000285	0.000843	
	(0.762)	(0.831)		(0.697)	(0.345)	
L2. Reserve Coverage (months)	-0.00454	-0.00552	-0.00652	-0.00474	-0.00565	-0.00576
	(0.287)	(0.264)	(0.190)	(0.166)	(0.131)	(0.121)
L1. Overall Balance (% of GDP)	0.00244			0.000117		
	(0.239)			(0.925)		
L2. FDI (% of GDP)	-0.00524**	-0.00532**	-0.00518**	-0.00189	-0.00224	-0.00166
	(0.027)	(0.040)	(0.033)	(0.192)	(0.129)	(0.238)
L1. Official aid	-0.000212	-0.000157	-0.000161	-0.000368**	-0.000359*	-0.000353*
	(0.121)	(0.217)	(0.214)	(0.045)	(0.064)	(0.069)
L2. World food prices	0.00399**	0.00526***	0.00495***	0.00299***	0.00379***	0.00345***
	(0.011)	(0.004)	(0.006)	(0.000)	(0.000)	(0.000)
L1. GDP growth (dev.from average)	0.00281	0.00594**	0.00497**	0.00257	0.00458**	0.00413*
	(0.173)	(0.010)	(0.042)	(0.178)	(0.031)	(0.067)
L3. Real Primary Expenditures (%Ch.)		0.000174	0.000145		0.0000333	0.0000669
		(0.428)	(0.440)		(0.805)	(0.630)
L1. Concessional debt (% of GDP)		-0.000162			0.000288	
		(0.615)			(0.236)	
Observations	923	735	744	1424	1208	1226
pseudo R sq.	0.04	0.06	0.05	0.03	0.04	0.04
No. crises	95	77	78	139	121	122
Type 1 error (%)	36	39	36	32	41	34
Type 2 error (%)	40	27	29	48	33	41
Threshold prob.(%)	10.6	10.2	10.5	10.5	9.8	10.5
AUROC	0.64	0.69	0.68	0.62	0.65	0.65

Note: Reported are marginal effects, p-values in parentheses (*p<0.1, **p<0.05,***p<0.01). The dependent variable is binary (1 for the first year of fiscal crisis; 0 otherwise). The type 2 error corresponds to the share of missed crises and the type 1 error to the share of false alarms. The sample covers the period 1970-2015. The In-sample is 1970-2006.

As in the signals approach, external factors do appear to be a key element (Table 5.4). The most significant in helping predict a crisis are increases in global food prices and decline in FDI inflows and, to a lesser degree, declines in official aid and lower reserve coverage.[19] Another robust predictor is whether the economy is growing at a faster pace relative to past years.[20] We find weaker evidence of an impact of traditional fiscal variables, although rising public expenditures do help improve overall predictive power. The fiscal balance, however, does not seem relevant on

[19] The results are similar between the small and large samples, although official aid and reserve coverage are more significant in the larger sample.

[20] Using measures of the output gap as an explanatory variable produced worse results, partly because it is difficult to get robust estimates of output gaps in LICs.

its own. One possibility is that some countries tighten the fiscal balance when encountering budget pressures, but not enough to prevent the start of a crisis. It could also reflect that the budget is heavily affected by changes in external aid in some countries, implying collinearity between aid and fiscal variables.

The results improve when looking at commodity exporters separately. In sample, we can predict accurately almost 80 percent of the crises (Tables A.13–A.14). Importantly, type 1 errors are lower than for the larger sample. The prediction power is weaker out of sample, but the model can still predict up to 67 percent of the crises. The most significant variables are external, although indicators on domestic activity also matter. Reserve coverage, external aid, global food prices, and "overheating" are important in predicting crises. Somewhat surprisingly, commodity prices do not seem relevant.[21] This could be because their impact is felt via other activities—namely, commodity booms may lead to overheating in the domestic economy, which is a strong signal of a crisis. In addition, many of these commodity exporters are poor and heavily dependent on foreign aid. Fiscal vulnerabilities are high in LICs where domestic revenue mobilization has not kept pace with rising public spending. These countries have relatively small revenue bases, which limits their ability to increase tax collections in the short run to offset declines in aid flows.

The results for the diversified exporters show important differences to the commodity exporters (Tables A.15–A.16). Some external factors remain important, namely global food prices, but external aid is no longer significant. The in-sample performance of the pooled logit approach is mixed compared to the total LICs sample. It can predict more crises, close to 80 percent, but with a larger frequency of false alarms. The prediction power is similar out of sample.

VI. Conclusion

Our analysis identifies robust indicators of vulnerabilities that can help signal a high probability of the onset of a crisis in the near future. Building early warning indicators that help predict future fiscal crises is inherently difficult, including because countries may take mitigating action as they see the growing vulnerabilities. However, we find that some types of vulnerabilities are consistently relevant to explain fiscal crises. This raises the question why governments do not act as they see signals. In large measure they do, as crises among advanced economies are rare. Still, the occurrence of crises may reflect overly optimistic projections about the future (e.g., economic growth, cost of debt), and as such governments underestimate the risks and fail to take mitigating measures. Another possibility could be that other shocks or crisis (e.g., banking) could lead to fiscal pressures.[22]

[21] When they become statistically significant, an increase in oil prices increases the probability of a crises. This could reflect that several of these exporters are mainly metal exporters.

[22] Gerling and others (2017) note that a significant share of fiscal crises overlap with either a banking or currency crisis in AMs and EMs. Laeven and Valencia (2012) find that the fiscal cost of banking crises net of recoveries averages 13⅓ percent of GDP.

Our results show that a relatively small set of robust leading indicators can help assess the probability of a fiscal crisis in advanced and emerging markets with high accuracy. Past studies focused on small samples, which can bias the results towards a specific crisis or type of country (e.g., European countries). Using a larger sample, we find that both fiscal and non-fiscal variables send robust signals that a crisis is probable in the next 1-2 years. Domestic imbalances (large output or credit gaps), external imbalances, and rising public expenditures increase the probability of a crisis. Encouragingly, the performance of the EWS is robust to testing out of sample. The models could have predicted 75 percent of the crises in the years around the global financial crises (2007-15).

There are also important differences in the early warning indicators between LICs and other economies. While some vulnerabilities are common, LICs face unique challenges that need to be considered to monitor effectively for signals of future crises. First, global variables are an important factor. LICs are vulnerable to changes in global economic growth and food prices. In addition, deterioration in official aid or FDI, and low FX reserve coverage also help predict future crises. Second, crises tend to be preceded by overheating of the domestic economy. When growth is significantly larger than the average in previous years, a fiscal crisis tends to follow the next year (as growth falls). Finally, the evidence also indicates fiscal and debt-related indicators matter. In particular, high expenditure growth and less concessional debt structure do provide some signal on the risk of a future crisis. The predictive power of the models tends to be similar as for advanced and emerging markets. For all LICs, we can predict about 75 percent of the crises in sample. The prediction power is somewhat higher when analyzing separately commodity and diversified exporters.

The analysis highlights that countries can reduce the frequency of fiscal crises by adopting prudent policies and strengthening risk management. Fiscal crises are more likely when economies build domestic and external imbalances. This calls for avoiding excessively loose polices when domestic growth is above average. For fiscal policy, this means avoiding pro-cyclical increases in expenditures that would need to be sharply reversed when the cycle turns. The analysis also points towards building buffers to protect from external shocks. For LICs, the results suggest even bigger challenges. The crises are much more frequent and the leading indicators reflect structural vulnerabilities that will take time to address. For example, the dependence on foreign aid will require continued efforts to enhance own sources of domestic revenue.

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APPENDIX I. DATA

We use data for 188 countries for the period 1970-2015. Countries are split into groups of advanced and emerging economies (AEs and EMs, 118) and low-income countries (LICs, 70). For analytical purposes, we also divide LICs into two groups: commodity exporters (28), and diversified exporters (42). There are, however, large differences in data availability among variables.

We use the database of fiscal crises and their duration developed by Gerling et al. (2017). The rest of the variables mostly come from the IMF World Economic Outlook (WEO) database. We also use BIS Securities Data, OECD Quarterly Debt Statistics, and Baldacci (2011) data to expand the general government short-term debt time series.

Financial data (credit to the private sector, central bank claims on the government) are from IMF International Financial Statistics (IFS).

We use the World Bank WDI database for the following variables: concessional debt; external debt stock-public and publicly guaranteed; interest payments on external debt - public and publicly guaranteed; average maturity on new external debt; and average interest on new external debt. The database however does not cover AEs for those variables. We used the same database for remittances and net official development assistance and official aid.

For advanced economies and emerging markets, the output gap was derived as deviation of real GDP from its trend, using HP filter. However, to avoid biasing the results we use a measure of the real-time output gap based on the IMF's World Economic Outlook vintages (given output gaps based on all data will already incorporate information on future crises). That is, the output gap estimated at any given year is based on the information known at that time. For low-income countries we use deviation of real GDP growth from the average growth in the previous five years.

The credit gap is defined as the difference between the ratio of total credit relative to GDP, and its long-run statistical trend derived using the HP filter. We use a one-sided filtering approach, based only on data available up to the relevant time period, analogous to when forecasting in real time.

Table A.1. Sample Countries

AEs and EMs (118)				LICs (70)	
Albania	Estonia	Mongolia	Syria	Afghanistan	Maldives
Algeria	Fiji	Montenegro	Thailand	Bangladesh	Mali
Angola	Finland	Morocco	Trinidad & Tobago	Benin	Marshall Islands, Rep.
Antigua & Barbuda	France	Namibia	Tunisia	Bhutan	Mauritania
Argentina	Gabon	Netherlands	Turkey	Burkina Faso	Micronesia
Armenia	Georgia	New Zealand	Turkmenistan	Burundi	Moldova
Australia	Germany	Nigeria	U.A.E.	C.A.R.	Mozambique
Austria	Greece	Norway	Ukraine	Cambodia	Myanmar
Azerbaijan	Guatemala	Oman	United Kingdom	Cameroon	Nepal
Bahamas, The	Hungary	Pakistan	United States	Cape Verde	Nicaragua
Bahrain	Iceland	Palau	Uruguay	Chad	Niger
Barbados	India	Panama	Venezuela	Comoros	Papua New Guinea
Belarus	Indonesia	Paraguay	Vietnam	Congo, Dem. Rep. of	Rwanda
Belgium	Iran	Peru		Congo, Republic of	Samoa
Belize	Iraq	Philippines		Cote D'Ivoire	Senegal
Bolivia	Ireland	Poland		Djibouti	Sierra Leone
Bosnia & Herzegovina	Israel	Portugal		Dominica	Solomon Islands
Botswana	Italy	Qatar		Eritrea	Somalia
Brazil	Jamaica	Romania		Ethiopia	South Sudan
Brunei Darussalam	Japan	Russian Federation		Gambia, The	St. Lucia
Bulgaria	Jordan	San Marino		Ghana	St. Vincent & the Grenadines
Canada	Kazakhstan	Saudi Arabia		Grenada	Sudan
Chile	Korea, Rep. of	Serbia		Guinea	São Tomé& Príncipe
China, Mainland	Kosovo	Seychelles		Guinea-Bissau	Tajikistan
Colombia	Kuwait	Singapore		Guyana	Tanzania
Costa Rica	Latvia	Slovak Republic		Haiti	Timor Leste
Croatia	Lebanon	Slovenia		Honduras	Togo
Cyprus	Libya	South Africa		Kenya	Tonga
Czech Republic	Lithuania	Spain		Kiribati	Tuvalu
Denmark	Luxembourg	Sri Lanka		Kyrgyz Republic	Uganda
Dominican Republic	Macedonia, FYR	St. Kitts and Nevis		Laos	Uzbekistan
Ecuador	Malaysia	Suriname		Lesotho	Vanuatu
Egypt	Malta	Swaziland		Liberia	Yemen
El Salvador	Mauritius	Sweden		Madagascar	Zambia
Equatorial Guinea	Mexico	Switzerland		Malawi	Zimbabwe

Source: AMs are defined by the IMF WEO, LICs are defined by the PRGT-eligible IMF members adding Zimbabwe.

Table. A.2. (1970-2015). Leading Indicators (1 Lag); Advanced and Emerging Economies

Indicator	SNR	Signaling Power	Better: Higher (H) or Lower (L)	Threshold Percentile	Error		No. of Obs.	
					Type 1	Type 2	Crises	Non-Crises
1970-2006 Sample								
Macro								
Real GDP per capita (percentage change)	1.15	0.07	H	45	0.46	0.48	145	3178
Private credit								
share of GDP	1.29	0.09	L	65	0.33	0.58	112	2718
gap (one sided)	1.13	0.06	L	51	0.47	0.47	102	2208
gap (ex post)	1.43	0.15	L	63	0.34	0.51	112	2589
Fiscal								
Overall balance (share of GDP)	1.33	0.15	H	46	0.47	0.38	79	1814
Primary balance (share of GDP, 1st difference)	1.35	0.17	H	48	0.49	0.33	57	1266
Gross financing need								
based on GG short-term debt (share of GDP, 1st difference)	3.32	0.70	L	65	0.30	0.00	2	113
Expenditures (share of GDP, 1st difference)	1.27	0.09	L	65	0.32	0.59	90	1904
Wage Bill (share of revenue)	1.42	0.14	L	62	0.34	0.52	21	675
Interest (share of revenue)	0.92	-0.04	L	53	0.44	0.60	70	1596
Central bank claims on the government (share of GDP)	1.35	0.11	L	65	0.32	0.57	118	2403
Public debt								
Gross debt								
share of GDP	1.68	0.21	L	65	0.31	0.47	36	1318
share of revenue	1.53	0.17	L	65	0.31	0.52	29	1093
IRGD (nominal terms)	1.71	0.22	L	65	0.31	0.47	30	1095
Short-term debt (share of total debt, 1st difference)	1.36	0.13	L	51	0.37	0.50	4	174
FX-denominated debt (share of total debt, 1st difference)	1.55	0.16	L	65	0.29	0.55	11	701
External PPG debt								
Concessional debt (share of total PPG, first difference)	1.29	0.11	H	38	0.39	0.50	86	1173
Interest on new debt (1st difference)	1.29	0.13	L	51	0.44	0.43	90	1159
External								
Current account balance (share of GDP)	1.43	0.16	H	38	0.38	0.45	150	3191
Nominal exchange rate (pch)	1.27	0.09	L	61	0.33	0.58	156	3262
Reserves (percentage change)	1.40	0.15	H	37	0.38	0.47	126	2718
Openness (level)	1.16	0.07	H	42	0.42	0.51	148	3217
Remittances (share of GDP)	1.28	0.13	H	46	0.47	0.40	89	1799
Foreign Direct Investment (percentage change)	1.20	0.08	H	37	0.38	0.55	110	2385
World								
World real GDP per capita (percentage change)	1.30	0.10	H	35	0.35	0.55	148	3143
Commodity prices (level)	1.36	0.14	L	55	0.38	0.48	56	1352
1970-2015 Sample								
Macro								
Real GDP per capita (percentage change)	1.14	0.06	H	44	0.44	0.50	179	4085
Private credit								
share of GDP	1.38	0.13	L	64	0.34	0.53	145	3545
gap (one sided)	1.15	0.05	L	65	0.33	0.62	137	3108
gap (ex post)	1.34	0.11	L	65	0.33	0.56	149	3499
Fiscal								
Overall balance (share of GDP, 1st difference)	1.22	0.09	H	39	0.40	0.52	116	2716
Primary balance (share of GDP, 1st difference)	1.25	0.12	H	47	0.48	0.40	100	2285
Gross financing need								
based on GG short-term debt (share of GDP, 1st difference)	1.28	0.09	L	65	0.31	0.60	25	802
Expenditures (share of GDP, 1st difference)	1.37	0.12	L	65	0.33	0.55	127	2911
Wage Bill (share of GDP, 1st difference)	1.65	0.20	L	65	0.31	0.48	58	1516
Interest (share of revenue)	0.90	-0.04	L	61	0.37	0.67	112	2560
Central bank claims on the government (share of GDP, 1st differen	1.36	0.15	L	51	0.42	0.42	144	3204
Net overseas development assistance (share of GDP)	1.27	0.10	H	36	0.36	0.54	157	2730
Public debt								
Gross debt								
share of GDP (1st difference)	1.32	0.11	L	62	0.35	0.54	78	2215
share of revenue	1.14	0.07	L	51	0.46	0.47	72	2159
IRGD (nominal terms)	1.18	0.06	L	64	0.33	0.61	76	2145
Short-term debt (share of total debt, 1st difference)	1.53	0.19	L	58	0.36	0.45	20	841
Debt held by nonresident creditors (share of total debt, 1st differe	1.58	0.18	L	65	0.32	0.50	4	234
External PPG debt								
Concessional debt (share of total PPG, first difference)	1.30	0.13	H	44	0.45	0.42	109	1606
Interest on new debt (1st difference)	1.20	0.09	L	51	0.45	0.46	115	1601
External								
Current account balance (share of GDP)	1.51	0.21	H	42	0.42	0.37	182	4050
Nominal exchange rate (pch)	1.18	0.05	L	65	0.29	0.65	196	4169
Reserves (percentage change)	1.30	0.11	H	35	0.35	0.54	163	3596
Openness (1st difference)	1.17	0.06	H	35	0.35	0.59	191	4048
Remittances (share of GDP)	1.17	0.08	H	48	0.48	0.43	120	2644
Foreign Direct Investment (percentage change)	1.25	0.09	H	36	0.36	0.55	151	3339
World								
World real GDP per capita (percentage change)	1.30	0.10	H	35	0.35	0.55	184	4240
Commodity prices (percentage change)	1.23	0.09	L	56	0.40	0.51	87	2145

Source: Authors' calculations.

Note: The type 2 error corresponds to the portion of missed crises (i.e. false negative or p(no signal of a crisis|crisis=1)) and the type 1 error to the portion of false alarms (i.e. false positive or p(signal of a crisis|crisis=0)). The signal-to-noise ratio (SNR) is calaculated as (1-type 2 error)/(type 1 error), and the signaling power as 1-(type 1 error+type 2 error).

Table. A.3. (1970-2015): Leading Indicators (2 Lags); Advanced and Emerging Economies

Indicator	SNR	Signaling Power	Better: Higher (H) or Lower (L)	Threshold Percentile	Error		No. of Obs.	
					Type 1	Type 2	Crises	Non-Crises
1970-2006 Sample								
Macro								
Output gap real time (share of potential GDP)	1.19	0.08	L	51	0.435	0.483	58	1177
Private credit								
share of GDP	1.38	0.12	L	65	0.327	0.550	120	2588
gap (one sided)	1.11	0.05	L	51	0.467	0.480	102	2093
gap (ex post)	1.21	0.07	L	65	0.329	0.602	118	2479
Fiscal								
Overall balance (share of GDP, first difference)	1.30	0.11	H	35	0.358	0.532	77	1588
Primary balance (share of GDP, 1st difference)	1.35	0.14	H	37	0.385	0.480	50	1167
Gross financing need								
based on GG amortization (share of GDP)	1.92	0.32	L	63	0.347	0.333	3	475
Expenditures (percentage change)	1.49	0.22	L	51	0.458	0.319	91	1844
Wage Bill (share of GDP)	1.61	0.20	L	64	0.325	0.476	21	582
Interest (share of revenue)	0.84	-0.05	L	64	0.325	0.726	62	1424
Central bank claims on the government (share of GDP, 1st differen	1.44	0.14	L	65	0.310	0.555	110	2143
Public debt								
Gross debt (percentage change)	1.40	0.13	L	64	0.328	0.542	24	1027
Short-term debt (share of total debt, 1st difference)	1.97	0.25	L	65	0.254	0.500	4	114
External PPG debt								
Concessional debt (share of total PPG, first difference)	1.42	0.18	H	43	0.434	0.381	84	1098
Maturity of new debt (1st difference)	1.17	0.08	H	41	0.436	0.488	84	1090
Interest on new debt (1st difference)	1.22	0.09	L	54	0.405	0.506	85	1118
External								
Terms of trade (level)	1.17	0.09	H	49	0.492	0.423	142	3076
Current account balance (share of GDP, 1st difference)	1.27	0.11	H	41	0.413	0.475	141	3036
Reserves (percentage change)	1.20	0.09	H	47	0.482	0.424	125	2601
Openness (1st difference)	1.26	0.09	H	35	0.353	0.556	151	3070
Remittances (share of GDP)	1.30	0.14	H	46	0.467	0.391	87	1675
World								
World food price (percentage change)	1.20	0.07	L	59	0.380	0.546	119	2231
Commodity prices (level)	1.23	0.10	L	51	0.416	0.489	45	1225
1970-2015 Sample								
Macro								
Output gap real time (share of potential GDP)	1.23	0.08	L	62	0.345	0.576	92	2100
Private credit								
share of GDP	1.31	0.12	L	58	0.399	0.477	155	3447
gap (one sided)	1.13	0.04	L	65	0.329	0.627	142	3000
gap (ex post)	1.17	0.06	L	65	0.331	0.613	155	3395
Fiscal								
Overall balance (share of GDP, first difference)	1.21	0.10	H	45	0.455	0.448	116	2565
Primary balance								
Primary balance (share of GDP, 1st difference)	1.18	0.08	H	42	0.432	0.489	94	2173
Gross financing need								
based on GG amortization (share of GDP, 1st difference)	1.42	0.18	L	54	0.436	0.381	21	904
Expenditures (percentage change)	1.50	0.18	L	61	0.363	0.453	128	2823
Wage Bill (share of GDP)	1.39	0.14	L	61	0.361	0.500	60	1564
Interest (share of revenue)	0.92	-0.04	L	51	0.461	0.574	108	2470
Central bank claims on the government (share of GDP, 1st differen	1.31	0.10	L	62	0.330	0.569	144	3083
Public debt								
Short-term debt (share of total debt, 1st difference)	1.60	0.20	L	61	0.328	0.476	21	765
Debt held by nonresident creditors (share of total debt)	1.59	0.19	L	65	0.314	0.500	4	226
FX-denominated debt								
share of total debt (1st difference)	1.19	0.08	L	51	0.421	0.500	50	1476
External PPG debt								
Concessional debt (share of total PPG, first difference)	1.35	0.13	H	37	0.374	0.495	107	1561
Maturity of new debt (1st difference)	1.18	0.07	H	38	0.404	0.523	107	1573
Interest on new debt (1st difference)	1.30	0.09	L	65	0.314	0.591	110	1563
External								
Current account balance (share of GDP)	1.34	0.14	H	39	0.393	0.472	180	3951
Reserves (percentage change)	1.17	0.06	H	36	0.367	0.572	159	3503
Openness (level)	1.18	0.09	H	49	0.490	0.423	182	4001
Remittances (share of GDP)								
World								
World food price (percentage change)	1.26	0.11	L	56	0.414	0.479	144	3066
Commodity prices (percentage change)	1.47	0.17	L	59	0.365	0.464	84	2034

Source: Authors' calculations.

Note: The type 2 error corresponds to the portion of missed crises (i.e. false negative or p(no signal of a crisis|crisis=1)) and the type 1 error to the portion of false alarms (i.e. false positive or p(signal of a crisis|crisis=0)). The signal-to-noise ratio (SNR) is calaculated as (1-type 2 error)/(type 1 error), and the signaling power as 1-(type 1 error+type 2 error).

Table A.4. Early Warning System for AE and EMs: Signals Approach

	One year ahead[1]		Two years ahead	
	In Sample 1970-2006	Out of Sample 2007-2015	In Sample 1970-2006	Out of Sample 2007-2015
Number of Crises[2]	70	19	43	20
Number of Non-Crisis Years	1330	528	824	524
Number of Countries	69	69	69	69
Type I Error[3]	0.34	0.30	0.31	0.22
Type II Error	0.44	0.53	0.49	0.55
Signal to Noise Ratio	1.65	1.60	1.65	2.05

[1] In sample statistics are based on the sample period 1970-2006. Out of sample performance is based on projections made over the period 2007-2015 using the early warning system estimated using data up until 2006.

[2] The number of crises, non-crisis years and number of countries are calculated over 1970-2006 and 2007-2015 respectively.

[3]Type I error, type II error and the signal to noise ratio describe performance in sample (1970-2006) and predictive performance over (2007-2015) respectively.

Table A.5. Pooled Logit. Advanced and Emerging Economies

	In sample (1970-2006)			Out of sample (2007-2015)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Observations	1331	1306	1206	1331	1306	1206
pseudo R sq.	0.04	0.04	0.05	0.04	0.04	0.05
No. crises	56	56	47	38	38	38
Type 1 error (%)	34	33	38	41	40	29
Type 2 error (%)	38	39	28	24	24	42
Threshold prob.(%)	4.3	4.4	3.5	3.4	3.5	3.6
AUROC	0.66	0.66	0.69	0.66	0.66	0.69

Note: The type 2 error corresponds to the share of missed crises and the type 1 error to the share of false alarms. The in sample covers the period 1970-2006. Out of sample refers to projections for 2007-2015.

Table A.6. Predictive Performance

	Signal model	Logit model	Bruns and Poghosyan (2016) 1/	Sumner and Berti (2017) 1/2/	Berti et al. (2012) 1/	Ciarlone and Trebeschi (2005)	Manasse et al. (2003) 3/	Dawood et al. (2017)
In sample:								
crisis starts correctly predicted (%)	56	72	78	69-85	77	76	74	54
False alarms (%)	34	38	31	14-16	20	36	7	9
Out of sample:								
Crisis starts correctly predicted	45	68-76	78			80	45	
False alarms (%)	22	33-41	34			20	6	
Number of countries	116 AE and EMs	116 AE and EMs	81 AE and EMs	28 EU countries	33 EU and other AEs	28 EMs	37 EMs	

1/Does not present results for in-sample. Results shown are for all the sample.
2/Results for Logit models.
3/ Results for Logit-based model. The results based on tree-analysis were better for in-sample, but did not present out of sample forecasts.

Table A.7. Leading Indicators of Fiscal Crises (1 Lag); Low Income Countries

Indicator	SNR	Signaling Power	Better: Higher (H) or Lower (L)	Threshold Percentile	Error Type 1	Error Type 2	No. of Obs. Crises	No. of Obs. Non-Crises
1970-2006 Sample								
Macro								
Growth (deviation from 5 year rolling average (percentage points))	1.09	0.03	L	61	0.363	0.604	139	1456
Private credit gap (one sided)	1.13	0.06	L	51	0.461	0.479	117	1099
Private credit gap (ex post)	1.21	0.07	L	65	0.327	0.604	134	1283
Fiscal								
Overall balance (percentage change)	1.36	0.13	H	36	0.360	0.511	92	876
Gross financing need (based on GG short-term external debt)								
share of GDP (1st difference)	1.41	0.13	L	65	0.318	0.550	60	641
Expenditures (real primary growth)	1.28	0.12	L	53	0.430	0.451	71	630
Wage bill (share of revenue)	1.42	0.15	L	59	0.363	0.484	31	369
Central bank claims on govt. (share of GDP (1st difference))	1.12	0.04	L	65	0.329	0.633	120	1132
Net overseas development assistance (share of GDP)	1.14	0.07	H	47	0.471	0.462	156	1669
Public debt								
Gross debt (percentage change)	1.24	0.07	L	65	0.294	0.636	22	211
Interest payments (share of revenue)	1.13	0.06	L	51	0.459	0.481	79	809
IRGD (real terms)	1.26	0.08	L	64	0.310	0.609	23	203
FX-denominated debt (share of total debt (1st difference))	1.69	0.26	L	51	0.381	0.357	14	113
External PPG Multilateral debt (share of total PPG debt, 1st difference)	1.18	0.07	H	41	0.412	0.514	146	1390
Current account (share of GDP)	1.33	0.13	H	38	0.379	0.494	160	1716
Openness (1st difference)	1.15	0.07	H	49	0.487	0.442	156	1647
Remittances (share of GDP (1st difference))	1.30	0.11	H	37	0.376	0.512	86	789
Foreign Direct Investment (share of GDP)	1.10	0.06	H	47	0.664	0.273	154	1732
World								
World real GDP per capita (percentage change)	1.13	0.05	H	35	0.353	0.601	158	1747
World food price index (percentage change)	1.05	0.02	L	65	0.328	0.655	116	1279
Crude oil price (percentage change)	1.40	0.13	L	65	0.324	0.545	165	1922
Commodity prices (percentage change)	1.44	0.12	L	64	0.273	0.608	51	502
Non-Fuel Commodity prices (percentage change)	1.13	0.04	L	64	0.330	0.627	118	1241
Metals prices (percentage change)	1.07	0.03	L	53	0.437	0.532	124	1317
1970-2015 Sample								
Macro								
Growth (deviation from 5 year rolling average (percentage points))	1.15	0.05	L	64	0.34	0.61	182	1905
Private credit gap (one sided)	1.17	0.06	L	62	0.36	0.58	160	1517
Private credit gap (ex post)	1.29	0.11	L	58	0.39	0.49	179	1711
Fiscal								
Overall balance (percentage change)	1.29	0.10	H	35	0.35	0.55	152	1465
Gross financing need (based on GG short-term external debt)								
share of GDP (1st difference)	1.25	0.08	L	65	0.32	0.60	106	1089
Expenditures (share of GDP)	1.09	0.03	L	61	0.37	0.60	147	1554
Wage bill (share of GDP)	1.31	0.10	L	65	0.31	0.59	93	887
Central bank claims on govt. (share of GDP (1st difference))	1.19	0.07	L	62	0.36	0.58	163	1567
Net overseas development assistance (share of GDP (1st difference))	1.20	0.07	H	36	0.36	0.57	203	2025
Public debt								
Gross debt (percentage change)	1.09	0.03	L	64	0.33	0.64	87	807
Interest payments (share of revenue)	1.10	0.03	L	61	0.36	0.60	133	1292
IRGD nominal terms	1.16	0.06	L	61	0.35	0.59	80	761
External PPG debt								
Maturity of new debt (1st difference)	1.11	0.04	H	36	0.39	0.56	189	1767
Interest on new debt (1st difference)	1.06	0.02	L	58	0.39	0.59	184	1786
Multilateral debt (share of total PPG debt, 1st difference)	1.17	0.06	H	38	0.38	0.55	193	1821
External								
Current account balance (share of GDP)	1.23	0.09	H	38	0.38	0.53	201	2169
Reserve coverage (months of prospective imports)	1.10	0.05	H	46	0.46	0.49	189	1864
Openness (1st difference)	1.11	0.04	H	36	0.36	0.60	197	2125
Remittances (share of GDP)	1.12	0.05	H	39	0.39	0.56	131	1238
Foreign Direct Investment (share of GDP)	1.15	0.07	H	37	0.45	0.48	195	2207
World								
World real GDP per capita (percentage change)	1.15	0.07	H	48	0.47	0.45	196	2278
World food price index (percentage change)	1.10	0.03	L	65	0.33	0.64	146	1722
Crude oil price (percentage change)	1.29	0.10	L	65	0.33	0.57	211	2432
Commodity prices (percentage change)	1.15	0.05	L	62	0.35	0.60	105	1145
Non-Fuel Commodity prices (percentage change)	1.15	0.05	L	65	0.33	0.62	163	1720
Metals prices (percentage change)	1.07	0.03	L	52	0.46	0.51	167	1758

Source: Authors' calculations.

Note: The type 2 error corresponds to the portion of missed crises (i.e. false negative or p(no signal of a crisis|crisis=1)) and the type 1 error to the portion of false alarms (i.e. false positive or p(signal of a crisis|crisis=0)). The signal-to-noise ratio (SNR) is calaculated as (1-type 2 error)/(type 1 error), the noise-to signal ratio (NSR) as 1/SNR, and the signaling power as 1-(type 1 error+type 2 error).

Table. A.8. Leading Indicators of Fiscal Crises (2 Lags); LIC Countries

Indicator	SNR	Signaling Power	Better: Higher (H) or Lower (L)	Threshold Percentile	Error		No. of Obs.	
					Type 1	Type 2	Crises	Non-Crises
1970-2006 Sample								
Macro								
Growth (deviation from 5 year rolling average (percentage points))	1.21	0.07	L	64	0.334	0.597	134	1400
Private credit gap (one side)	1.00	0.00	L	51	0.467	0.535	114	1048
Private credit gap (ex post)	1.12	0.05	L	51	0.465	0.481	133	1219
Fiscal								
Overall balance (share of GDP (1st difference))	1.10	0.04	H	35	0.363	0.600	90	804
Gross financing need (based on GG short-term external debt)								
share of GDP	1.17	0.06	L	60	0.375	0.561	66	648
Expenditures (share of GDP (1st difference))	1.03	0.01	L	51	0.455	0.531	96	904
Wage bill (share of GDP)	1.23	0.09	L	58	0.379	0.533	30	338
Central bank claims on govt. (share of GDP (1st difference))	1.02	0.01	L	51	0.462	0.529	119	1094
Net overseas development assistance (share of GDP (1st differenc	1.03	0.01	H	38	0.388	0.600	150	1507
Public debt								
Gross debt (share of revenue)	1.42	0.18	L	51	0.422	0.400	20	192
Interest Payments (share of revenue)	1.09	0.04	L	51	0.457	0.500	78	755
IRGD (real terms)	1.40	0.12	L	64	0.301	0.579	19	156
FX-denominated debt (share of total debt)	1.20	0.06	L	59	0.295	0.647	17	129
External PPG debt								
Concessional debt (share of total PPG, first difference)	1.02	0.01	H	43	0.445	0.548	135	1355
Maturity of new debt (1st difference)	1.11	0.05	H	47	0.497	0.449	138	1306
Interest on new debt (1st difference)	1.21	0.07	L	63	0.335	0.594	138	1305
Multilateral debt (share of total PPG debt, 1st difference)	1.17	0.07	H	40	0.403	0.529	138	1339
External								
Terms of trade (percentage change)	1.12	0.05	H	45	0.454	0.493	150	1603
Current account balance (share of GDP)	1.06	0.03	H	49	0.491	0.477	155	1667
Reserve coverage (months of prospective imports)	1.08	0.03	H	38	0.384	0.585	147	1380
Openness (1st difference)	1.02	0.01	H	47	0.475	0.514	148	1605
Remittances (share of GDP (1st difference))	1.08	0.04	H	43	0.445	0.518	83	751
Foreign Direct Investment (share of GDP)	1.07	0.05	H	45	0.650	0.303	152	1685
World								
World real GDP per capita (percentage change)	1.21	0.07	H	35	0.354	0.573	150	1680
World food price index (percentage change)	1.23	0.11	L	51	0.459	0.436	117	1222
Crude oil price (percentage change)	1.06	0.02	L	65	0.332	0.648	162	1864
Non-Fuel Commodity prices (percentage change)	1.20	0.09	L	53	0.424	0.490	98	1200
Metals prices (percentage change)								
1970-2015 Sample								
Macro								
Growth (deviation from 5 year rolling average (percentage points))	1.14	0.05	L	65	0.33	0.62	177	1852
Private credit								
share of GDP	1.31	0.10	L	65	0.32	0.57	167	1696
gap (one sided)	1.05	0.03	L	51	0.47	0.50	153	1461
gap (ex post)	1.07	0.03	L	53	0.45	0.52	179	1663
Fiscal								
Overall balance (share of GDP (1st difference))	1.14	0.06	H	41	0.41	0.53	138	1316
Gross financing need (based on GG short-term external debt)								
share of GDP	1.17	0.06	L	64	0.33	0.61	115	1083
Expenditures (real primary growth)	1.19	0.07	L	61	0.36	0.57	119	1070
Wage bill (share of GDP)	1.08	0.03	L	55	0.42	0.55	88	819
Central bank claims on govt. (share of GDP)	1.13	0.06	L	51	0.47	0.47	167	1578
Net overseas development assistance (share of GDP (1st differenc	1.10	0.04	H	35	0.35	0.61	198	1966
Public debt								
Gross debt (share of revenue)	1.35	0.12	L	61	0.35	0.53	87	806
Interest Payments (share of revenue)	1.10	0.05	L	53	0.45	0.51	128	1212
FX-denominated debt (share of total debt (1st difference))	1.28	0.11	L	55	0.39	0.50	44	411
External PPG debt								
Concessional debt (share of total PPG, first difference)	1.07	0.03	H	46	0.47	0.50	182	1792
Maturity of new debt (1st difference)	1.12	0.05	H	43	0.47	0.48	181	1726
Interest on new debt (1st difference)	1.16	0.06	L	55	0.41	0.53	179	1737
Multilateral debt (share of total PPG debt, 1st difference)	1.13	0.05	H	38	0.39	0.56	183	1776
External								
Terms of trade (percentage change)	1.17	0.06	H	38	0.38	0.56	194	1988
Current account balance (share of GDP)	1.01	0.01	H	45	0.45	0.54	198	2120
Reserves (coverage, 1st difference)	1.16	0.07	H	41	0.41	0.52	180	1736
Openness (1st difference)	1.02	0.01	H	43	0.44	0.55	190	2071
Remittances (share of GDP (1st difference))	1.09	0.04	H	46	0.46	0.49	116	1117
Foreign Direct Investment (share of GDP)	1.09	0.04	H	37	0.46	0.50	193	2156
World								
World real GDP per capita (percentage change)	1.16	0.05	H	35	0.35	0.60	201	2224
World food price index (percentage change)	1.19	0.07	L	63	0.34	0.59	147	1660
Crude oil price (percentage change)	1.22	0.08	L	62	0.36	0.56	208	2370
Non-Fuel Commodity prices (percentage change)	1.53	0.17	L	65	0.32	0.51	161	1679
Metals prices (percentage change)	1.38	0.12	L	65	0.32	0.55	159	1702

Source: Authors' calculations.

Note: The type 2 error corresponds to the portion of missed crises (i.e. false negative or p(no signal of a crisis|crisis=1)) and the type 1 error to the portion of false alarms (i.e. false positive or p(signal of a crisis|crisis=0)). The signal-to-noise ratio (SNR) is calaculated as (1-type 2 error)/(type 1 error), the noise-to signal ratio (NSR) as 1/SNR, and the signaling power as 1-(type 1 error+type 2 error).

Table A.9. Early Warning System for LICs (all countries): Signals Approach

	One year ahead[1]		Two years ahead	
	In Sample 1970-2006	Out of Sample 2007-2015	In Sample 1970-2006	Out of Sample 2007-2015
Number of Crises[2]	84	28	115	38
Number of Non-Crisis Years	679	243	916	315
Number of Countries	40	39	57	57
Type I Error[3]	0.27	0.32	0.29	0.38
Type II Error	0.54	0.50	0.54	0.45
Signal to Noise Ratio	1.70	1.56	1.59	1.45

[1] In sample statistics are based on the sample period 1970-2006. Out of sample performance is based on projections made over the period 2007-2015 using the early warning system estimated using data up until 2006.

[2] The number of crises, non-crisis years and number of countries are calculated over 1970-2006 and 2007-2015 respectively.

[3]Type I error, type II error and the signal to noise ratio describe performance in sample (1970-2006) and predictive performance over (2007-2015) respectively.

Table A.10. Early Warning System for LICs (commodity and diversified exporters): Signals Approach

	Commodity Exporters		*Diversified Exporters*		*Commodity Exporters*		*Diversified Exporters*	
	1 year ahead	2 years ahead	1 year ahead	2 years ahead	1 year ahead	2 years ahead	1 year ahead	2 years ahead
	In-Sample[1]				**Full-Sample[1]**			
Number of Crises[2]	25	18	57	74	49	42	91	102
Number of Non-Crisis Years[3]	253	186	405	547	430	346	714	769
Number of Countries[4]	14	13	25	35	22	21	39	39
Type I Error[5]	0.29	0.31	0.27	0.28	0.39	0.31	0.30	0.29
Type II Error	0.40	0.33	0.42	0.45	0.25	0.38	0.48	0.50
Signal to Noise Ratio	2.11	2.14	2.11	2.01	1.93	2.02	1.72	1.74
Variable weights for the composite indicator								
Private Credit (Gap %)	0.08	0.09	0.08		0.15	0.10	0.07	
Private Credit (% GDP)				0.29				0.24
Overall Balance (% Ch.)			0.25				0.24	
Current Account (% GDP)	0.13	0.16	0.24		0.14	0.06	0.11	
World Real GDP per capita (% Ch.)	0.16	0.13	0.04		0.18	0.15	0.05	
Avge. Maturity on New PPG External Debt Disbursements (%, 1st diff.)		0.12				0.11		
Reserve Coverage (months of imports, 1st diff.)			0.11				0.09	
Reserve Coverage (months of imports)								
Central Bank Claims on Government (% GDP)	0.10				0.12			
World Food Prices (% Ch.)		0.08				0.10		
Growth (deviation from 5 year average, ppts)				0.18				0.14
Expenditure (% GDP)	0.31				0.14			
Net Official Development Assistance (% Ch.)	0.09				0.17			
Net Official Development Assistance (% GDP)			0.09				0.17	
Multilateral Debt (Share of Total PPG Debt, 1st diff.)	0.14			0.22	0.10			0.12
Foreign Direct Investment (% GDP)		0.09				0.18		
Primary Balance (% GDP, 1st diff.)		0.15				0.19		
Average Interest Rate (New PPG External debt) (%, 1st diff.)		0.18				0.12		
Oil Prices (% Ch.)			0.20				0.27	
Terms of Trade (% Ch.)				0.15				0.20
World Non-Fuel Commodity Prices (% Ch.)				0.15				0.29

[1]Early Warning System estimated using an unbalanced panel 1970-2006 for the in-sample and 1970-2015 for the full sample.

[2]Number of crises in the period for which data are available on variables used to predict crises.

[3]Number of non-crisis years in the period for which data are available, plus crisis years if 3 or more years from the beginning of a crisis.

[4]Number of countries for which data are available on all variables used to predict crisis.

[5]Type I error, type II error and the signal to noise ratio describe performance over the period of the sample.

Table A.11. Early Warning System for LICs (commodity and diversified exporters): Signals Approach

	Commodity Exporters				*Diversified Exporters*			
	One year ahead[1]		**Two years ahead**		**One year ahead**		**Two years ahead**	
	In Sample 1970-2006	Out of Sample 2007-2015	In Sample 1970-2006	Out of Sample 2007-2015	In Sample 1970-2006	Out of Sample 2007-2015	In Sample 1970-2006	Out of Sample 2007-2015
Number of Crises[2]	25	13	18	13	57	14	74	21
Number of Non-Crisis Years	253	76	186	74	405	159	547	181
Number of Countries	14	31	13	13	25	25	35	35
Type I Error[3]	0.29	0.46	0.31	0.42	0.27	0.37	0.28	0.56
Type II Error	0.40	0.31	0.33	0.39	0.42	0.64	0.45	0.33
Signal to Noise Ratio	2.11	1.50	2.14	1.47	2.15	0.97	1.96	1.20

[1] In sample statistics are based on the sample period 1970-2006. Out of sample performance is based on projections made over the period 2007-2015 using the early warning system estimated using

[2] The number of crises, non-crisis years and number of countries are calculated over 1970-2006 and 2007-2015 respectively.

[3] Type I error, type II error and the signal to noise ratio describe performance in sample (1970-2006) and predictive performance over (2007-2015) respectively.

Table A.12. Pooled Logit. Low Income Countries

	In sample			**Out of sample**		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Observations	923	735	744	923	735	744
pseudo R sq.	0.04	0.06	0.05	0.04	0.06	0.05
No. crises	95	77	78	44	44	44
Type 1 error (%)	36	39	36	39	31	34
Type 2 error (%)	40	27	29	36	41	39
Threshold prob.(%)	10.6	10.2	10.5	17.8	22	20
AUROC	0.64	0.69	0.68	0.64	0.69	0.68

Note: The type 2 error corresponds to the share of missed crises and the type 1 error to the share of false alarms. The in sample covers the period 1970-2015. Out of sample is 2007-2015

Table A.13. LIC Commodity Exporters Logit Model

	In-Sample			Full sample		
Dependent variable: first year of crisis	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
L2. Reserve Coverage (months)	-0.0143**	-0.0132**	-0.0119	-0.00627	-0.0061	-0.00244
	(0.030)	(0.040)	(0.214)	(0.209)	(0.217)	(0.733)
L2. Private Credit (% of GDP)	0.00144	0.00166	0.00243	0.000752	0.000891	0.00141
	(0.346)	(0.248)	(0.262)	(0.603)	(0.543)	(0.446)
L3. Real Primary Expenditures (%Ch.)	0.000232	0.000209	-0.000392	0.000405	0.000431	0.0000519
	(0.672)	(0.706)	(0.650)	(0.444)	(0.419)	(0.943)
L2. World GDP growth	-0.00044	-0.019	0.000524	-0.0131	-0.0255*	-0.0247
	(0.977)	(0.401)	(0.989)	(0.238)	(0.065)	(0.201)
L1. Official aid	-0.000562	-0.000584*	-0.000426	-0.00104***	-0.00107***	-0.00117**
	(0.101)	(0.097)	(0.348)	(0.005)	(0.004)	(0.021)
L2. World food prices	0.00353	0.00414	0.00434	0.00550***	0.00678***	0.00776***
	(0.218)	(0.126)	(0.255)	(0.000)	(0.000)	(0.00)
L1. GDP growth (dev.from average)	0.00881**	0.00911***	0.00932*	0.00789**	0.00779**	0.00759
	(0.010)	(0.005)	(0.055)	(0.037)	(0.035)	(0.110)
L1. Oil price		0.00179*	0.0023		0.00101	0.00180*
		(0.085)	(0.130)		(0.184)	(0.087)
L1. Remmitances			-4.78E-05			-0.000142**
			(0.477)			(0.037)
Observations	269	269	172	437	437	313
pseudo R sq.	0.10	0.13	0.15	0.11	0.11	0.12
No. crises	24	24	17	42	42	30
Type 1 error (%)	27	30	26	29	27	25
Type 2 error (%)	29	21	24	31	33	33
Threshold prob.(%)	10.4	8.8	10.9	10.3	10.8	11.4
AUROC	0.73	0.76	0.78	0.72	0.73	0.75

Note: Reported are marginal effects, p-values in parentheses (*p<0.1, **p<0.05,***p<0.01). The dependent variable is binary (1 for the first year of fiscal crisis; 0 otherwise). The type 2 error corresponds to the share of missed crises and the type 1 error to the share of false alarms. The sample covers the period 1970-2015. The In-sample is 1970-2006.

Table A.14. LIC Commodity Exporters

	In sample			Out of sample		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Observations	269	269	172	269	269	172
pseudo R square	0.10	0.13	0.15	0.10	0.13	0.15
No. crises	24	24	17	18	18	13
Type 1 error (%)	27	30	26	17	36	21
Type 2 error (%)	29	21	24	44	33	54
Threshold prob.(%)	10.4	8.8	10.9	18.5	11.3	18
AUROC	0.73	0.76	0.78	0.73	0.76	0.78

Note: The type 2 error corresponds to the share of missed crises and the type 1 error to the share of false alarms. The in sample covers the period 1970-2015. Out of sample is 2007-2015

Table A.15. LIC Diversified Exporters Pooled Logit Model

	In-Sample			Full Sample		
Dependent variable: first year of crisis	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
L2. Reserve Coverage (months)	-0.0148	-0.112	-0.0125	-0.00361	-0.0091	-0.00321
	(0.81)	(0.29)	(0.84)	(0.435)	(0.116)	(0.485)
L3. Real Primary Expenditures (%Ch.)	-0.00299	-0.00208	-0.00287	-0.000696	-0.000786	-0.000719
	(0.57)	(0.61)	(0.57)	(0.224)	(0.323)	(0.239)
L2. FDI (% of GDP)	-0.0414	-0.0406	-0.0413	-0.000348	-0.000501	-0.000216
	(0.31)	(0.33)	(0.30)	(0.871)	(0.820)	(0.922)
L1. Official aid	0.00184	0.00278	0.00182	-0.0000364	-0.00000138	-0.0000427
	(0.48)	(0.31)	(0.49)	(0.780)	(0.990)	(0.742)
L2. World food prices	0.0622**	0.0597**	0.0626**	0.00305***	0.00296**	0.00300***
	(0.01)	(0.02)	(0.01)	(0.007)	(0.011)	(0.007)
L1. GDP growth (dev.from average)	0.0363	0.0551**	0.036	0.00317	0.00473**	0.00332
	(0.16)	(0.03)	(0.17)	(0.164)	(0.041)	(0.150)
L1. Concessional debt (% of GDP)	0.0000246			0.000263		
	(0.99)			(0.314)		
L2. Concessional debt (% of total)		-0.00148	-0.00186		-0.000105	-0.000117
		(0.87)	(0.82)		(0.861)	(0.837)
L1. Remmitances		-0.00584			-0.000293	
		(0.20)			(0.171)	
Observations	506	452	506	807	748	807
pseudo R sq.	0.03	0.06	0.03	0.02	0.03	0.02
No. crises	54	48	54	79	73	79
Type 1 error (%)	39	46	38	55	42	51
Type 2 error (%)	31	19	33	22	32	27
Threshold prob.(%)	11	9.6	11	8.7	9.9	9
AUROC	0.65	0.68	0.65	0.61	0.64	0.61

Note: Reported are marginal effects, p-values in parentheses (*p<0.1, **p<0.05,***p<0.01). The dependent variable is binary (1 for the first year of fiscal crisis; 0 otherwise). The type 2 error corresponds to the share of missed crises and the type 1 error to the share of false alarms. The sample covers the period 1970-2015. The In-sample is 1970-2006.

Table A.16. LIC Diversified Exporters

	In sample			Out of sample		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Observations	506	452	506	506	452	506
pseudo R sq.	0.03	0.06	0.03	0.03	0.06	0.03
No. crises	54	48	54	25	25	25
Type 1 error (%)	39	46	38	50	38	50
Type 2 error (%)	31	19	33	24	44	24
Threshold prob.(%)	11	9.6	11	17.1	17.9	16.8
AUROC	0.65	0.68	0.65	0.65	0.68	0.65

Note: The type 2 error corresponds to the portion of missed crises and the type 1 error to the portion of false alarms. The in sample covers the period 1970-2015. Out of sample is 2007-2015