# Using a Threshold Approach to Flag Vulnerabilities in CESEE Economies

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*In this paper we examine macroeconomic, external and financial vulnerabilities of 22 Central, Eastern and Southeastern European (CESEE) economies. Our assessment is based on a nonparametric signaling or threshold approach, which involves monitoring selected indicators that show unusual behavior in the periods leading to a crisis. For that purpose, we have collected annual data on more than 90 emerging economies spanning the period from 1995 to 2012. Our dataset covers a broad range of potential early warning indicators related to the banking sector, the external side, and the macroeconomic and fiscal situation of the economy. Our in-sample test shows that the threshold approach identifies 73% of crisis events correctly while issuing false alarms only for 31% of the noncrisis observations. For the purpose of this paper, crisis events comprise banking crises, currency crises and sovereign debt crises. Applying a composite vulnerability indicator to CESEE economies using the latest available data (2012), we identify Turkey, Belarus and Moldova as the countries that appear especially vulnerable to an unexpected adverse event based on our threshold approach.*

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In this paper, we propose a threshold approach akin to the one employed by the IMF (see e.g. IMF, 2010) and fully described in Chamon and Crowe (2013). Our dataset covers a wide range of potential early warning indicators related to the external, macroeconomic and banking sector of the economy. Our approach incorporates various enhancements compared to the original model. First of all, we do not focus solely on currency crises but also take into account sovereign debt crises and banking crises, as the frequency of these crises has increased over the past decades. Moreover, we are interested in vulnerabilities to any type of crisis that might occur in the future. Additionally, we use an extended dataset not only of CESEE countries but also of other emerging economies to incorporate as many crises in the sample as possible.

The paper is structured as follows: Section 1 provides a summarized literature review, while the next section briefly describes the methodology we applied and, specifically, how we calculated the thresholds we used. In section 3 we explain our data selection. Section 4 outlines how we compiled our composite vulnerability indicator and summarizes the individual threshold indicators. Our empirical results are discussed in section 5, and section 6 concludes.

## 1 Literature Review

Since the 1950s, researchers have tried to predict the likelihood of a crisis, mainly focusing on currency crises in developing countries. Early work was based on qualitative discussions or divided countries into a crisis and a noncrisis control group to identify possible differences between the two groups.

The de facto collapse of the European Exchange Rate Mechanism and the emerging market crises in the 1990s gave a new impetus to research on early warning systems. Since then, two main empirical approaches have evolved. The first early warning approach was developed by Frankel and Rose (1996), who

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modeled currency crashes using a probit regression model with annual data for developing countries from 1971 to 1992. They found that sharply decreasing FDI inflows, low reserves, high domestic credit growth, high interest rates in industrial countries and overvalued real exchange rates are good predictors of currency crashes. Since then, the strand of literature employing logit or probit panel regressions has been widely drawn on (see e.g. Berg and Pattillo, 1999; Comelli, 2013; or Bussière, 2013a).

The other main approach is the so-called signaling or threshold approach, which was introduced by Kaminsky and Reinhart (1999). The idea behind this nonparametric approach is to select a certain threshold for indicators that show altered behavior some periods ahead of a crisis. As soon as an indicator exceeds the defined threshold value, this can be interpreted as a warning signal that a crisis might occur shortly after. The threshold value is chosen by minimizing the sum of type I errors (missing a crisis because the indicator chosen was too strict) and type II errors (false alarms because the indicator chosen was too loose). Kaminsky et al. (1998) identify international reserves, the real exchange rate, inflation and credit-related variables as the leading indicators with the best predictive power to signal currency crises.

This strand of the literature was further developed by a number of scholars (e.g. Edison, 2003). Brüggemann and Linne (2002) combined the different indicators to form a composite indicator for five CESEE countries (Bulgaria, Czech Republic, Romania, Russia and Turkey) that experienced a currency crisis up to 2001.[2] Their results show that especially an overvalued exchange rate, weak exports and diminishing currency reserves are indicators of crisis vulnerabilities in these countries. By contrast, variables related to external debt as well as the current account balance and interest rate differentials did not prove useful as early warning indicators in other studies (Kaminsky et al., 1998). In addition, there is little evidence that markets' or analysts' views as expressed in spreads or ratings are reliable crisis predictors (Berg et al., 2005). More recently, Csortos and Szalai (2014) used Boolean combinations of signals from a small set of indicators to predict macroeconomic imbalances for ten Central and Eastern European economies. Their measures involved real exchange rate and capital flow misalignments and the credit-to-GDP gap.

Apart from the two main approaches, alternative methods have also been employed, for example binary classification trees (developed by Ghosh and Ghosh, 2003; see also Chamon et al., 2007), Markov switching models (Abiad, 2003) or Bayesian model averaging (Crespo Cuaresma and Slačík, 2009; Babecký et al., 2013; Christofides et al., 2012).

Traditionally, the goal of early warning systems has been predicting currency crises (e.g. the Asian crisis of 1997). The recent global financial crisis and the following economic and sovereign debt crises of 2008 and 2009 extended the use of early warning systems beyond the scope of currency crises (see for example Barrell et al., 2010, on bank crises, Manasse and Roubini, 2009, on sovereign debt crises and Babecký et al., 2013, on economic crises).

A few scholars have undertaken comprehensive meta-analyses of early warning systems to identify common indicators across the different methods, country and

[2] *For predicting currency crises in CESEE see also Schardax (2002).*

time samples, for example Kaminsky et al. (1998) or Abiad (2003). The most recent metastudy was conducted by Frankel and Saravelos (2012), who investigated more than 80 papers written between 1950 and 2002. The top two indicators identified in the review turned out to be the level of international reserves and real exchange rate overvaluation.

As regards the forecast period, different models use different time horizons, usually between 12 and 24 months. Kaminsky et al. (1998) show that in their model, the indicators, on average, send the first signal between one year and one-and-a-half years prior to the outbreak of a crisis. However, the time horizon has been proved not to be decisive for the performance of an indicator (see Berg and Pattillo, 1999).

So far, research on early warning models has shown that these models are subject to important limitations. One of the most important limitations is outlined by Berg and Pattillo. (1999, p. 109), who argue that because the number of crises in the historical data is relatively small, searches through the large number of early warning indicators may yield spurious success in explaining crises. Thus, it is not surprising that there is no "one-size-fits-all" list of early warning indicators (Claessens, 2010). Furthermore, there are a number of issues, including political and institutional ones, that may be relevant for a particular country and that are not reflected in the model.[3] Other limitations of early warning tools are problems associated with the assessment of the predictions of such tools. Prudent policymakers might act upon early warning signals and hence prevent the economy from slipping into a crisis. Since crises cannot be correctly predicted and avoided at the same time, this implies that early warning systems cannot work properly by definition (Berg and Pattillo, 1999, Bussière, 2013b). The same applies in a reverse scenario: If early warning assessments are made public and market participants act upon signals issued, the warning might become a "self-fulfilling prophecy" (Bussière, 2013b; Kaminsky et al., 1998). Finally, countries may be highly vulnerable for a longer period without experiencing a crisis, since it usually takes some time for vulnerabilities to become unsustainable. Instead, as Chamon and Crowe (2013) argue, it is far more promising to use these early warning models to identify vulnerabilities rather than the timing of a crisis. Against this background, it becomes clear from the literature that early warning tools must be complemented by a policy-oriented analysis and in-depth country surveillance (see Edison, 2003; Brüggemann, 2002).

## 2 Methodology

Our definition of a crisis period follows the classification of Laeven and Valencia (2008, 2012), who distinguish between currency crises, sovereign debt crises and banking crises. For currency crises, they follow the definition put forward in Frankel and Rose (1996). Accordingly, a currency crisis is deemed to have occurred if the nominal year-on-year depreciation of a currency vis-à-vis the U.S. dollar reaches at least 30% and if the increase in the rate of depreciation compared to the year before is at least 10%. Episodes of sovereign debt default and restructuring are defined by qualitative and quantitative information provided by IMF staff, the World Bank and other sources (see Laeven and Valencia, 2008, for a detailed description). In the model, only systemic banking crises are considered;

[3] *See Kaminsky et al. (1998) for possible indicators that account for political and institutional aspects.*

banking crises qualify as systemic banking crises only under the following conditions: significant signs of financial distress in the banking system, and at least three significant banking policy intervention measures, such as extensive liquidity support, bank nationalizations, issued guarantees, asset purchases, deposit freezes and forced bank holidays.

Following Chamon and Crowe (2013), we calculate a threshold by minimizing the sum of the percentage of crises missed and the percentage of false alarms. Depending on the indicator under scrutiny, values that exceed or go below a threshold indicate a vulnerability of the examined country to an unexpected negative shock.

We denote potential early warning indicators by $X_{i,t}$, with $t$ denoting annual data spanning the period from 1995 to 2012, and $i$ denoting the country in question. These variables are related to a binary crisis indicator, $y_{i,t}$, for which we draw on the classification proposed by Laeven and Valencia (2012), who date currency crises, sovereign debt crises and banking crises. Although leading indicators might depend on the specific type of crisis, we opt for pooling the information on the crisis subcategories for reasons of data availability. That is, $y_{i,t}$=1 if any of the above-mentioned types of crisis occurred in country $i$ in period $t$. Similar to Chamon and Crowe (2013), we choose one year as the forecast horizon and relate macroeconomic and financial market conditions $X_{i,t-1}$ to crises occurring in period $y_{i,t}$. Since we are interested in the predictive power of the independent variables and not the behavior they show during a crisis, we drop observations for crisis years when the year before has already been marked as a crisis year. Finally, we exclude observations for the year that follows a crisis, since we do not expect variables to show noncrisis (i.e. normal) behavior during periods of recovery (Chamon and Crowe, 2013).

To calculate the thresholds, we have divided the sample for each of the potential indicators into a crisis and a noncrisis subsample. The information these subsamples contain for a specific vulnerability indicator can be summarized as follows:

Based on the sample classification in table 1, a strong indicator will minimize the sum of the share of crises missed (C/(A+C), type I error) and the share of false alarms (B/(B+D), type II error). More specifically, the threshold value $\delta$ for each indicator variable $k$ is chosen according to the following objective function:

$$\min_{\delta}\left(\theta\frac{C(\delta)}{A(\delta)+C(\delta)}+(1-\theta)\frac{B(\delta)}{B(\delta)+D(\delta)}\right) \tag{1}$$

By minimizing (1) we assume a particular loss function for the policymaker that trades off type I versus type II errors by selecting $\theta$. Since crises are rare (i.e., A+C is typically much smaller than B+D), and fixing $\theta$=½ minimization of (1) implies that for selecting a threshold, missing a crisis event becomes much more costly than issuing a false alarm (Chamon and Crowe, 2013). Note that while varying $\theta$ for each indicator would increase the overall flexibility of the signaling approach, resulting indicators might be severely prone to the risk of overfitting. More general loss functions are discussed in detail in

Table 1

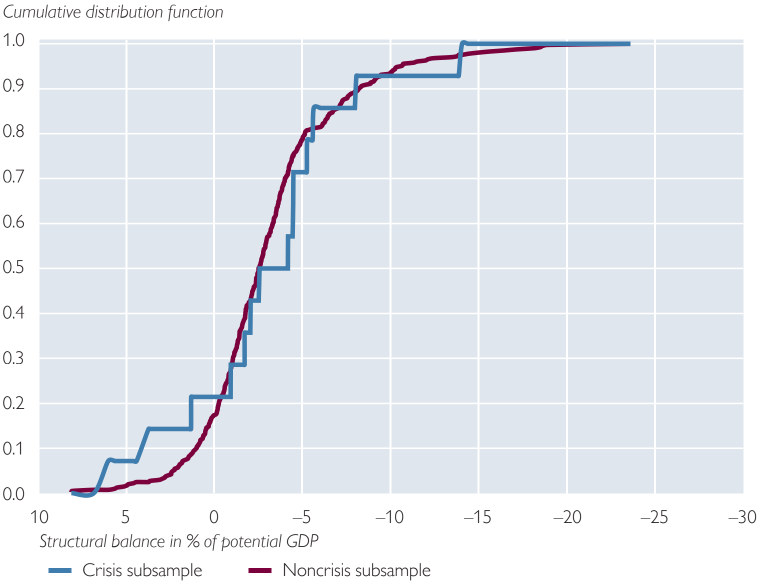
**Sample Classification**

| | Crisis | Noncrisis |
|---|---|---|
| Signal issued | A | B |
| No signal issued | C | D |
| Number of crises | A + C | – |
| Number of noncrises | – | B + D |

*Source: Authors' classification.*

Chart 1

**Cumulative Distribution Function for "Structural Balance" Indicator**




Source: Authors' calculations.

Elliott and Lieli (2013) and Csortos and Szalai (2014).[4]

In line with Chamon and Crowe (2013), we proceed by calculating common thresholds for all countries, thus deviating from the original signaling approach put forward in Kaminsky et al. (1998). Country-specific thresholds might potentially better cover countries with weak macrofundamentals that have never experienced a crisis event. The "resilience" of these countries, however, might be attributed to extraordinarily strong performance in other indicators. While the information about how different risks offset each other in an economy is lost with country-specific thresholds, for common thresholds to work, it is essential to have a broad portfolio of vulnerability indicators.

The threshold approach can be graphically illustrated by examining the cumulative distribution functions (CDFs) of the crisis and noncrisis subsamples. Chart 1 provides the respective cumulative distributions of crisis and noncrisis events for the indicator "structural balance."

Note that data points lying further to the right on the x-axis indicate a deterioration of the indicator, i.e. a higher risk of crisis exposure. Minimizing the sum of the shares of missed crises and false alarms in the illustration above would result in a threshold of –4% for the structural balance. As a consequence, for countries that feature a structural balance of –4% or an even larger deficit, the indicator would issue a warning signal. After having selected a threshold for each indicator in our dataset according to the method described above, we calculate a goodness-of-fit measure as follows:

$$\left( g = \frac{1}{2} * \frac{B + C}{A + B + C + D} \; ; g \in [0,1] \right) \qquad (2)$$

The goodness-of-fit measure enables us to evaluate the quality of an indicator compared to other indicators.

The approach described above has several advantages: First, if data points are missing, the observations do not drop out completely, which would be the case when applying a probit or logit regression model. Our dataset includes 93 emerging economies observed over a period of 17 years; thus, many observations would have

[4] *See Jorda and Taylor (2011) for loss-function free approaches for early warning assessments. A receiver operating characteristic (ROC) curve is constructed for each indicator evaluating the performance of the indicator for all possible threshold values as opposed to picking a single threshold. Indicators are then chosen that maximize the area under the curve.*

to be dropped. Second, probit or logit regressions calculate the marginal effect of each of the independent variables on the probability of a crisis, holding all other variables equal. However, this ceteris paribus assumption is not suitable for precrisis periods, as especially the interactions between variables might determine a country's vulnerability to external shocks.

Additionally, we employ a number of independent variables that are closely related and thus might drop out of a regression because of multicollinearity. However, these variables might also drop out when using binary classification trees in case they are slightly outperformed by another variable, thus making the selection of relevant crisis indicators in the early warning system very sensitive to slight changes in the country sample or time period.

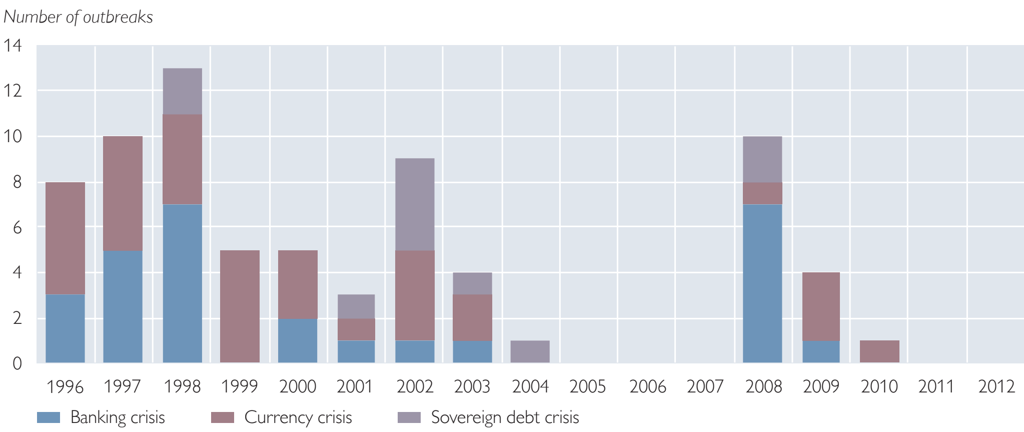
Finally, assessing the forecast performance of early warning systems is cumbersome and might depend crucially on the periods and countries under study. While Edison (2003) and Berg et al. (2005) find that the signaling approach delivers a superior and robust forecasting performance, the results provided in Manasse and Roubini (2009) are less spectacular. Recently, Comelli (2013) has found that parametric models can outperform the signaling approach on an out-of-sample basis.

## 3 Data

Originally, we collected data on 128 countries over the period from 1995 to 2012. While this leaves us with an extensive coverage of emerging markets, the country composition is largely tilted toward African countries. This bias might have been problematic for the purpose of this study, i.e. the assessment of vulnerabilities for countries in the CESEE region. Consequently, we decided to reduce the number of countries to limit cross-country heterogeneity of the sample. For this purpose, we collected data on GDP per capita at constant (2005) U.S. dollar prices and dropped countries belonging to the lower quartile of the distribution. This leaves us with a broadly balanced set of emerging markets comprising 25 Latin American and Caribbean countries, 31 Middle Eastern and African countries, 14 Asian and Pacific economies and 23 CESEE countries.

Chart 2

**Crisis Outbreaks between 1996 and 2012**




*Source: Authors' calculations based on the database of Laeven and Valencia, which is fully described in Laeven and Valencia (2012).*

Out of 1,581 observations in our sample, 60 are marked as crisis events (3.8%). These events often share characteristics that are common to various types of crises. However, since we drop observations belonging to the immediate post-crisis period, the number of "twin" or "triplet" crises is rather small. More specifically, we have only five observations for currency crises that occurred simultaneously with sovereign debt crises, as well as five observations for currency crises coupled with banking crises. For concurrent sovereign debt and banking crises, the number of observations is four. We also count four observations of triple crises. Because there are so few twin and triplet crisis episodes, we do not give them special treatment in our procedure. Chart 2 shows the number of outbreaks of the various types of crises in our country sample between 1996 and 2012, indicating that crisis outbreaks occur in waves.

## 4 Building a Composite Vulnerability Indicator

The literature review has shown that an effective warning system should consider a broad variety of indicators (Kaminsky et al., 1998). Below, we consider 48 potential early warning indicators. More specifically, we have collected 9 indicators related to the banking sector, 18 indicating vulnerabilities on the external side of the economy, and 21 indicators pertinent to the macroeconomic and fiscal situation. Table A2 in the annex provides the full set of indicators with detailed descriptions. The number of crises contained in each indicator dataset ranges from 13 (three-year average of net portfolio inflows) to 66 (basic balance). On average, each indicator dataset consists of 44 crisis periods and 1,200 noncrisis observations.

Before we aggregated the single indicators into one composite vulnerability indicator, we narrowed the set of 48 potential indicators based on three considerations: First, we selected the indicators that correctly flag crisis incidents in more than 40% of cases.[5] Second, we ranked the variables according to their goodness-of-fit quality, and third, we aimed to produce a broad set that includes at least three indicators from each category. This leaves us with the following 18 indicators.

### Banking/financial sector

- *Lending rate*[6]*:* The lending rate is the rate at which banks usually meet the short- and medium-term financing needs of the private sector. The terms and conditions attached to these rates differ from country to country, limiting their comparability. Large values might indicate disruptions in the banking sector and/or a high risk perception and thus resemble financial system fragility.
- *Interaction of domestic credit growth (three-year average) and credit in % of GDP:* Various empirical studies point out the link between (excessive) credit growth and the incidence of financial crises (see e.g. Jordà et al., 2011, and Feldkircher, 2014, on the recent global financial crisis). Since the rate of credit growth might depend on the level of financial deepening (Arpa et al., 2005, Herwartz and Walle, 2014), we multiply the three-year average of domestic credit growth by the level of credit to GDP. This variable identifies highly leveraged economies with strong lending growth as vulnerable.

[5] *Note that as pointed out earlier, we had to trade off identifying crises and issuing false alarms when selecting indicators.*

[6] *In a robustness exercise CPI-deflated lending rates performed slightly worse in terms of goodness-of-fit than the nominal rates.*

- *Capital-to-assets ratio (CAR):* This ratio represents bank capital and reserves to total assets. Low CAR levels might imply insufficient buffers of the financial system to withstand unexpected shocks and are thus flagged as a source of vulnerability for the country under scrutiny.

**External sector**

- *Current account balance in % of GDP (three-year moving average):* Historical evidence suggests that economies with persistent and pronounced current account deficits are prone to risks of sudden capital stops or currency crises. The empirical evidence is rather mixed, however (see findings provided in Kaminsky et al., 1998, on the one hand, and Frankel and Saravelos, 2012, on the other hand). Nevertheless, we include the current account as an indicator of vulnerability because it features prominently in other international early warning exercises like the Macroeconomic Imbalance Procedure (MIP) of the European Commission.[7]
- *Basic balance:* This refers to the part of the current account (deficit) that is not financed by net FDI inflows but by other sources considered more volatile than FDI. As above, larger deficits are likely to reflect greater vulnerability to external events.
- *Short-term external debt in % of external debt:* This variable is an estimate for the short-run external refinancing needs of the economy. Countries with a large share of short-term external debt in total external debt are regarded as more vulnerable, since they depend more strongly on current global refinancing conditions.
- *Total external debt service in % of exports:* This corresponds to the sum of principal repayments and interest on long-term external debt, interest paid on short-term debt, and repayments to the IMF. The indicator is measured as a share of exports, which reflects the economy's ability to obtain foreign exchange to service its external debt obligations. Economies that exhibit an elevated ratio of external debt service to exports are assumed to be more vulnerable to the occurrence of external shocks.
- *External debt in % of exports:* As a third measure of external debt sustainability, we calculate total external debt as a share of exports. Economies with a high ratio are expected to be less resilient to crises events.[8]
- *Annual change in export volumes:* Export growth features prominently among leading indicators (Eichengreen et al., 1995, Kaminsky and Reinhart, 1999). Economies with stagnating exports are more vulnerable to crisis events.
- *Exchange rate misalignments:* We use two factors to capture exchange rate misalignments as several empirical studies reveal the importance of exchange rate overvaluation as a leading indicator for (currency) crises (see e.g. Bussière, 2013a; Kaminsky et al., 1998; Frankel and Saravelos, 2012).

[7] *On top of the limited evidence in the literature, cross-country comparability of current account deficits might be limited for countries for which EU transfers are sizeable since the latter may be booked on either the current or the capital account depending on the type of transfer.*

[8] *Note that we follow the literature in employing the selected external debt indicators. In particular in countries that host special purpose entities and/or multinational holding companies, such as Hungary, external debt figures might be biased upward since these companies lead to an expansion of both external assets and liabilities.*

- The first factor is the *annual growth of the real effective exchange rate* (maximum annual change of three-quarter moving average). A positive change in the exchange rate is associated with a real appreciation. Pronounced growth of the real effective exchange rate might trigger pressures on the currency and hence might make a subsequent depreciation more likely.
- The second indicator to capture misalignments in the exchange rate is the *exchange market pressure* (EMP) index, which is defined as:

$$EMP_t = \left( \frac{e_t - e_{t-1}}{e_{t-1}} - \frac{ir_t - ir_{t-1}}{ir_{t-1}} \right),$$

with $e_t$ denoting the monthly nominal exchange rate per 1 U.S. dollar and $ir_t$ international reserves (minus gold) in U.S. dollar at time $t$ (Aizenman and Pasricha, 2012). An increase in the EMP index reflects depreciation pressure on the currency under consideration. We aggregate data on the monthly EMP index by selecting the maximum value per year (i.e., the value for the month in which the strongest pressure on the currency was observed).[9]

- *Total reserves in months of imports:* The empirical literature frequently flags the level of international reserves as an important buffer to adverse external events (e.g. Frankel and Saravelos, 2012). We expect countries with a low level of reserves to be more vulnerable, as they have less room for maneuver in case a crisis hits.

**Macroeconomic and fiscal risks**

- *Risk premium on lending:* This corresponds to the interest rate banks charge on loans to private sector customers minus the "risk free" Treasury bill interest rate at which short-term government securities are issued or traded in the market. A large and positive risk premium indicates potential financing problems of the private sector.
- *Multiplication of gross debt (in % of GDP) by fiscal balance:* This should indicate fiscal vulnerability for countries that simultaneously have a fiscal deficit and a high debt burden.
- *Three-year average of year-on-year CPI inflation:* Periods of high inflation are often associated with economic booms that induce economic crises (Babecký et al., 2013). We thus calculate a three-year average of year-on-year CPI inflation and expect countries with high inflation rates to be more prone to crises.
- *Money growth:* This refers to the average annual growth rate in money and quasi-money.[10] Considerable growth in money might indicate overheating tendencies of the economy and is hence flagged as a potential vulnerability.
- *Deviation from real GDP trend growth:* We compute the deviation from a three-year average and calculate both a negative and a positive threshold in the empirical exercise. The positive threshold should reflect tendencies of overheating while

[9] *Both exchange rate misalignment indicators have been alternatively calculated by taking the mean instead of the maximum over the respective periods stated in the definition above. The results do not change qualitatively, while the fit tends to deteriorate.*

[10] *In a robustness exercise we also examined real money growth as a potential vulnerability indicator. The results, however, where slightly worse compared to money growth in nominal terms.*

the threshold attributed to the negative deviation from trend growth might pick up first signs of a recession that can manifest itself into an economic crisis.

- *Structural balance in % of potential GDP:* The structural budget balance refers to the general government balance cyclically adjusted for nonstructural elements of the economic cycle. It is expected to indicate a worsening in debt sustainability independently of cyclical factors. Consequently, larger deficits are expected to point to an increased fiscal vulnerability of the underlying country.

Since we are ultimately interested in assessing vulnerabilities for the CESEE region, it is essential that data coverage of the selected indicators is sufficiently large for these particular countries. Table A.1 in the annex details the data availability for each of the 18 indicators per country as well as the crisis events as defined by Laeven and Valencia (2012). The table shows that only Bosnia and Herzegovina, Estonia and Poland did not witness a crisis event during the period under study. By contrast, three crises were recorded in Belarus, Turkey and Ukraine. With respect to the indicators, total reserves in months of imports are only available from 2005 onward. While data coverage is thus smaller compared to the remaining indicators, the threshold itself was evaluated based on more than 600 observations.

We proceed with aggregating these 18 indicators into a *composite leading indicator.*[11] The single indicators are assigned weights that resemble their goodness-of-fit properties and are then pooled in each of the three crisis categories. Finally, the composite indicator is put together in three different ways: First, we assign to each category the same weight of one-third. Second, we attach a higher weight to the external category (two-thirds external, one-sixth macro, one-sixth banking), since crises related to emerging markets are often associated with the external side of the economy. Last, we downweight the banking category (two-fifths external, two-fifths macro, one-fifth banking), since data on this subgroup is less available than for the other subgroups.

For each of the composite vulnerability variants we evaluate its associated in-sample performance using the same method as in section 2. That is, we calculate the respective shares of correctly issued alarms, false alarms, crises missed and correctly not-issued warnings. While the composite indicators lie in the range of 0 to 1 and hence allow for a continuous assessment of vulnerability, for the purpose of a performance evaluation we have to decide on an overall threshold value which is indicative of a crisis event. Again, we define the threshold value in an empirical fashion evaluating the 0 to 1 grid of potential threshold values and picking

Table 2

**In-Sample Evaluation of the Composite Vulnerability Indicator**

| | Crisis | Noncrisis |
|---|---|---|
| | % | |
| **Uniform weighting** | | |
| Signal issued | 72.83 | 30.63 |
| No signal issued | 27.16 | 69.37 |
| **More weight to external risk subcategory** | | |
| Signal issued | 77.78 | 33.27 |
| No signal issued | 22.22 | 66.73 |
| **Less weight to banking subcategory** | | |
| Signal issued | 70.37 | 32.33 |
| No signal issued | 29.63 | 67.67 |

*Source: Authors' calculations.*

*Note: The table shows the share of crisis/noncrisis events for which a signal was issued/no signal was issued.*

[11] *See the recent contribution by Csortos and Szalai (2014) for an approach that advocates Boolean combination of the single indicators rather than constructing a composite indicator.*

the threshold that yields both the largest share of correctly identified crises and correctly not-issued warnings.

For all three variants of overall vulnerability, this exercise yields a threshold of 0.4. Consequently, a country with an overall vulnerability of 0.45 is rather likely to experience a crisis episode in one year's time. The results for the three composite indicator variants based on this threshold are summarized in table 2.

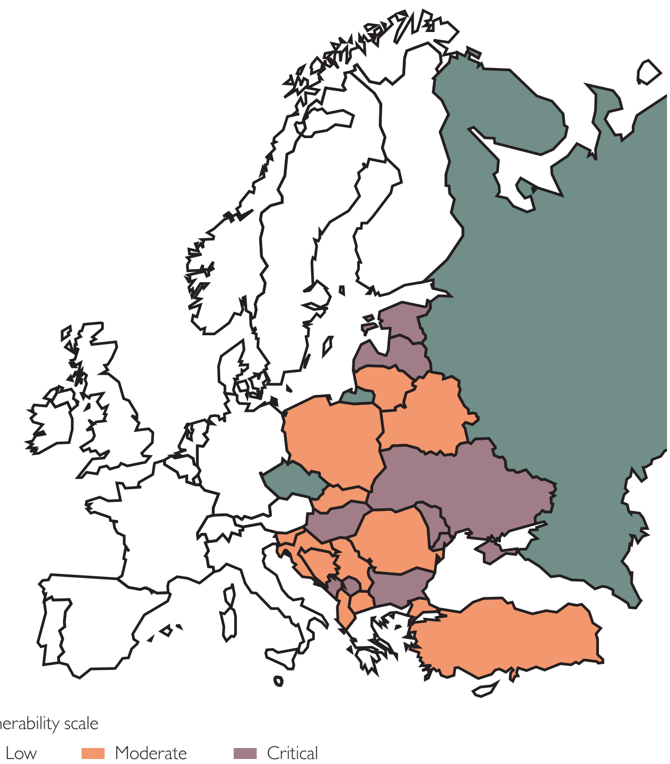
Table 2 indicates only small performance differences across the different weighting schemes. The composite indicator that is based on a uniform weighting identifies roughly 73% of all crises correctly. In almost 70% of noncrisis periods, the indicator did correctly not issue a warning signal. The composite indicator attaching more weight to the external risk subcategory shows a slightly better in-sample performance in correctly identifying crisis periods, while it produces slightly more false alarms (some 33% compared to 31%). The weighting scheme putting less emphasis on the banking category produces very similar results. For the sake of simplicity we stick with the uniform composite indicator, for which we discuss the respective country results in the next section.

## 5 Discussion of Results

To get another impression of the quality of the composite indicator besides the in-sample evaluation above, we take a look at how the indicator would have performed in the past. Thus, we compute the results for 2007, i.e. one year prior to the outbreak of the global financial crisis. We divide the countries into three groups, depending on the outcome of the composite indicator. Countries with composite indicator values below 0.2 are categorized as exhibiting low vulnerabilities, countries with values between 0.2 and 0.4 as moderate, and finally countries where the composite indicator takes on a value of more than 0.4 are considered critical. The outcome is shown in chart 3.

Chart 3

**Vulnerability Indicators for CESEE in 2007**




*Source: Authors' calculations.*

The picture flags strong vulnerabilities for most of the countries under consideration. In particular, we find substantial vulnerabilities for Estonia, Latvia, Ukraine, Moldova, Hungary and Bulgaria.[12]

And indeed, we see that in 2008 three countries under consideration did

[12] *For Kosovo and Montenegro there are only a few indicators available for 2007; although the two countries appear to have been vulnerable in 2007, we therefore do not discuss the outcome of the composite indicator for 2007.*

actually experience a crisis according to the definition put forward in Laeven and Valencia (2008, 2012), namely Hungary, Latvia and Ukraine. Turning to these countries, we take a brief look at what vulnerabilities our indicators flagged.

In *Hungary,* vulnerabilities were mainly related to very high current account and fiscal deficits as well as public debt levels. What our indicators do not capture is the increasing vulnerability of the financial sector at that time, also related to a high share of (mostly unhedged) foreign currency-denominated loans coupled with an insufficient deposit base.[13]

In 2008, *Latvia* was hit by the most pronounced boom-bust cycle in CESEE. Latvia had accumulated substantial imbalances already long before the crisis. Two-digit growth rates, large capital inflows from Nordic banks, rapid credit expansion and a bubble in real estate prices hit the country massively once the crisis started to unfold. Real GDP growth fell from 10% in 2007 to –3.3% in 2008 (and even –17.7% in 2009) (see also Bakker and Klingen, 2012).

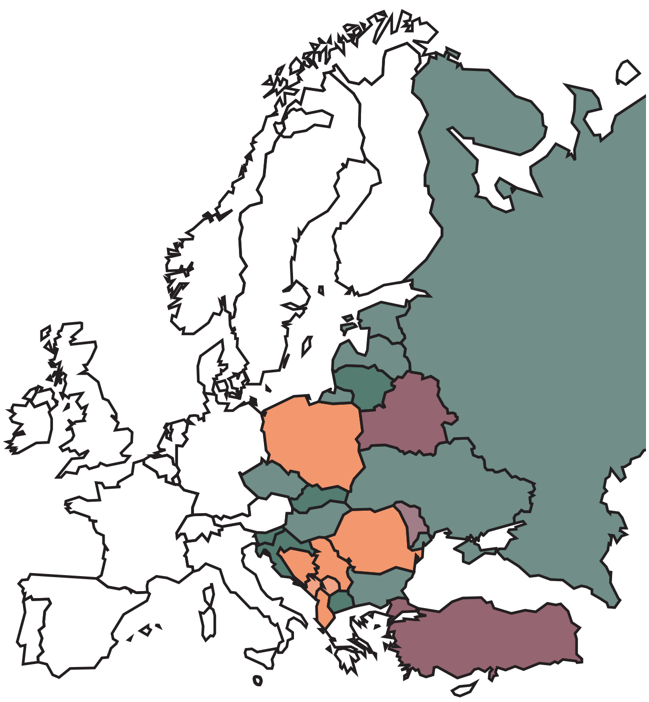
*Ukraine* has been the only country in CESEE that has proven nearly equally vulnerable to adverse developments stemming either from the European Union or from Russia (see EBRD, 2012). Thus, it comes as no surprise that the country slipped into a deep recession in 2009, when sluggish demand, compounded by the reversal of capital flows from the EU and Russia (followed by a strong depreciation of the exchange rate) and cuts in energy subsidies from Russia, caused fiscal deficits and public debt to increase sharply.

Although Bulgaria, Estonia and Moldova did not experience a crisis in 2008 as defined by Laeven and Valencia (2008, 2012), the three countries subsequently experienced recessions with strong GDP contractions, especially in the year 2009. By contrast, among those CESEE countries that showed the lowest vulnerabilities in 2007 were notably the Czech Republic and Russia. However, Russia experienced a recession in 2009, but mainly because of a steep fall in oil prices in 2008, a factor which is not included in our composite indicator. All in all, the composite indicator we developed would have done well predicting crises in 2007.

Based on the vulnerability indicator for 2012, three countries with worrisome vulnerabilities could be identified (see chart 4).

Chart 4

**Vulnerability Indicators for CESEE in 2012**




*Source: Authors' calculations.*

[13] *Unfortunately, the degree of dollarization (or euroization) could not be tested as a vulnerability indicator due to low data availability for the countries under consideration.*

The highest critical value is exhibited by *Belarus,* which experienced a crisis in early 2009. In the wake of that crisis, the Belarusian economy has not yet overcome existing deficiencies in a sustainable manner. Thus, for 2012[14] our composite indicator shows a high vulnerability level for Belarus, in particular due to some serious impairment of the current account balance and total reserves in months of imports. In addition, although Belarus' banking sector is sufficiently capitalized with a capital-to-assets ratio of 15.1, this is partly because the government employs substantial parafiscal measures (2% to 4% of GDP per year) to support the capitalization of banks. We consider this a signal of serious fragilities in the Belarusian banking sector. Furthermore, the country retains many elements of central planning, so state involvement in the economy is substantial. According to our composite indicator, Belarus is therefore very vulnerable to a crisis. However, the Belarusian economy and its foreign exchange reserves have received a boost from Russian loans. Thus, if Russia continues its financial support, the Belarusian economy might have enough of a cushion to deflect a severe crisis.

As chart 4 shows, another country with serious vulnerabilities in 2012 appears to be *Turkey.* Price pressure remains strong and consumer price inflation is well above the central bank's inflation target of 5%. Turkey has recorded large current account deficits financed mainly by portfolio and other investment inflows. On the back of soaring manufacturing unit labor costs, the real exchange rate of the Turkish lira appreciated substantially vis-à-vis the euro until the first half of 2013. Unit labor costs were fueled by strong wage increases granted to partially offset pronounced inflation, whereas productivity stagnated. Given the tapering of the U.S. Fed's quantitative easing program, the fragile financing structure of the Turkish current account exposes the economy to the risk of sudden capital outflows. A very strong expansion of credit to companies and (only in local currency) to households outpaced substantial deposit growth and increased the deposit funding shortfall substantially on the back of a large rise in net foreign liabilities.

Finally, our vulnerability indicators point to a severe vulnerability of *Moldova* for 2012, especially in the external and in the real sector. Moldova exhibits a very high current account deficit (7% of GDP in 2012), which is financed by short-term external debt, putting the country in a fragile external position. Additionally, the economy experienced strong money growth and thus an acceleration of price dynamics, accompanied by a recession in 2012.

For the remainder of the countries under consideration, the composite indicator does not suggest major vulnerabilities in 2012.[15] This outcome is not surprising, since many CESEE economies are still feeling the aftermath of the global financial crisis and are in the process of removing the legacies of unsustainable developments in the boom years.

[14] *Only very few data for 2013 have become available for the countries covered in this study.*

[15] *In chart 4, Ukraine has not been designated as vulnerable based on 2012 data as it exhibited only minor vulnerabilities in the external sector and none in the real and banking sectors. Only at the beginning of 2013, and triggered by political circumstances, did the depreciation of the hryvnia and the decline of official reserves start. The authors want to emphasize that the present early warning system is not aimed at political crises.*

## 6 Conclusions

Based on the idea that certain indicators alter their behavior in the run-up to a crisis, we developed an early warning system using a threshold approach. To evaluate the vulnerability of the CESEE region, we employed a global sample of 93 emerging economies over 17 years. We looked at three types of crises, namely currency crises, sovereign debt crises and banking crises, and tested the usefulness of 48 potential warning indicators. Out of these, 18 indicators proved to be valuable in building a composite indicator that evaluates a country's vulnerability in the external sector, the macroeconomic and fiscal positions, and the banking sector. Overall, we found that in 2012 only three countries in CESEE appear to be particularly vulnerable: Belarus, Turkey and Moldova. In an in-sample test we found that, out of 81 crisis periods, our composite indicator identifies about 73% correctly. In almost 70% out of 1,593 noncrisis periods, the indicator correctly did not issue a warning signal. This result indicates that our approach will be useful for monitoring economic developments in CESEE in the future.

However, the approach also has certain drawbacks. First of all, we are not able to incorporate structural indicators, such as indices that measure corruption or the quality of institutions, although they do in fact play a large role in the economic development of emerging economies. The reason is that structural indicators do not tend to alter their behavior much in the run-up to a crisis and therefore do not have good crisis prediction qualities. Another issue is that an early warning system built on economic indicators cannot predict political crises. Thus, it is very important to monitor the political and social developments in the respective countries as an additional input to the assessment of crisis vulnerability. Last but not least, we rely on annual data in our sample and have not examined the usefulness of high frequency indicators. A promising avenue for future research would be to develop an extended model that features vulnerability indicators with observations of higher frequency. Moreover, a more detailed assessment of how early each of the proposed indicators issues a warning might yield further important insights.

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# Annex

Table A1

## Data Availability for the Individual CESEE Countries and Indicators

| | Crisis | Lending rate | Interaction of domestic credit growth and credit in % of GDP | Capital-to-assets ratio | Current account balance in % of GDP | Basic balance | Short-term external debt in % of external debt | Total debt service in % of exports | External debt in % of exports | Annual change in export volumes |
|---|---|---|---|---|---|---|---|---|---|---|
| | *Years* | *% (data availability)* | | | | | | | | |
| Albania | 1997 | 88.89 | 88.89 | 50 | 100 | 100 | 100 | 100 | 100 | 88.89 |
| Belarus | 1995, 1999, 2009 | 100 | 88.89 | 61.11 | 100 | 100 | 100 | 100 | 100 | 100 |
| Bosnia and Herzegovina | | 77.78 | 72.22 | 66.67 | 83.33 | 83.33 | 77.78 | 77.78 | 77.78 | 77.78 |
| Bulgaria | 1996 | 100 | 100 | 72.22 | 100 | 100 | 100 | 100 | 100 | 100 |
| Croatia | 1998 | 100 | 94.44 | 72.22 | 100 | 100 | 0 | 0 | 0 | 100 |
| Czech Republic | 1996 | 100 | 94.44 | 72.22 | 100 | 100 | 0 | 0 | 0 | 94.44 |
| Estonia | | 100 | 100 | 72.22 | 100 | 100 | 0 | 0 | 0 | 100 |
| Hungary | 2008 | 100 | 100 | 61.11 | 100 | 100 | 100 | 44.44 | 44.44 | 100 |
| Latvia | 1995, 2008 | 100 | 94.44 | 72.22 | 100 | 100 | 0 | 0 | 0 | 100 |
| Lithuania | 1995 | 88.89 | 94.44 | 72.22 | 100 | 100 | 0 | 0 | 0 | 0 |
| Moldova | 1999, 2002 | 94.44 | 100 | 72.22 | 100 | 100 | 100 | 100 | 100 | 100 |
| Poland | | 66.67 | 100 | 72.22 | 100 | 100 | 0 | 0 | 0 | 94.44 |
| Romania | 1996 | 0 | 0 | 0 | 100 | 0 | 0 | 0 | 0 | 100 |
| Russia | 1998, 2008 | 100 | 94.44 | 72.22 | 100 | 100 | 0 | 0 | 0 | 100 |
| Serbia | 2000 | 88.89 | 72.22 | 55.56 | 72.22 | 72.22 | 100 | 33.33 | 33.33 | 72.22 |
| Slovakia | 1998 | 77.78 | 72.22 | 72.22 | 100 | 94.44 | 0 | 0 | 0 | 100 |
| Slovenia | 2008 | 83.33 | 100 | 61.11 | 100 | 100 | 0 | 0 | 0 | 100 |
| Turkey | 1996, 2000, 2001 | 0 | 100 | 72.22 | 100 | 100 | 100 | 100 | 100 | 100 |
| Ukraine | 1998, 2008, 2009 | 100 | 100 | 72.22 | 100 | 100 | 100 | 100 | 100 | 100 |

*Source: Authors' calculations.*

*Note: The table provides the percentage of available data for the period from 1995 to 2012 per CESEE country and indicator. Total reserves in months of imports available from 2005 onward only.*

Table A1 continued

## Data Availability for the Individual CESEE Countries and Indicators

| | Change in the real effective exchange rate | Exchange market pressure | Total reserves in months of imports | Risk premium on lending | Gross debt x fiscal balance | CPI inflation | Money growth | Deviation from real GDP trend growth | Structural balance in % of potential GDP |
|---|---|---|---|---|---|---|---|---|---|
| | *% (data availability)* | | | | | | | | |
| Albania | 0 | 100 | 44.44 | 88.89 | 88.89 | 94.44 | 100 | 100 | 0 |
| Belarus | 0 | 100 | 44.44 | 0 | 50 | 88.89 | 100 | 100 | 0 |
| Bosnia and Herzegovina | 0 | 83.33 | 44.44 | 0 | 0 | 94.44 | 83.33 | 72.22 | 72.22 |
| Bulgaria | 100 | 100 | 44.44 | 94.44 | 61.11 | 94.44 | 100 | 100 | 72.22 |
| Croatia | 100 | 100 | 44.44 | 0 | 61.11 | 94.44 | 100 | 100 | 61.11 |
| Czech Republic | 100 | 100 | 44.44 | 100 | 100 | 94.44 | 100 | 88.89 | 100 |
| Estonia | 100 | 100 | 44.44 | 0 | 55.56 | 94.44 | 88.89 | 100 | 0 |
| Hungary | 100 | 100 | 44.44 | 100 | 88.89 | 94.44 | 100 | 100 | 44.44 |
| Latvia | 100 | 100 | 44.44 | 100 | 55.56 | 94.44 | 100 | 100 | 33.33 |
| Lithuania | 100 | 100 | 44.44 | 88.89 | 72.22 | 16.67 | 100 | 88.89 | 72.22 |
| Moldova | 100 | 100 | 44.44 | 94.44 | 0 | 94.44 | 100 | 100 | 0 |
| Poland | 100 | 100 | 44.44 | 66.67 | 100 | 94.44 | 100 | 100 | 72.22 |
| Romania | 100 | 100 | 0 | 0 | 50 | 88.89 | 0 | 100 | 50 |
| Russia | 100 | 100 | 44.44 | 38.89 | 77.78 | 94.44 | 100 | 100 | 83.33 |
| Serbia | 0 | 0 | 33.33 | 55.56 | 0 | 94.44 | 83.33 | 72.22 | 27.78 |
| Slovakia | 100 | 100 | 44.44 | 0 | 88.89 | 94.44 | 77.78 | 100 | 88.89 |
| Slovenia | 100 | 100 | 44.44 | 61.11 | 100 | 94.44 | 0 | 100 | 94.44 |
| Turkey | 100 | 100 | 44.44 | 0 | 50 | 100 | 100 | 100 | 61.11 |
| Ukraine | 100 | 100 | 44.44 | 0 | 88.89 | 94.44 | 100 | 100 | 55.56 |

*Source: Authors' calculations.*

*Note: The table provides the percentage of available data for the period from 1995 to 2012 per CESEE country and indicator. Total reserves in months of imports available from 2005 onward only.*

Table A2

## Description of Indicators

| No. | Category | Indicator | Description | Source | Number of obser-vations | Number of crises | Good-ness of fit (g) | Crises missed: C/(A+C) | Noncrises misclassi-fied: B/(B+D) |
|---|---|---|---|---|---|---|---|---|---|
| 1 | Banking | Three-year average credit growth x domestic credit provided by the banking sector in % of GDP | Multiplication of three-year average credit growth by domestic credit provided by the banking sector in % of GDP. | Authors' calcula-tions | 1,454 | 52 | 0.64 | 0.48 | 0.23 |
| 2 | Banking | Domestic credit growth, three-year average | Three-year average of year-on-year domestic credit growth. Domestic credit refers to the sum of net claims on the central government and claims on other sectors of the domestic economy. | WDI | 1,504 | 52 | 0.66 | 0.29 | 0.39 |
| 3 | Banking | Change in domestic credit over three years | Change in domestic credit over three years. Domestic credit refers to the sum of net claims on the central government and claims on other sectors of the domestic economy. | WDI | 1,494 | 53 | 0.66 | 0.30 | 0.37 |
| 4 | Banking | Domestic credit provided by the banking sector in % of GDP | Domestic credit provided by the banking sector includes all credit to various sectors on a gross basis, with the exception of credit to the central govern-ment, which is calculated on a net basis. | WDI | 1,532 | 58 | 0.56 | 0.14 | 0.74 |
| 5 | Banking | Lending rate | Bank rate at which the short- and medium-term financing needs of the private sector are usually met. | WDI | 1,366 | 51 | 0.65 | 0.41 | 0.30 |
| 6 | Banking | Capital-to-assets ratio in % | Ratio of bank capital and reserves to total assets. Capital and reserves include funds contributed by owners, retained earnings, general and special reserves, provisions and valuation adjustments. Total assets include all nonfinancial and financial assets. | WDI | 678 | 15 | 0.41 | 0.47 | 0.71 |
| 7 | Banking | Interest rate spread | Interest rate banks charge on loans to private sector customers minus the interest rate paid by commercial or similar banks for demand, time or savings deposits. | WDI | 1,341 | 51 | 0.57 | 0.67 | 0.20 |
| 8 | Banking | NPLs in % of total loans | Value of nonperforming loans (gross value of the loan as recorded on the balance sheet) divided by the total value of the loan portfolio. | WDI | 693 | 18 | 0.44 | 0.89 | 0.23 |
| 9 | Banking | Domestic credit to private sector in % of GDP | Domestic credit to the private sector refers to financial resources provided to the private sector, e.g. through loans, purchases of nonequity securities, trade credits and other accounts receivable, that establish a claim for repayment. | WDI | 1,531 | 57 | 0.51 | 0.77 | 0.21 |
| 10 | External/ BoP | Total reserves in months of imports | Holdings of monetary gold, special drawing rights, reserves of IMF members held by the IMF, and holdings of foreign exchange under the control of monetary authorities. | WDI | 605 | 14 | 0.68 | 0.50 | 0.14 |
| 11 | External/ BoP | Total reserves in % of external debt | International reserves to total external debt stocks. | WDI | 1,304 | 52 | 0.64 | 0.19 | 0.54 |
| 12 | External/ BoP | Short term external debt in % of external debt | Short-term external debt is defined as debt that has an original maturity of one year or less, both public and private nonguaranteed. | WDI | 1,312 | 52 | 0.62 | 0.46 | 0.29 |

*Source: Authors' calculations, BIS, IFS, IMF (World Economic Outlook), UNSTAT, World Bank (World Development Indicators).*

Table A2 continued

## Description of Indicators

| No. | Category | Indicator | Description | Source | Number of obser-vations | Number of crises | Good-ness of fit (g) | Crises missed: C/(A+C) | Noncrises misclassi-fied: B/(B+D) |
|---|---|---|---|---|---|---|---|---|---|
| 13 | External/ BoP | Exchange market pressure (EMP) | Defined as the difference between the change in the nominal exchange rate (expressed as local currency vis-à-vis the U.S. dollar) and the change in international reserves. Calculations of the EMP are based on monthly data, which have been aggregated to yearly figures by choosing the maximum EMP for each year. See Aizenman and Pasricha (2012), Klaassen and Jager (2011) for a discussion on the definition of the EMP and Feldkircher et al. (2014) on macroeconomic determinants that drive the EMP in crisis times. | IFS data, authors' calcula-tions | 1,372 | 56 | 0.62 | 0.52 | 0.24 |
| 14 | External/ BoP | Maximum of three-quarter moving average of year-on-year change in real effective exchange rate | The BIS calculates effective exchange rate (EER) indices for a total of 58 economies (including individual euro area countries and, separately, the euro area as an entity). Nominal EERs are calculated as geometric weighted averages of bilateral exchange rates. Real EERs are the same weighted averages of bilateral exchange rates adjusted for relative consumer prices. The weighting pattern is time-varying, and the most recent weights are based on trade in 2005–07. The EER indices are available as monthly averages. | BIS, IFS | 557 | 30 | 0.60 | 0.30 | 0.70 |
| 15 | External/ BoP | Real effective exchange rate (2005=100) | Nominal effective exchange rate divided by a price deflator or index of costs. | WDI | 752 | 36 | 0.60 | 0.47 | 0.32 |
| 16 | External/ BoP | Current account balance in % of GDP | The current account balance is the sum of net exports of goods and services, net primary income and net secondary income. | WDI | 1,304 | 52 | 0.58 | 0.28 | 0.57 |
| 17 | External/ BoP | Annual change in export volumes | Annual change in export of goods volumes. | WEO | 1,042 | 36 | 0.57 | 0.45 | 0.42 |
| 18 | External/ BoP | External debt in % of exports | Total external debt stocks to exports of goods, services and income. | WDI | 1,221 | 49 | 0.57 | 0.57 | 0.28 |
| 19 | External/ BoP | Total debt service in % of exports | Sum of principal repayments and interest actually paid in currency, goods, or services on long-term debt, interest paid on short-term debt, and repayments (repurchases and charges) to the IMF in % of exports of goods, services and income. | WDI | 1,221 | 49 | 0.56 | 0.55 | 0.33 |
| 20 | External/ BoP | Basic balance | Sum of the current account balance and net FDI flows. | Authors' calcula-tions | 1,589 | 66 | 0.52 | 0.12 | 0.84 |
| 21 | External/ BoP | Current account balance in % of GDP, three-year moving average. | Three-year moving average of the current account balance. | WDI | 1,077 | 45 | 0.40 | 0.5 | 0.6 |

*Source: Authors' calculations, BIS, IFS, IMF (World Economic Outlook), UNSTAT, World Bank (World Development Indicators).*

Table A2 continued

## Description of Indicators

| No. | Category | Indicator | Description | Source | Number of observations | Number of crises | Goodness of fit (g) | Crises missed: C/(A+C) | Noncrises misclassified: B/(B+D) |
|---|---|---|---|---|---|---|---|---|---|
| 22 | External/ BoP | Total change in external debt stocks in % of GDP | International reserves to total external debt stocks. | WDI | 1,304 | 52 | 0.57 | 0.24 | 0.62 |
| 23 | External/ BoP | Net flows on external debt in % of external debt | Net flows on external debt are disbursements on long-term external debt and IMF purchases minus principal repayments on long-term external debt and IMF repurchases and the change in stock of short-term debt (including interest arrears for long-term debt). | WDI | 1,312 | 52 | 0.61 | 0.37 | 0.42 |
| 24 | External/ BoP | Net FDI flows | Net inflow of investments into a lasting management interest (10% or more of voting stock) in an enterprise operating in an economy other than that of the investor. | WDI | 1,344 | 46 | 0.57 | 0.39 | 0.48 |
| 25 | External/ BoP | Net portfolio inflows in % of GDP, three-year average | Portfolio investment covers transactions in equity securities and debt securities. | WDI | 389 | 13 | 0.61 | 0.69 | 0.10 |
| 26 | External/ BoP | Nominal unit labor costs, year on year | Based on data for compensation of employees; consists of all payments in cash, as well as in kind (such as food and housing), to employees in return for services rendered, and government contributions to social insurance schemes such as social security and pensions that provide benefits to employees. | WDI, authors' calculations | 1,170 | 51 | 0.59 | 0.73 | 0.10 |
| 27 | External/ BoP | External debt in % of gross national income (GNI) | Total external debt stocks to gross national income. Total external debt: debt owed to nonresidents repayable in currency, goods, or services; the sum of public, publicly guaranteed and private nonguaranteed long-term debt, use of IMF credit, and short-term debt. | WDI | 1,298 | 51 | 0.55 | 0.73 | 0.17 |
| 28 | Macro | Money growth in %, year on year | Average annual growth rate of money and quasi-money. | WDI | 1,530 | 58 | 0.65 | 0.45 | 0.26 |
| 29 | Macro | CPI inflation in %, year on year | Inflation as measured by the consumer price index reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services. | WDI | 1,471 | 56 | 0.63 | 0.46 | 0.27 |
| 30 | Macro | CPI inflation, three-year average | Three-year average of (29) | WDI | 1,361 | 50 | 0.64 | 0.30 | 0.42 |
| 31 | Macro | Risk premium on lending | Interest rate charged by banks on loans to private sector customers minus the "risk free" Treasury bill interest rate at which short-term government securities are issued or traded in the market. | WDI | 698 | 22 | 0.61 | 0.36 | 0.42 |
| 32 | Macro | Structural balance in % of potential GDP | The structural budget balance refers to the cyclically adjusted general government balance further adjusted for nonstructural elements beyond the economic cycle. | WEO | 419 | 14 | 0.61 | 0.50 | 0.29 |

*Source: Authors' calculations, BIS, IFS, IMF (World Economic Outlook), UNSTAT, World Bank (World Development Indicators).*

Table A2 continued

**Description of Indicators**

| No. | Category | Indicator | Description | Source | Number of obser-vations | Number of crises | Good-ness of fit (g) | Crises missed: C/(A+C) | Noncrises misclassi-fied: B/(B+D) |
|---|---|---|---|---|---|---|---|---|---|
| 33 | Macro | Multiplication of gross debt (in % of GDP) by the fiscal balance | Multiplication of gross debt (in % of GDP) by the general government primary net lending/borrowing, which resembles net lending (+)/borrowing (-) plus net interest payable/paid (interest expense minus interest revenue). | WEO, authors' calcula-tions | 385 | 15 | 0.57 | 0.33 | 0.53 |
| 34 | Macro | Deviation from the three-year average real GDP growth rate | Gross domestic product at constant prices. | WEO | 1,498 | 57 | 0.44 | 0.57 | 0.48 |
| 35 | Macro | GDP growth, three-year average | Average three-year growth of real GDP. | WEO | 1,547 | 58 | 0.41 | 0.29 | 0.89 |
| 36 | Macro | GDP contribu-tion: exports | Contribution of exports to GDP growth. | UNSTAT | 1,495 | 58 | 0.43 | 0.45 | 0.69 |
| 37 | Macro | GDP contribu-tion: changes in inventories | Contribution of changes in inventories to GDP growth. | UNSTAT | 1,304 | 51 | 0.57 | 0.45 | 0.40 |
| 38 | Macro | Primary balance in % of GDP | Primary net lending/borrowing is net lending (+)/borrowing (–) plus net interest payable/paid (interest expense minus interest revenue). | WEO | 879 | 26 | 0.57 | 0.46 | 0.41 |
| 39 | Macro | Market capitalization in % of GDP | Market capitalization (also known as market value) is the share price times the number of shares outstanding. | WDI | 974 | 39 | 0.41 | 0.51 | 0.68 |
| 40 | Macro | GDP contribution: government consumption | Contribution of government consumption to GDP growth. | UNSTAT | 1,496 | 58 | 0.44 | 0.47 | 0.66 |
| 41 | Macro | Stocks traded in % of GDP | Total value of shares traded during a given period in % of GDP. | WDI | 961 | 41 | 0.46 | 0.44 | 0.65 |
| 42 | Macro | Gross debt in % of GDP | Gross debt consists of all liabilities that require payment or payments of interest and/or principal by the debtor to the creditor at a date or dates in the future. This includes debt liabilities in the form of SDRs, currency and deposits, debt securities, loans, insurance, pensions and standardized guarantee schemes, and other accounts payable. | WEO | 1,270 | 37 | 0.41 | 0.54 | 0.63 |
| 43 | Macro | Stocks traded, turnover ratio | Total value of shares traded during the period divided by the average market capitalization for the period. | WDI | 922 | 34 | 0.57 | 0.56 | 0.30 |
| 44 | Macro | GDP contribu-tion: household consumption | Contribution of household consumption to GDP growth. | UNSTAT | 1,512 | 59 | 0.57 | 0.58 | 0.29 |

*Source: Authors' calculations, BIS, IFS, IMF (World Economic Outlook), UNSTAT, World Bank (World Development Indicators).*

Table A2 continued

**Description of Indicators**

| No. | Category | Indicator | Description | Source | Number of obser-vations | Number of crises | Good-ness of fit (g) | Crises missed: C/(A+C) | Noncrises misclassi-fied: B/(B+D) |
|---|---|---|---|---|---|---|---|---|---|
| 45 | Macro | GDP contribu-tion: imports | Contribution of imports to GDP growth | UNSTAT | 1,496 | 58 | 0.58 | 0.62 | 0.21 |
| 46 | Macro | GDP contribu-tion: gross fixed capital formation | Contribution of gross fixed capital formation to GDP growth. | UNSTAT | 1,511 | 59 | 0.57 | 0.63 | 0.23 |
| 47 | Macro | Overall balance in % of GDP | Net lending (+)/ borrowing (–) is calculated as revenue minus total expenditure. | WEO | 1,373 | 43 | 0.57 | 0.65 | 0.21 |
| 48 | Macro | Gross savings in % of GDP | Gross savings are calculated as gross national income less total consumption, plus net transfers. | WDI | 1,295 | 47 | 0.45 | 0.72 | 0.38 |

*Source: Authors' calculations, BIS, IFS, IMF (World Economic Outlook), UNSTAT, World Bank (World Development Indicators).*