OECD Journal: Economic Studies
Volume 2016
© OECD 2017

Economic resilience: The usefulness of early warning indicators in OECD countries

by
Mikkel Hermansen *and* Oliver Röhn*

The global financial crisis and the high associated costs have revived the academic and policy interest in "early warning indicators" of crises. This paper provides empirical evidence on the usefulness of a new set of vulnerability indicators, proposed in a companion paper (Röhn et al., 2015), in predicting severe recessions and crises in OECD countries. To evaluate the usefulness of the indicators the signalling approach is employed, which takes into account policy makers' preferences between missing crises and false alarms. Our empirical evidence shows that the majority of indicators would have helped to predict severe recessions in OECD economies between 1970 and 2014. In the domestic areas, indicators that measure asset market imbalances (real house and equity prices, house price-to-income and house price-to-rent ratios), perform consistently well both in and out-of-sample. Domestic credit related variables appear particularly useful in signalling upcoming banking crises and in predicting the global financial crisis out-of-sample. Indicators of global risks consistently outperform domestic indicators in terms of their usefulness, highlighting the importance of taking international developments into account when assessing a country's vulnerabilities. The good performance of the global indicators is however subject to a caveat: they are particularly suited to pick up recessions that affect a large number of countries simultaneously, such as the global financial crisis in 2008/09. The results are broadly robust to different definitions of costly events, different forecasting horizons and different time and country samples.

JEL classification: E32; E44; E51; F47

Keywords: Resilience, early warning indicators, vulnerabilities, imbalances, severe recessions, crises

* The authors are members of the Economics Department of the OECD. They would like to thank Aida Caldera Sanchez, Alain de Serres, Edward Leamer, Morten Rasmussen, Jean-Luc Schneider, and David Turner for helpful comments and Caroline Abettan for technical and editorial assistance. The views expressed in this paper are those of the authors and do not necessarily reflect those of the OECD and its member countries.

المنارة للاستشارات
www.manaraa.com

1. Introduction and main findings

The global financial crisis and the high costs associated with it have revived the academic and policy interest in "early warning indicators" of crises (e.g. Rose and Spiegel, 2011; Frankel and Saravelos, 2012; Alessi and Detken, 2011; Lo Duca and Peltonen, 2013 among many others). The early warning literature typically defines a crisis as the result of vulnerabilities and a trigger event. Despite recent methodological improvements of early warning models, predicting the timing of crises remains an extremely difficult task. Early warning models' most important value-added therefore is to identify variables (or "early warning indicators") that should be monitored to detect vulnerabilities, rather than to predict the exact start date of the next crisis. Vulnerability indicators can thus be a valuable input for monitoring economic risks, but should be complemented with other monitoring tools, including expert judgement.

The new wave of research has led many national and international institutions (e.g. European Commission and the International Monetary Fund) to develop their own set of vulnerability indicators and early warning models in the last few years. The OECD has also started to systematically monitor and publish indicators of potential macroeconomic and financial vulnerabilities in the *Economic Outlook* (EO) since the end of 2013 and more recently as part of country Economic Surveys.

The paper extends these OECD efforts by providing empirical evidence on the usefulness of a large set of vulnerability indicators in predicting costly events, measured as severe recessions. The paper draws on a set of vulnerability indicators proposed in a companion paper (Röhn et al., 2015). In Röhn et al. (2015) more than 70 vulnerability indicators are identified as particularly relevant for OECD countries based on a thorough review of the most recent evidence from the early warning literature and lessons learned from the global financial crisis. The indicators are grouped into six areas: i) financial sector imbalances, ii) non-financial sector imbalances, iii) asset market imbalances, iv) public sector imbalances, v) external sector imbalances, and vi) spillovers, contagion and global risks. The contribution of this paper is to assess the informational content of these vulnerability indicators for which sufficiently long time series exist by presenting both in-sample and out-of-sample results. The paper also complements earlier OECD research, which has focused on the impact of the size and composition of capital inflows on a country's risk of suffering banking and currency crises or sudden stops (Furceri et al., 2011; Ahrend and Goujard, 2012), by considering a wider range of vulnerability areas and bad economic outcomes, including severe recessions, banking, currency and sovereign debt crises.

We focus on predicting severe recessions which is a novelty compared to most of the early warning literature, which has typically focused on particular types of economic crises, such as currency (e.g. Kaminsky et al., 1998) or banking crises (e.g. Demirgüç-Kunt and Detragiache, 2000) and more recently broader systemic financial events (e.g. Alessi and Detken, 2011; Lo Duca and Peltonen, 2013). This choice is motivated by two aspects: First, large drops in GDP per capita provide an efficient way to capture a range of costly economic

www.manaraa.com

events and represents an outcome that policymakers are presumably most concerned to avoid. Second, severe recessions can be transparently defined and thus overcome the difficulty of identifying economic crises in an objective way.

The usefulness of the indicators is assessed on the basis of the signalling approach, one of the most commonly used early warning methodologies (e.g. Kaminsky et al., 1998; Borio and Lowe, 2002; Behn et al., 2013). The advantage of the signalling approach is that it can accommodate differences in data availability across countries and allows for the inclusion of a potentially larger number of vulnerability indicators than alternatives based on multivariate regression methods. This advantage is important because the aim of this study is to assess the predictive ability of each individual indicator rather than to devise a composite early warning indicator. According to the signalling approach, an indicator signals a vulnerable state of the economy if it crosses a threshold. Threshold levels are chosen so as to strike a balance between the risks of missing vulnerable states (so-called type I errors) and issuing many false alarms (so-called type II errors). In particular, a loss function is used to determine the optimal thresholds, which explicitly takes into account policymaker preferences between type I and type II errors. An indicator is labelled useful if its predictions result in a lower loss compared to a benchmark in which the indicator is ignored.

The main findings can be summarised as follows:

- The majority of vulnerability indicators appear to be useful early warning indicators for severe recessions when policymakers are strongly averse to missing severe recessions. Most indicators issue first warning signals on average more than 1.5 years before the onset of a severe recession, providing policymakers with a sufficiently long lead to react. However, the extent of the signalling power varies across indicators and the results are sensitive to the exact specification of policymakers' preferences between missing crises and false alarms.
- In the domestic areas, indicators that measure asset market imbalances (real house and equity prices, house price-to-income and house price-to-rent), perform consistently well both in and out-of-sample. Domestic credit related variables appear particularly useful out-of-sample and in signalling upcoming banking crises. The usefulness of indicators of external imbalances such as current account balances, official reserves and foreign currency exposure perform well in certain specifications. Fiscal imbalances are generally not found to be useful in signalling severe recessions and crises.
- Indicators of global risks consistently outperform domestic variables in terms of relative usefulness. In particular, measures of the global credit-to-GDP ratio (growth and gaps from a trend), a global equity price gap and a global house price gap perform particularly well both in-sample and out-of-sample. This highlights the importance of taking international developments into account when assessing a country's vulnerabilities. In an increasingly integrated world economy, vulnerabilities that build-up on the global level potentially transmit to countries around the world. The good performance of the global indicators is however subject to a caveat: as the indicators do not vary across countries they are particularly suited to pick up recessions that affect a large number of countries simultaneously, such as the global financial crisis in 2008/09.
- The results are broadly robust to different definitions of costly events (severe recessions versus defined economic crises, including banking, currency and sovereign debt crises), different forecasting horizons and different time and country samples.

المنارة للاستشارات
www.manaraa.com

The paper proceeds as follows. Section 2 discusses the data, including the choice of severe recessions as the dependent variable and the vulnerability indicators. Section 3 outlines the empirical approach and section 4 presents the results.

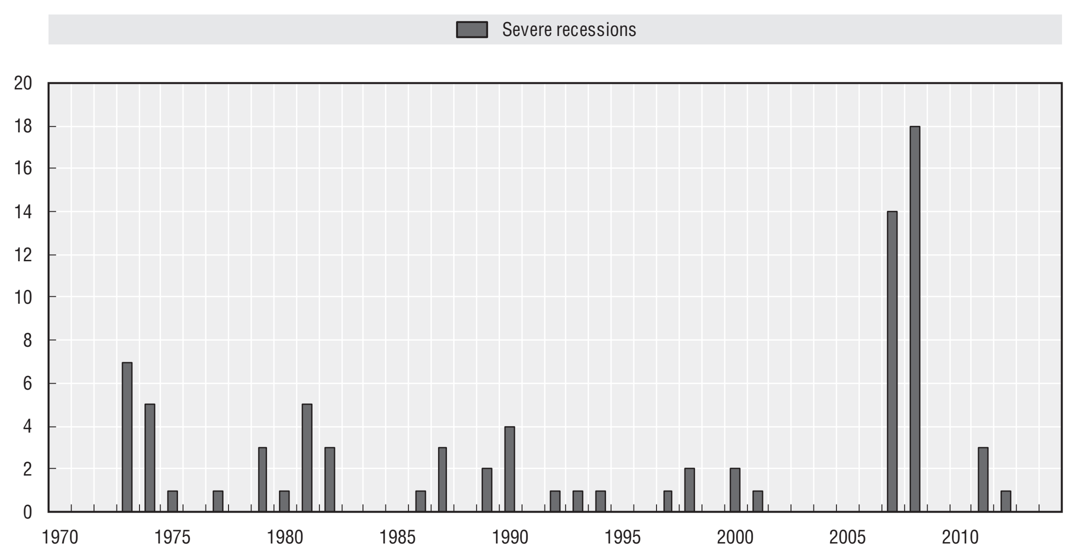
2. Data

2.1. Severe recessions as a measure of costly economic events

For the baseline evaluation, costly economic events are defined as severe recessions, putting the focus on tail events (left tail) as opposed to regular business cycle fluctuations. First, the Bry and Boschan (1971) algorithm is applied to identify peak and trough dates of business cycles in the level of GDP per capita over the period 1970-2014 for all 35 OECD countries. Next, severe recessions are defined as recessions with a fall in the level of GDP per capita from peak to trough above the median fall over the entire country-year sample, which is close to 3.5% of peak GDP per capita. The identified severe recessions are associated with an increase in the unemployment rate of on average 2.6 percentage points, confirming that the episodes come with a significant increase in idleness. Figure 1 displays the dates of the pre-severe recession GDP per capita peak and Table A1.1 in the Appendix shows the number of recessions and severe recessions for each country.

Figure 1. **Severe recession dates**

Number of countries



Note: The dates show the pre-recession peak in GDP per capita.

The use of severe recessions as the dependent variable constitutes a departure from most of the early warning literature, which has typically focused on particular types of economic crises, such as currency (e.g. Kaminsky et al., 1998) or banking crises (e.g. Demirgüç-Kunt and Detragiache, 2000) and more recently broader systemic financial events (e.g. Alessi and Detken, 2011; Lo Duca and Peltonen, 2013). Our focus on severe recessions is motivated by two aspects. First, we take a pragmatic approach with the aim to identify a set of indicators which can be used to make a broad and comprehensive assessment of potential vulnerabilities. For this purpose, large drops in GDP per capita provides an efficient way to capture a range of costly economic events and represents an outcome that policymakers are presumably most concerned to avoid.

المنارة للاستشارات
www.manaraa.com

Second, it is inherently difficult to define economic crises in an objective way. Crisis definitions often differ from one study to the next and it is not unusual for studies to disagree whether a particular episode constitutes a crisis and to differ on the exact timing of a particular crisis (e.g. Romer and Romer, 2015). Consequently, differences in crises definitions have led to differences in results. Moreover, most crisis indicators do not provide information on the relative severity of crises, but rather focus on the timing. In contrast, we focus on severe recessions which can be computed in an objective and transparent manner for large panels of countries over long time periods. The robustness section shows, nonetheless, that the results are broadly robust to different definitions of costly events including episodes of banking, currency and sovereign debt crises on the basis of the data collected by Babecký et al. (2014).

We pool severe recessions across countries, which is a standard approach in the recent early warning literature (e.g. Alessi and Detken, 2011; Lo Duca and Peltonen, 2013). Pooling across countries is necessary because each country only experiences a very limited number of severe recessions (on average around 2 to 3 over the time period considered). However, a larger sample size of course implies a more heterogeneous set of country experience and the model may be too simple to pick up these heterogeneities. As explained in more detail below, we partly account for these heterogeneities by allowing the *threshold values* to differ across countries. In addition, in the robustness section we also split the sample into high and low income OECD countries.

2.2. Vulnerability indicators

In this paper we rely on a set of vulnerability indicators that have been identified in a companion working paper (Röhn et al., 2015) based on a review of the most recent early warning literature and lessons learned from the global financial crisis. In Röhn et al. (2015) indicators are classified into five types of domestic vulnerabilities (or "imbalances"). These include i) financial sector imbalances, ii) non-financial sector imbalances, iii) asset market imbalances, iv) public sector imbalances and v) external sector imbalances. Besides domestic imbalances, economies are also vulnerable to shocks and crises originating in other countries through international spillovers and contagion through financial, trade and confidence channels. In addition, a set of global indicators common to all countries are thus also included.

Data availability across the indicators and across countries varies significantly. To capture a broad range of different severe recessions, we therefore only include vulnerability indicators for which data is available for at least 50% of the severe recessions identified over the period 1970-2014. Unfortunately, this excludes all financial sector imbalances indicators from the analysis as they are generally only available for a short time span of less than 10 years (see Röhn et al. [2015] for the precise data availability of the different indicators). To save space we do not report results for the public sector imbalance indicators, which have generally not been found to be useful for early warning in this study. The interested reader is referred to the working paper version of this article (Hermansen and Röhn, 2015). Table A1.2 in the Appendix provides details on the indicators included in the analysis and Table A1.3 reports pairwise correlations among the indicators. Indicators in the same imbalance area are generally positively correlated, with the highest correlations among credit and some real estate indicators. Across imbalance areas pairwise correlations are generally lower.

As is standard in the literature, we experiment with different transformations of the indicators. In particular, for several variables we also use deviations from a trend. The trends

المنارة للاستشارات
www.manaraa.com

have been calculated according to three different approaches: a) a slowly-adjusting one-sided HP-filter (gap1); b) a faster-adjusting one-sided HP-filter (gap2); and c) a 20 quarter (5 year) one-sided moving average (gap3).[1] All three trends are calculated recursively using only available data up to each point in time, ensuring only real time available information are utilised. In addition, several indicators are also expressed as growth rates: year-on-year growth rates (gr1); quarter-on-quarter growth rates (gr2); and cumulated growth rates over the preceding 6 quarters (4 years for annual series) (gr3). Table A1.2 in the Appendix lists the transformations employed for each indicator.

3. Empirical methodology: the signalling approach

The early warning literature has predominantly relied on two empirical approaches: signalling models (see e.g. Kaminsky et al. (1998) for an influential study) and multivariate logit/probit models (e.g. Demirgüc-Kunt and Detriagiache, 1998).[2] The advantage of the signalling approach is that it accommodates differences in data availability across countries and allows for the inclusion of a potentially larger number of vulnerability indicators than the multivariate regression method. This is an important advantage, since the aim of this study is to assess the predictive ability of each individual indicator rather than to devise a composite early warning indicator. Hence we employ the signalling approach. A drawback of this method is that in its simplest form it ignores potential interactions among indicators and does not allow for standard statistical tests to assess the significance of the indicators.

The signalling approach is a non-parametric approach, which is based on the idea that a useful early warning indicator behaves differently in pre-crisis episodes compared to normal periods. A vulnerability indicator issues a warning signal of an upcoming crisis if the indicator exceeds a threshold, here defined by a percentile of an indicator's own distribution. Each indicator can then be evaluated according to the matrix below in which crisis occurrence and warning issuance are compared. A is the number of quarters across countries and time in which an indicator provides a correct signal, B is the number of quarters in which a wrong signal is issued, that is a signal was provided, but there was no crisis. C is the number of quarters the indicator does not issue a signal despite a crisis occurring. Finally, D is the number of quarters in which the indicator does not provide any warning signal, and rightly so because there was no crisis.

Evaluation matrix

	Crisis (within the following 8 quarters)	No crisis (within the following 8 quarters)
Signal issued	A	B
No signal issued	C	D

A signal is considered as correct if a crisis occurs within a fixed number of quarters after the signal is issued. In the baseline we set the number of quarters to 8, which is a commonly applied window in the literature (e.g. Kaminsky et al., 1998). In the robustness section we investigate whether the results are sensitive to the choice of this forecasting horizon. The first four quarters following the start of a severe recession are excluded from the evaluation sample since the behaviour of the vulnerability indicators is likely to be different during a severe recession compared to normal or pre-recession times (Bussiere and Fratzscher, 2006).

www.manaraa.com

Ideally a threshold for each indicator should be chosen such that all observations fall into the A (a signal was issued and indeed there was a crisis) and D (a signal was not issued and indeed there was no crisis) cells. In reality, however, setting the threshold involves balancing two types of errors policy makers face. A high threshold would imply few crisis signals and a higher risk of missing a crisis (type I error). A low threshold on the other hand would increase the number of signals, but would also raise the number of false crisis signals (type II error). The optimal threshold is set by minimising the following loss function, which reflects the two types of errors as well as policymakers' relative preferences for either type. In particular we follow Sarlin (2013) and define the loss function as follows:[3]

$$
\begin{aligned}
L(x) &= \theta \cdot P \cdot T1 + (1-\theta) \cdot (1-P) \cdot T2 \\
&= \theta \cdot \frac{A+B}{A+B+C+D} \cdot \frac{C}{A+C} + (1-\theta) \cdot \frac{B+D}{A+B+C+D} \cdot \frac{B}{B+D} \\
&= \theta \cdot \frac{C}{A+B+C+D} + (1-\theta) \cdot \frac{B}{A+B+C+D}, \qquad \theta \in [0,1]
\end{aligned}
$$

where the threshold *x* determines the distribution between A-D and P and (1–P) captures the unconditional probability of pre-crises and normal periods, respectively. The parameter θ reflects the preferences of policymakers between type I (T_1) and type II (T_2) errors and is related to the relative costs of missing crises versus costs of false alarms (e.g. Demirgüc-Kunt and Detragiache, 2000). In case an alarm goes off, preventive action should be taken to avoid or at least reduce the cost of a possible crisis (see e.g. Caldera Sanchéz et al. (2016) for a discussion of policy tools). If the alarm turns out to be false, costs are likely to be associated with the preventive action for example in terms of lower growth. T_1, T_2, and P can be estimated from the in-sample frequencies of A-D given a threshold *x* as shown in the second line of the equation above.[4] With the experience of the global financial crisis, policymakers are likely to be more concerned about missing crises. Hence, below we focus on values of the preference parameter in the range of $\theta \in$ [0.5-0.9].

The threshold *percentile* is optimised over all countries, i.e. a common percentile is chosen which minimises the aggregate loss over all countries.[5] However, to allow for the fact that the distributions of indicators are likely to differ substantially across countries, this optimal threshold percentile is applied to country-specific distributions of the indicators. Hence, the threshold *values* are allowed to differ across countries. For example, the 65th percentile might be the optimal threshold percentile for an indicator, i.e. the optimal threshold leaves 65% of the observations below the threshold for each country. In the case of the private credit gap indicator (the difference between the actual credit-to-GDP ratio and a trend) this corresponds to a threshold value of 4.4 percentage points of GDP for the United States above which a signal is issued, whereas the threshold value is 5.7 percentage points of GDP for Spain.

The performance of each indicator is assessed according to the following criteria:

- Absolute Usefulness: $U_a(x) = \min[\theta P, (1-\theta)(1-P) - L(x)]$. If the absolute usefulness is positive, there is a benefit in using the early warning indicator as it results in a lower loss (L(x)) for the policymaker than simply disregarding the indicator, which would result in a loss of min [θP; (1-θ)(1-P)]. This is because if the policymaker disregards the indicator, she has the choice between always or never signalling a crisis. If she always signals a crisis, so that C = D = 0, the resulting loss is (1-θ)(1-P). If she never signals a crisis, so that A = B = 0, the resulting loss is θP. The policymaker would choose the option which results in a lower loss given preferences θ and the unconditional crisis probability P.

www.manaraa.com

Hence, the loss from disregarding the indicator is min [θP; (1-θ)(1-P)]. An indicator is then useful if it results in a lower loss than this benchmark loss. Moreover, it can be shown that for any given indicator threshold x the usefulness of the indicator is maximised at θ = (1-P). Since P is low in practice, this implies that for an indicator to achieve a high usefulness the policymaker needs to be significantly more concerned about the detection of crises than avoiding false alarms. Otherwise the policymaker could easily achieve a lower loss compared to the non-perfectly performing indicator by always assuming to be in a state of the high-frequency class, which is a normal period in our case.

- Relative Usefulness: $U_r(x) = \dfrac{U_a(x)}{\min[\theta P, (1-\theta)(1-P)]}$. Relative usefulness is the share of an indicators' absolute Usefulness U_a relative to the maximum possible Usefulness. A perfectly performing indicator would result in a value of the above loss function of zero so that the absolute usefulness of the measure would be min [θP; (1-θ)(1-P)]. Hence, U_r reports U_a as a percentage of the usefulness that a policymaker could achieve with a perfectly performing indicator. The relative usefulness is our preferred performance indicator as it allows for the comparison of models for policymakers with different preference parameters θ.

In addition to these two main criteria we also report several additional performance measures that have been frequently used in the literature:

- Adjusted noise-to-signal ratio (aNtS) = [B/(B+D]/[A/(A+C)], captures the ratio of the share of false alarms (noise) versus the share of correctly predicted crises (signal). A useful indicator is supposed to have an aNtS of less than 1. A value of 1 would result if an indicator provides purely random signals.
- Conditional probability = $A/(A+B)$. The probability of a crisis conditional on a signal being issued.
- Difference probability = $A/(A+B) - (A+C)/(A+B+C+D)$. The difference between the conditional probability and the unconditional probability of a crisis occurring. The larger the difference the better quality of the indicator. A negative difference probability implies that the indicator performs worse than an early warning system based on the simple unconditional probability of a crisis. In this case the indicator should not be applied.
- Average lead time (ALT). The average number of quarters prior to a crisis in which the first signal is issued.

In the results section below, the assessment of the indicators is mainly based on the (relative) usefulness criterion. This is because the usefulness measures allow to explicit accounting for policymaker preferences between missing crises and avoiding false alarms in contrast to the additional criteria such as the noise-to-signal ratio. To the extent that the other criteria provide additional insights we report them in some cases.

4. Results

4.1. *Full-sample results*

Table 1 shows the performance of each indicator according to the relative usefulness criterion together with the optimal threshold percentile for different values of the preference parameter θ. For a particular indicator, only the transformation that yields the highest relative usefulness is reported in the tables. The focus is on values of the preference parameter $\theta \in$ [0.7, 0.9], i.e. when policymakers have strong preferences for the detection of pre-severe recession episodes. For lower values of the preference parameter the indicators

المنارة للاستشارات

www.manaraa.com

Table 1. **Full-sample performance of individual indicators**

	Direction to be safe	$\theta = 0.7$			$\theta = 0.8$			$\theta = 0.9$		
		Transformation	Threshold	Relative usefulness	Transformation	Threshold	Relative usefulness	Transformation	Threshold	Relative usefulness
Non-financial sector imbalances										
Total private credit (% of GDP)	<				none	80	0.08	gap1	10	0.05
Private bank credit (% of GDP)	<	**gr1**	**95**	**0.02**	**gr3**	**75**	**0.13**	gap1	10	0.06
Household credit (% of GDP)	<				gap3	70	0.08			
Corporate credit (% of GDP)	<	gap1	95	0.01	gap2	90	0.05	**gap1**	**25**	**0.09**
Asset market imbalances										
Real house prices	<	**gap3**	**95**	**0.06**	**gap3**	**85**	**0.15**	**gr3**	**40**	**0.09**
House price-to-disposable income ratio	<	**none**	**90**	**0.17**	**none**	**80**	**0.26**	**none**	**60**	**0.15**
House price-to-rent ratio	<	**none**	**90**	**0.08**	**none**	**80**	**0.18**	**gr3**	**40**	**0.12**
Residential investment (% of GDP)	<	none	95	0.01	none	90	0.08	none	10	0.01
Real equity prices	<	**gap1**	**90**	**0.04**	gap1	85	0.12	**gap3**	**45**	**0.07**
External imbalances										
Current account balance (% of GDP)	>	none	5	0.01	none	10	0.07			
Foreign currency exposure index*	>									
Quantitative foreign currency exposure*	>				gr3	65	0.10	gr1	80	0.03
Foreign exchange reserves (% of GDP)	>	**none**	**5**	**0.05**	none	10	0.10			
Foreign reserves to M2*	>	**none**	**15**	**0.05**	**none**	**15**	**0.14**			
Real effective exchange rate (CPI)	<							gap3	5	0.01
Real effective exchange rate (ULC)	<							gr3	10	0.01
Export performance	>				gap3	10	0.03			
Spillovers, contagion and global risks	>									
Trade openness (% of GDP)	<				none	80	0.11			
Global private credit (% of GDP)	<				**gr1**	**55**	**0.18**	**gr3**	**30**	**0.17**
Global private bank credit (% of GDP)	<	**gap1**	**80**	**0.10**	**gr3**	**70**	**0.31**	**gr3**	**60**	**0.22**
VIX volatility index	<				**gap2**	**65**	**0.25**	**gap2**	**55**	**0.24**
Global real equity prices	<	**gap1**	**90**	**0.23**	**gap3**	**75**	**0.30**	**gap3**	**50**	**0.27**
Global real house prices	<	**gr3**	**95**	**0.03**	**gap3**	**65**	**0.27**	**gap3**	**55**	**0.24**

Note: The indicators are measured on a quarterly frequency, except for indicators marked with *, which are measured on an annual frequency. Relative usefulness measures the share of the usefulness of the indicator relative to a perfectly performing indicator (see section 3). Up to six different transformations have been tested for each indicator and only the best in terms of the relative usefulness criteria is reported. Gap1: deviation from a recursive, slowly-adjusting HP-filter with smoothing parameter $\lambda = 400000$ for quarterly series ($\lambda = 1600$ for annual series); gap2: deviation from a recursive, faster-adjusting HP-filter with smoothing parameter $\lambda = 26000$ for quarterly series ($\lambda = 100$ for annual series); gap3: deviations from a 20 quarter (5 year) moving average; gr1: year-on-year growth rates; gr2: quarter-on-quarter growth rates; gr3: cumulated growth rates over the preceding 6 quarters (4 years for annual series). Figures in bold indicate that the indicator is among the best 10 performing indicators in terms of the relative usefulness criterion for a given preference parameter θ. When indicators have a relative usefulness of zero the corresponding cells in the table are left blank.
Source: Authors' calculations.

are usually not useful and results are not reported here.[6] The fact that the indicators only become useful for higher values of θ, as the reasoning above about the features of this loss function has shown, is a direct result of the low unconditional probability of pre-severe recession episodes in the sample around 10-20%. For $\theta \in [0.7, 0.9]$ most of the indicators are useful even if in several cases only marginally so. Table A1.4 in the Appendix also shows that most of the top performing indicators issue first warning signals on average more than 6 quarters before the onset of a severe recession, providing policymakers with a sufficiently long lead to react.

Global vulnerability indicators consistently outperform domestic indicators in terms of relative usefulness irrespective of the preference parameter θ. For $\theta \in [0.8, 0.9]$, the

المنارة للاستشارات
www.manaraa.com

(cumulative) growth of the global private bank credit-to-GDP ratio, a global equity price gap and a global house price gap perform particularly well. For example, growth of the global bank credit-to-GDP ratio is the best performing indicator for a value of the preference parameter of $\theta = 0.8$. The indicator reaches a relative usefulness of 31%, which means the indicator achieves 31% of the usefulness a policymaker would gain from an indicator that calls all severe recession episodes correctly and issues no false alarms. Table A1.4 provides further details on the performance of the indicators. The table shows that the global bank credit-to-GDP ratio indicator correctly calls 62% (1 minus type I error (0.38)) of the pre-severe recession episodes. Conditional on a signal being issued, the probability of a severe recession is 33%, which is 19 percentage points higher than the unconditional probability of a severe recession in the sample. Finally, the indicator issues a first warning signal on average 7 quarters ahead of the onset of a severe recession, providing policymakers with a sufficiently long lead to react.

The good performance of the global indicators is in line with the findings in the literature (e.g. Lo Duca and Peltonen, 2013; Babecký et al., 2014; Behn et al., 2013; Alessi and Detken, 2011) and highlights the importance to take international developments into account when assessing a country's vulnerabilities. In an increasingly integrated world economy, vulnerabilities that build-up on the global level potentially transmit to countries around the world. The good performance of the global indicators is however subject to a caveat: as the indicators do not vary across countries they are particularly suited to pick up recessions that affect a large number of countries simultaneously, such as the global financial crisis in 2008/09. Global indicators may be less suited to pick up vulnerabilities to more locally confined severe recessions. Figure 2 illustrates the performance of the two global risk indicators: global equity prices and house prices. It shows that good performance of the indicators is not solely driven by the global financial crisis. The indicators also pick up earlier episodes in which a range of countries experienced crisis simultaneously such as in the early 90s and mid-70s.[7]

Turning to the domestic vulnerability indicators, house price related indicators perform particularly well. The house price-to-disposable-income indicator is the best performing domestic indicator across different values of the preference parameter. In addition, the house price-to-rent ratio and real house price gap perform well. These results confirm findings in the literature that unsustainable real estate booms are often followed by costly economic downturns (e.g. Borio and Drehmann, 2009; Claessens et al., 2012).

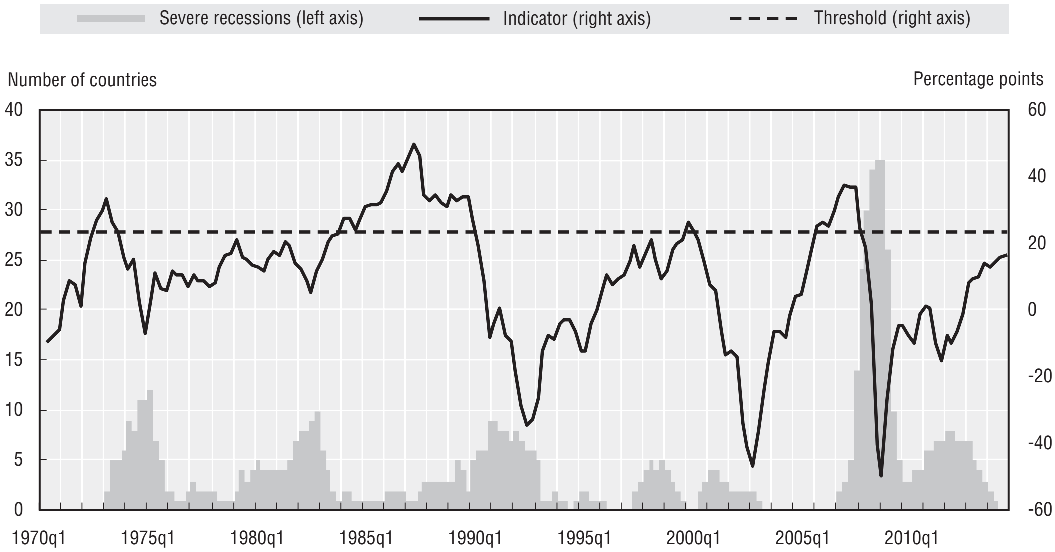
Domestic credit related variables also perform well, but are less robust to small variations in the preference parameter. In particular, growth in domestic bank credit-to-GDP ($\theta = 0.7$ and $\theta = 0.8$) and the gap of corporate credit-to-GDP are among the top-10 indicators in terms of the relative usefulness. While the literature has found credit variables to be among the most robust early warning indicators of financial crises (Borio and Lowe, 2002; Kaminsky and Reinhart, 1999; Reinhart and Rogoff, 2013; Schularick and Taylor, 2012; Taylor, 2012; Jordà et al., 2011), our results show that they are also relevant for the detection of severe recessions more broadly. Our results, however, also indicate that credit variables are less robust when the focus is more broadly on severe recessions in contrast to financial crises which have been the focus of the previous literature. We explore this issue further in the robustness section when we test whether the results change when we employ banking crises as our dependent variable. Finally, the results also suggest that official reserves (as a ratio of M2) are useful in predicting severe recessions (for $\theta = 0.8$).

المنارة للاستشارات

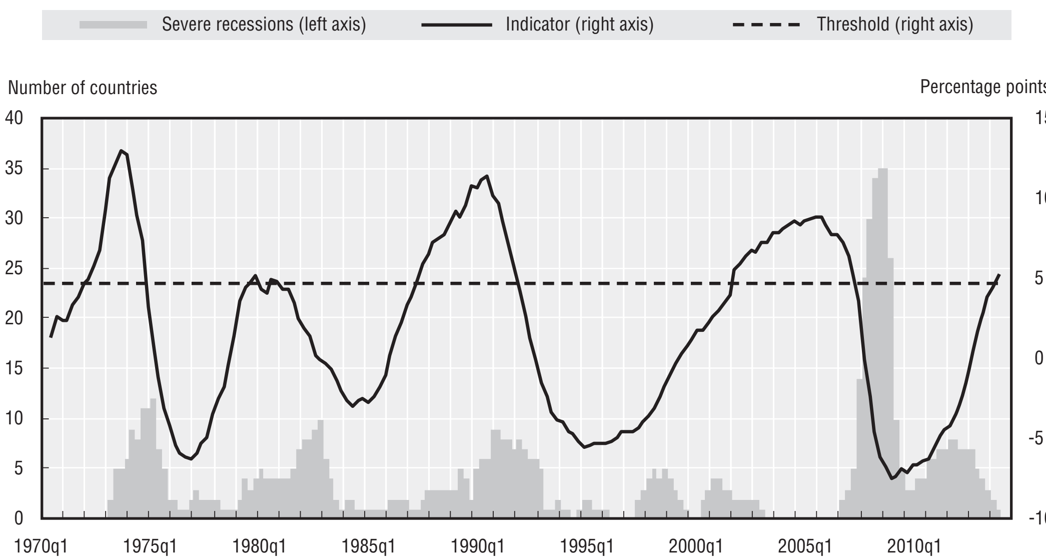
www.manaraa.com

Figure 2. **Performance of global vulnerability indicators**

A. Global share price index



B. Global real house price index



Note: Grey areas represent the number of countries identified as being in a severe recession (from peak to trough). The global share price index and real house price index are both measured in deviation from a moving average (gap 3, see above). The optimal threshold is illustrated for $\theta = 0.8$. Global indicators are constructed as a weighted average across OECD countries (using GDP weights, see Table A1.2).
Source: Author's calculations.

These general observations notwithstanding, the findings also highlight the sensitivity of the results to small changes in the preference parameter θ. The relative usefulness and the ranking of best performing indicators (including the best transformation of an indicator in terms of relative usefulness) can vary with the value of θ. This sensitivity is further illustrated in Figures 3 and 4 which show the relationship between θ and the relative usefulness as well as the trade-off between type I and type II errors for two selected indicators: house price-to-disposable income ratio and global private bank credit-to-GDP. The figures show that the usefulness generally increases in θ up to a certain point after

المنارة للاستشارات
www.manaraa.com

Figure 3. **Usefulness of house price-to-disposable income ratio**

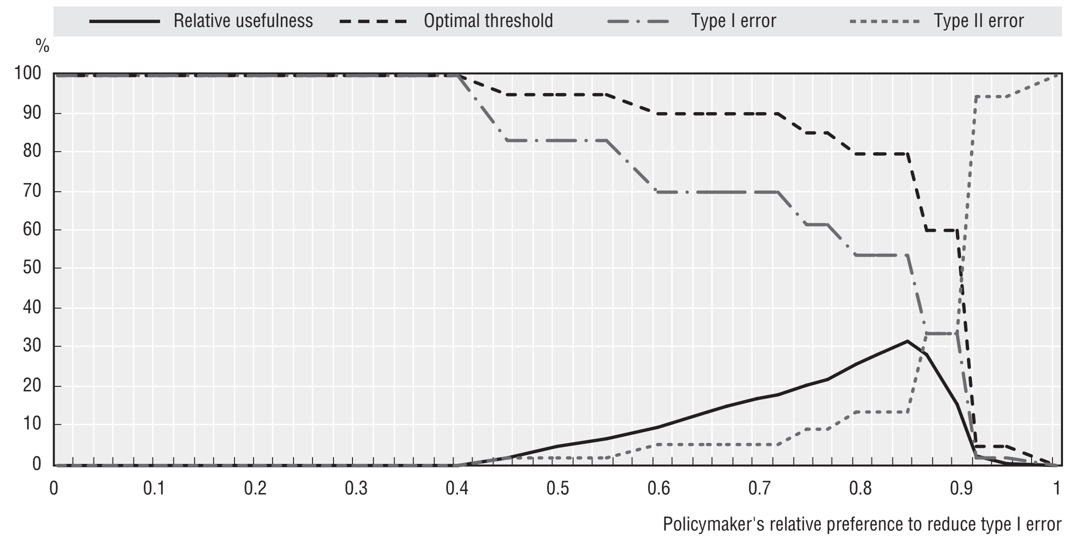
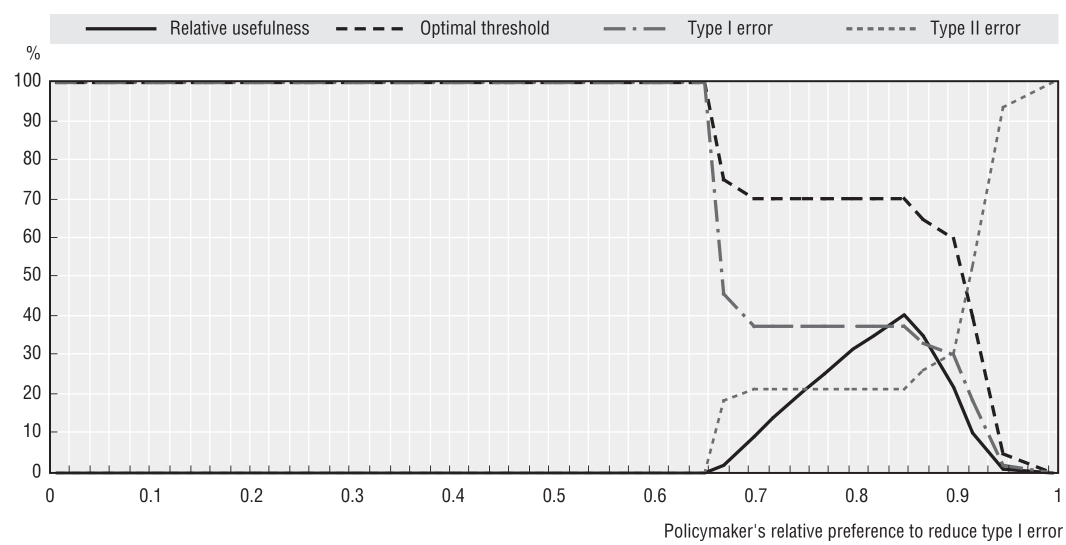


Figure 4. **Usefulness of global private bank credit-to-GDP**



Note: The indicator is transformed into cumulated growth rates over the preceding 6 quarters.

which the usefulness drops quite sharply. After this point, because of the strong preference against missing crises, it is difficult for an indicator to beat the benchmark of always signalling a crisis (and therefore never missing a crisis). To reflect the fact that the results are sensitive to the exact value of θ but to keep the discussion tractable at the same time, we restrict presentation of the results to values of the preference parameter $\theta \in [0.8, 0.9]$ in the following. Given our focus on highly costly events, the choice of preference parameters reflecting strong preferences for their detection appears reasonable.

4.2. Out-of-sample results

As the ultimate objective of early warning indicators is to help predict future costly events, we also evaluate the performance of the indicators out-of-sample. In particular, we

المنارة للاستشارات
www.manaraa.com

want to evaluate whether the indicators provided useful information to detect the severe recessions associated with the global financial crisis and the European sovereign debt crisis. To this end, we split the sample into an "in-sample" estimation period and an "out-of-sample" evaluation period. The starting date of the in-sample estimation period depends on the data availability of the indicators. The in-sample estimation period ends in 2004Q4 to exclude the global financial crisis from the in-sample estimation period given our baseline forecasting horizon of 8 quarters. The out-of-sample evaluation period spans from 2005Q1 to 2012Q4. The out-of-sample evaluation period ends in 2012Q4 as we have only data to evaluate predictions until 2014Q4. Note that by splitting the sample in this way, almost half of the severe recession episodes are excluded from the estimation sample, highlighting the challenges involved in the out-of-sample exercise. In addition, the evaluation sample is heavily dominated by the global financial crisis. However, given the limited number of severe recessions it is difficult to devise an out-of-sample exercise in which a dominance of the global financial crisis would not occur.

The out-of-sample evaluation proceeds in the following steps. In a first step, the optimal threshold percentile for each indicator is calculated by minimising the loss function over the in-sample estimation period up to 2004Q4. These thresholds are then applied for each indicator in the evaluation sample. Given the threshold, the signals from the indicators are collected and type I, type II and the usefulness criterion are computed for values of the preference parameter $\theta \in [0.8, 0.9]$.[8] It should be noted that if an indicator did not yield positive usefulness in the estimation sample, the indicator is excluded from the out-of-sample exercise by setting the threshold percentile to 100 (or 0).

The results are presented in Table 2. While for $\theta = 0.8$ only very few indicators achieve a positive relative usefulness, for $\theta = 0.9$ most of the indicators are useful and for several indicators the relative usefulness is even higher than in the full sample (see Table 1). Global indicators perform very well, confirming their superior full sample performance. For example, the global equity price gap indicator achieves a very high relative usefulness of 64%. It signals 84% of the pre-recession episodes correctly and only issues 17% false alarms. In addition, on average it issued a first warning signal 7.5 quarters ahead of the onset of the severe recessions (not reported). In addition, indicators of global credit and global real house prices also perform very well out-of-sample.

Turning to the domestic indicators, we find that credit and asset market indicators perform particularly well, similar to the full sample results. Domestic credit gap indicators perform very well and achieve a higher relative usefulness compared to the full sample results, highlighting the particular importance of unsustainable domestic credit booms in the global financial crises. From the asset market imbalance indicators the real equity price gap performs particularly well achieving a relative usefulness of 36%, substantially higher than for the full sample. The indicator also signals 90% of all pre-recession episodes correctly and started issuing warning signals on average more than 7.5 quarters before the onset of the financial crises (not reported). The gap of the residential investment-to-GDP ratio from trend also performs well out-of-sample and substantially better than in the full sample. The house price related indicators perform slightly worse out-of-sample compared to the full sample. In the case of the price-to-rent and price-to-disposable income ratios gaps from long-term trends now perform better than the levels of the ratios. External imbalance indicators do not perform very well out-of-sample and once again we do not find any role for the investigated fiscal imbalance indicators.

المنارة للاستشارات
www.manaraa.com

Table 2. **Out-of-sample performance of individual indicators**

		$\theta = 0.8$					$\theta = 0.9$				
	Direction to be safe	Transformation	Threshold	Relative usefulness	Type I error	Type II error	Transformation	Threshold	Relative usefulness	Type I error	Type II error
Non-financial sector imbalances											
Total private credit (% of GDP)	<						**gap1**	**15**	**0.25**	**0.16**	**0.57**
Private bank credit (% of GDP)	<	gr1	95	0.00	0.93	0.03	**gap1**	**15**	**0.25**	**0.19**	**0.54**
Household credit (% of GDP)	<						**gap3**	**75**	**0.19**	**0.56**	**0.23**
Corporate credit (% of GDP)	<						**gap1**	**30**	**0.25**	**0.25**	**0.47**
Asset market imbalances											
Real house prices	<	gr2	95	0	1	0.01	gap3	80	0.13	0.74	0.12
House price-to-disposable income ratio	<	gr2	95	0	0.99	0.02	gap3	85	0.11	0.78	0.08
House price-to-rent ratio	<	gap2	95	0	0.98	0.01	gr3	75	0.11	0.74	0.12
Residential investment (% of GDP)	<	**none**	**85**	**0.06**	**0.85**	**0.04**	**gap3**	**65**	**0.21**	**0.57**	**0.17**
Real equity prices	<						**gap3**	**15**	**0.36**	**0.10**	**0.52**
External imbalances											
Current account balance (% of GDP)	>	none	5	0	0.83	0.12	none	50	0	0.49	0.42
Foreign currency exposure index*	>						none	30	0	0.73	0.20
Quantitative foreign currency exposure*	>										
Foreign exchange reserves (% of GDP)	>	**gr3**	**5**	**0.08**	**0.81**	**0.06**	gap3	95	0.03	0.09	0.86
Foreign reserves to M2*	>	gr1	5	0	0.67	0.29					
Real effective exchange rate (CPI)	<						gap1	10	0.03	0.10	0.84
Real effective exchange rate (ULC)	<						gr1	15	0.05	0.12	0.79
Export performance	>						gap1	25	0.05	0.75	0.15
Spillovers, contagion and global risks	>										
Trade openness (% of GDP)	<						gr1	5	0.07	0.04	0.87
Global private credit (% of GDP)	<	gr3	95	0	0.97	0.1	**gap1**	**25**	**0.42**	**0.12**	**0.45**
Global private bank credit (% of GDP)	<	gap2	95	0	1	0.04	**gr3**	**70**	**0.39**	**0.18**	**0.41**
VIX volatility index	<						gap1	95	0	1	0.01
Global real equity prices	<						**gap3**	**50**	**0.64**	**0.16**	**0.17**
Global real house prices	<	gr3	75	0	0.99	0.01	**gap3**	**55**	**0.36**	**0.47**	**0.16**

Note: The in-sample dataset includes data until 2004q4 and the out-of-sample dataset spans from 2005q1 to 2012q4. See note to Table 1.
Source: Authors' calculations.

4.3. *Robustness*

Alternative definitions of costly events

In the baseline we have been agnostic about the cause of a severe recession. This is in contrast to much of the early warning literature that has focused on particular types of crises, such as currency or banking crises (see Section 2). Therefore, we check whether the results hold when instead of using severe recessions as a definition of costly events, we use crises episodes instead.

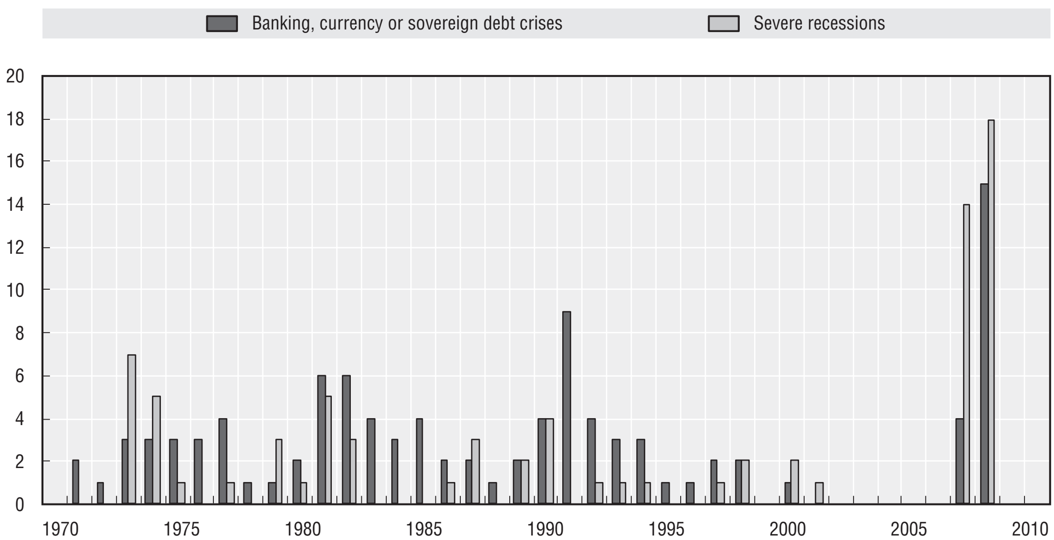
Crises data are taken from Babecký et al. (2014). Their database covers banking, currency and sovereign debt crises among OECD countries over the period 1970Q1-2010Q4. Babecký et al. (2014) collect crisis dates from a range of studies, including the recent and well-known databases of Reinhart and Rogoff (2011) and Laeven and Valencia (2012). A crisis is identified if at least one study claims that a crisis occurred. The dataset has several advantages. First, annual crises dates have been cross-checked by country experts, who also converted them into quarterly frequency, to avoid relying overly on a specific crisis definition based on

المنارة للاستشارات
www.manaraa.com

changes in one or few variables. Second, its quarterly frequency allows a more precise assessment of the usefulness of early warning indicators. Figure 5 shows the dates of defined crises in comparison with the dating of severe recessions. The figure shows that crises and severe recession dates do not always coincide. Overall fewer severe recessions compared to crises are identified. On the other hand, during the global financial crisis the number of countries experiencing a severe recession is larger than the number of countries experiencing a (banking) crisis.

Figure 5. **Crises and severe recession dates**

Number of countries



Source: Babecký et al. (2014).

Table 3 reports the results for all types of crises included in the Babecký et al. (2014) database and for banking crises in particular. The results are qualitatively similar to the baseline. In particular global variables outperform domestic variables. In addition, the house price-to-disposable income ratio and the house price-to-rent ratio are among the best performing domestic variables. However, several differences also stand out. The official reserves-to-GDP ratio and an index of foreign currency exposure perform better in both crises samples compared to the baseline (for $\theta = 0.8$). In the "banking crises" sample, the domestic credit variables perform somewhat better than in the baseline, highlighting the particular role that credit booms play for banking crises.

Forecasting horizon

Next, we test the robustness of our results to the choice of the forecast horizon. In the baseline this horizon was set to 8 quarters. Table 4 shows that the results are very similar when the forecast horizon is set to 12 quarters for $\theta = 0.8$. Indeed relative usefulness of several of the indicators actually increases for this longer forecasting horizon. The indicators are less useful for $\theta = 0.9$. In contrast, for a forecasting horizon of 4 quarters the indicators become more useful for very strong preferences against missing crises. For $\theta = 0.9$ the top indicators are again similar to the baseline results even if the transformations of the best performing indicators sometimes differ compared to the baseline.

www.manaraa.com

Table 3. **Robustness: economic crises**

		Baseline: severe recessions						Banking currency and sovereign debt crises						Banking crises					
		$\theta = 0.8$			$\theta = 0.9$			$\theta = 0.8$			$\theta = 0.9$			$\theta = 0.8$			$\theta = 0.9$		
	Direction to be safe	Transformation	Threshold	Relative usefulness	Transformation	Threshold	Relative usefulness	Transformation	Threshold	Relative usefulness	Transformation	Threshold	Relative usefulness	Transformation	Threshold	Relative usefulness	Transformation	Threshold	Relative usefulness
Non-financial sector imbalances																			
Total private credit (% of GDP)	<	none	80	0.08	gap1	10	0.05	**none**	**85**	**0.11**	**all**	**10**	**0.02**	**none**	**85**	**0.17**	**gap3**	**55**	**0.20**
Private bank credit (% of GDP)	<	**gr3**	**75**	**0.13**	gap1	10	0.06	**gap3**	**85**	**0.12**	gap1	10	0.01	**gap3**	**90**	**0.14**	**gap3**	**55**	**0.20**
Household credit (% of GDP)	<	gap3	70	0.08				none	75	0.06				none	75	0.08	none	20	0.14
Corporate credit (% of GDP)	<	gap2	90	0.05	**gap1**	**25**	**0.09**	gap3	80	0.09	**gap1**	**5**	**0.02**	gap3	90	0.10	gap3	40	0.09
Asset market imbalances																			
Real house prices	<	**gap3**	**85**	**0.15**	**gr3**	**40**	**0.09**	gap3	90	0.06	**gap3**	**10**	**0.02**	gap3	90	0.07	gap3	60	0.06
House price-to-disposable income ratio	<	**none**	**80**	**0.26**	**none**	**60**	**0.15**	**none**	**80**	**0.18**				**none**	**85**	**0.19**	**none**	**80**	**0.21**
House price-to-rent ratio	<	**none**	**80**	**0.18**	**gr3**	**40**	**0.12**	**none**	**85**	**0.13**	**gap3**	**5**	**0.02**	**none**	**90**	**0.17**	**none**	**55**	**0.16**
Residential investment (% of GDP)	<	none	90	0.08	none	10	0.01	none	60	0.08							gap2	5	0.03
Real equity prices	<	gap1	85	0.12	**gap3**	**45**	**0.07**	gap1	90	0.07	**gap3**	**20**	**0.06**	gap1	90	0.09	**gap3**	**50**	**0.16**
External imbalances																			
Current account balance (% of GDP)	>	none	10	0.07				none	25	0.09				none	10	0.03	none	50	0.06
Foreign currency exposure index*	>							**none**	**15**	**0.13**				**none**	**15**	**0.13**	none	100	0
Quantitative foreign currency exposure*	>	gr3	65	0.10	gr1	80	0.03	gap1	15	0.02	gr3	90	0				gap3	95	0.01
Foreign exchange reserves (% of GDP)	>	none	10	0.10				**none**	**25**	**0.18**				**none**	**15**	**0.13**	none	20	0.14
Foreign reserves to M2*	>	**none**	**15**	**0.14**				none	90	0.00				none	10	0.12	none	90	0.03
Real effective exchange rate (CPI)	<				gap3	5	0.01	gap3	35	0.01	**gap3**	**20**	**0.02**				gap3	35	0.11
Real effective exchange rate (ULC)	<				gr3	10	0.01	gap3	40	0.03	gr3	5	0.01				gap3	30	0.08
Export performance	>	gap3	10	0.03				gap3	15	0.04				gap3	5	0.02	gap3	75	0.06
Spillovers, contagion and global risks	>																		
Trade openness (% of GDP)	<	none	80	0.11				none	85	0.09				**none**	**90**	**0.13**	none	85	0.08
Global private credit (% of GDP)	<	**gr1**	**55**	**0.18**	**gr3**	**30**	**0.17**	**none**	**75**	**0.13**	**gap3**	**25**	**0.10**	**none**	**75**	**0.13**	**gr1**	**55**	**0.27**
Global private bank credit (% of GDP)	<	**gr3**	**70**	**0.31**	**gr3**	**60**	**0.22**	**none**	**80**	**0.20**	**gap3**	**5**	**0.02**	**none**	**80**	**0.26**	**gap3**	**60**	**0.32**
VIX volatility index	<	**gap2**	**65**	**0.25**	**gap2**	**55**	**0.24**	gap2	60	0.10	**gap1**	**15**	**0.15**	gap2	60	0.04	**gap2**	**50**	**0.21**
Global real equity prices	<	**gap3**	**75**	**0.30**	**gap3**	**50**	**0.27**	**gap3**	**75**	**0.14**	**gap3**	**30**	**0.10**	**gap1**	**90**	**0.17**	**gap3**	**75**	**0.28**
Global real house prices	<	**gap3**	**65**	**0.27**	**gap3**	**55**	**0.24**	gap3	60	0.10				gap3	80	0.08	**gap3**	**70**	**0.17**

Note: See note to Table 1.
Source: Authors' calculations.

www.manaraa.com

Table 4. **Robustness: forecasting horizon**

		Baseline: 8 quarters						12 quarters						4 quarters					
		$\theta = 0.8$			$\theta = 0.9$			$\theta = 0.8$			$\theta = 0.9$			$\theta = 0.8$			$\theta = 0.9$		
	Direction to be safe	Transformation	Threshold	Relative usefulness	Transformation	Threshold	Relative usefulness	Transformation	Threshold	Relative usefulness	Transformation	Threshold	Relative usefulness	Transformation	Threshold	Relative usefulness	Transformation	Threshold	Relative usefulness
Non-financial sector imbalances																			
Total private credit (% of GDP)	<	none	80	0.08	gap1	10	0.05	none	75	0.12	gap1	5	0.02				gr3	75	0.10
Private bank credit (% of GDP)	<	**gr3**	**75**	**0.13**	gap1	10	0.06	**gr3**	**60**	**0.21**	**gap1**	**10**	**0.02**	**gap3**	**95**	**0.02**	**gr3**	**75**	**0.16**
Household credit (% of GDP)	<	gap3	70	0.08				gap3	60	0.13							gap3	70	0.12
Corporate credit (% of GDP)	<	gap2	90	0.05	**gap1**	**25**	**0.09**	gap1	25	0.13	**gap1**	**10**	**0.02**				gap1	70	0.13
Asset market imbalances																			
Real house prices	<	**gap3**	**85**	**0.15**	**gr3**	**40**	**0.09**	**gr3**	**40**	**0.18**	gr3	5	0.02	**gap3**	**95**	**0.05**	**gap3**	**70**	**0.19**
House price-to-disposable income ratio	<	**none**	**80**	**0.26**	**none**	**60**	**0.15**	**none**	**65**	**0.29**	**gr3**	**10**	**0.05**	**none**	**95**	**0.15**	**none**	**80**	**0.29**
House price-to-rent ratio	<	**none**	**80**	**0.18**	**gr3**	**40**	**0.12**	**gr3**	**40**	**0.21**	**gr1**	**10**	**0.03**	**none**	**95**	**0.07**	**gap3**	**55**	**0.22**
Residential investment (% of GDP)	<	none	90	0.08	none	10	0.01	gap3	60	0.10				none	95	0.01	none	85	0.11
Real equity prices	<	gap1	85	0.12	**gap3**	**45**	**0.07**	**gr3**	**45**	**0.17**	**gap3**	**10**	**0.03**				gap3	60	0.14
External imbalances																			
Current account balance (% of GDP)	>	none	10	0.07										none	5	0.01	**none**	**25**	**0.16**
Foreign currency exposure index*	>							none	95	0.01							none	80	0
Quantitative foreign currency exposure*	>	gr3	65	0.10	gr1	80	0.03	gr1	80	0.01				gr1	5	0.01	gr1	75	0.11
Foreign exchange reserves (% of GDP)	>	none	10	0.10				none	65	0.02				**none**	**5**	**0.05**	none	15	0.11
Foreign reserves to M2*	>	**none**	**15**	**0.14**										**none**	**15**	**0.05**	gap1	90	0.02
Real effective exchange rate (CPI)	<				gap3	5	0.01	gr3	15	0.05							gr1	45	0.06
Real effective exchange rate (ULC)	<				gr3	10	0.01	gr3	10	0.05							gap3	65	0.04
Export performance	>	gap3	10	0.03				gap1	80	0.03							gap3	25	0.03
Spillovers, contagion and global risks	>																		
Trade openness (% of GDP)	<	none	80	0.11				none	65	0.09							none	80	0.12
Global private credit (% of GDP)	<	**gr1**	**55**	**0.18**	**gr3**	**30**	**0.17**	**gr1**	**55**	**0.22**	**gap3**	**15**	**0.08**				**gr3**	**55**	**0.23**
Global private bank credit (% of GDP)	<	**gr3**	**70**	**0.31**	**gr3**	**60**	**0.22**	**gr1**	**50**	**0.30**	**gr3**	**20**	**0.07**	**gap1**	**80**	**0.04**	**gap3**	**65**	**0.35**
VIX volatility index	<	**gap2**	**65**	**0.25**	**gap2**	**55**	**0.24**	**gap2**	**50**	**0.36**	**gap2**	**30**	**0.05**	gr1	95	0.01	**gap1**	**65**	**0.36**
Global real equity prices	<	**gap3**	**75**	**0.30**	**gap3**	**50**	**0.27**	**gap3**	**50**	**0.28**	**gap3**	**20**	**0.10**	**gap1**	**95**	**0.18**	**gap3**	**60**	**0.36**
Global real house prices	<	**gap3**	**65**	**0.27**	**gap3**	**55**	**0.24**	**gap3**	**55**	**0.36**	**gr3**	**40**	**0.11**	**gap3**	**95**	**0.04**	**gap3**	**55**	**0.25**

Note: See note to Table 1.
Source: Authors' calculations.

المنارة للاستشارات
www.manaraa.com

Country sample

The baseline results are based on the set of OECD countries which are arguably a heterogeneous set of countries. Therefore, we investigate whether the results change when we consider more homogeneous sets of countries. In particular, we test whether the ranking of the best performing indicators changes between high-income and lower-income OECD countries. Table 5 shows that the results are broadly similar for low- and high-income OECD countries and also broadly comparable to the baseline results.[9]

Conclusions

The global financial crisis and the high associated costs associated with it have revived the academic and policy interest in "early warning indicators" of crises. The paper extends OECD efforts to monitor and detect early-on country risks, by providing empirical evidence on the usefulness of a new set of vulnerability indicators, proposed in a companion paper (Röhn et al., 2015), in predicting severe recessions and crises in OECD countries. To evaluate the usefulness of the indicators the signalling approach is employed, which takes into account policy makers' preferences between missing crises and false alarms.

Our empirical evidence shows that the majority of indicators would have helped to predict severe recessions in the OECD economies between 1970 and 2014. In addition, most indicators issue first warning signals on average more than 1.5 years before the onset of a severe recession, providing policymakers with a sufficiently long lead to react. However, the extent of the signalling power varies across indicators and the results are sensitive to the exact specification of policymakers' preferences between missing crises and false alarms.

In the domestic areas, indicators that measure asset market imbalances (real house and equity prices, house price-to-income and house price-to-rent), perform consistently well both in and out-of-sample. Domestic credit related variables appear particularly useful in signalling upcoming banking crises and in predicting the global financial crisis out-of-sample. Indicators of global risks consistently outperform domestic indicators in terms of their usefulness, highlighting the importance of taking international developments into account when assessing a country's vulnerabilities. The good performance of the global indicators is however subject to a caveat: they are particularly suited to pick up recessions that affect a large number of countries simultaneously, such as the global financial crisis in 2008/09. The results are broadly robust to different definitions of costly events, different forecasting horizons and different time and country samples. The indicators identified as particular useful in this paper can be a valuable input for monitoring economic risks, but should be complemented with other monitoring tools, including expert judgement.

In this paper we have looked at vulnerability indicators in isolation. However, important interactions among indicators may be ignored. For example, some studies suggest that asset busts have larger repercussions on the wider economy if the preceding asset boom was credit financed (e.g. Jorda et al., 2015). Taking these interactions into account may improve forecasting accuracy (e.g. Keilis-Borok et al., 2000) and hence may also reduce the costs of policy responses associated with false alarms. We view work in this area as an important avenue for future research.

المنارة للاستشارات

www.manaraa.com

Table 5. **Robustness: country sample**

		Baseline						17 lowest income countries						18 highest income countries					
		$\theta = 0.8$			$\theta = 0.9$			$\theta = 0.8$			$\theta = 0.9$			$\theta = 0.8$			$\theta = 0.9$		
	Direction to be safe	Transformation	Threshold	Relative usefulness	Transformation	Threshold	Relative usefulness	Transformation	Threshold	Relative usefulness	Transformation	Threshold	Relative usefulness	Transformation	Threshold	Relative usefulness	Transformation	Threshold	Relative usefulness
Non-financial sector imbalances																			
Total private credit (% of GDP)	<	none	80	0.08	gap1	10	0.05	gap1	70	0.13	**gap1**	**10**	**0.06**	none	80	0.13	gr3	50	0.05
Private bank credit (% of GDP)	<	**gr3**	**75**	**0.13**	gap1	10	0.06	gr3	65	0.17	**gap1**	**10**	**0.08**	gr3	80	0.14	**gr3**	**60**	**0.13**
Household credit (% of GDP)	<	gap3	70	0.08				none	55	0.05	**gap1**	**15**	**0.07**	gap3	70	0.10	gap3	60	0.05
Corporate credit (% of GDP)	<	gap2	90	0.05	**gap1**	**25**	**0.09**	gap1	65	0.15	**gap1**	**15**	**0.09**	gap2	90	0.04	gap1	25	0.10
Asset market imbalances																			
Real house prices	<	**gap3**	**85**	**0.15**	**gr3**	**40**	**0.09**	gap3	70	0.21	gr2	5	0.01	**gap3**	**85**	**0.17**	**gr3**	**40**	**0.17**
House price-to-disposable income ratio	<	**none**	**80**	**0.26**	**none**	**60**	**0.15**	**none**	**90**	**0.28**	**gr1**	**15**	**0.09**	**none**	**80**	**0.26**	**none**	**60**	**0.24**
House price-to-rent ratio	<	**none**	**80**	**0.18**	**gr3**	**40**	**0.12**	**gr1**	**50**	**0.22**	**gr1**	**25**	**0.08**	**none**	**80**	**0.19**	**gap3**	**40**	**0.21**
Residential investment (% of GDP)	<	none	90	0.08	none	10	0.01	none	75	0.16	**none**	**10**	**0.06**	gap3	75	0.08			
Real equity prices	<	gap1	85	0.12	**gap3**	**45**	**0.07**	**gap3**	**50**	**0.22**	gap3	10	0.04	**gap1**	**85**	**0.19**	**gap3**	**35**	**0.11**
External imbalances																			
Current account balance (% of GDP)	>	none	10	0.07				**none**	**30**	**0.21**				none	5	0.02			
Foreign currency exposure index*	>							none	90	0.04	none	90	0.00	none	10	0.00			
Quantitative foreign currency exposure*	>	gr3	65	0.10	gr1	80	0.03	gr3	40	0.12	gr3	95	0.00	gr3	65	0.07	gr1	80	0.07
Foreign exchange reserves (% of GDP)	>	none	10	0.10				gr3	15	0.10	gap3	95	0.03	none	10	0.14	gap3	70	0.00
Foreign reserves to M2*	>	**none**	**15**	**0.14**				**gap3**	**45**	**0.22**	**gr1**	**90**	**0.06**	**none**	**15**	**0.17**			
Real effective exchange rate (CPI)	<				gap3	5	0.01	gap3	40	0.13							gap1	10	0.03
Real effective exchange rate (ULC)	<				gr3	10	0.01	gap3	45	0.18							gr3	10	0.03
Export performance	>	gap3	10	0.03				gap1	20	0.04	gap1	95	0.01	gap3	10	0.06	gap3	50	0.02
Spillovers, contagion and global risks	>																		
Trade openness (% of GDP)	<	none	80	0.11				none	65	0.09				**none**	**80**	**0.19**	none	65	0.03
Global private credit (% of GDP)	<	**gr1**	**55**	**0.18**	**gr3**	**30**	**0.17**	**gr1**	**55**	**0.21**	gr3	20	0.06	gr1	55	0.15	**gr1**	**55**	**0.29**
Global private bank credit (% of GDP)	<	**gr3**	**70**	**0.31**	**gr3**	**60**	**0.22**	**gap1**	**70**	**0.31**	gap1	5	0.04	**gr3**	**70**	**0.32**	**gr3**	**65**	**0.39**
VIX volatility index	<	**gap2**	**65**	**0.25**	**gap2**	**55**	**0.24**	**gap2**	**65**	**0.26**	**gap1**	**20**	**0.17**	**gap2**	**65**	**0.25**	**gap2**	**55**	**0.35**
Global real equity prices	<	**gap3**	**75**	**0.30**	**gap3**	**50**	**0.27**	**gap3**	**60**	**0.38**	**gap3**	**45**	**0.19**	**gap1**	**90**	**0.29**	**gap3**	**55**	**0.33**
Global real house prices	<	**gap3**	**65**	**0.27**	**gap3**	**55**	**0.24**	**gap3**	**55**	**0.30**	gap3	35	0.02	**gap3**	**65**	**0.26**	**gap3**	**55**	0.34

Note: See note to Table 1.
Source: Authors' calculations

www.manaraa.com

Notes

1. For the choice of smoothing parameters we follow Alessi and Detken (2014) for quarterly series and use the conversion rule suggested by Ravn and Uhlig (2002) for annual series. In particular, for the slowly-adjusting HP-filter we use a smoothing parameter of $\lambda = 400\,000$ for quarterly series and $\lambda = 1\,600$ for annual series; for the faster-adjusting HP-filter we use a smoothing parameter of $\lambda = 26\,000$ for quarterly series and $\lambda = 100$ for annual series. See also Drehman et al. (2010) for a detailed analysis of the trend in credit-to-GDP for different smoothing parameters.
2. Focusing on business cycle forecasting, Keilis-Borok et al. (2000) use a pattern recognition algorithm developed for earthquake prediction to forecast recessions in the United States.
3. See Demirgüc-Kunt and Detragiache (2000) for a seminal contribution introducing loss functions to evaluate early warning indicators. Another commonly employed method for setting the optimal threshold is to minimise the (adjusted) noise to signal (aNtS) ratio (e.g. Kaminsky et al., 1998). The aNtS ratio is defined as the ratio of type II errors to one minus type I errors. This criterion has been shown to result in very high type I errors (i.e. large share of missed crises) (e.g. Berg and Pattillo, 1999) and is hence not considered here.
4. This formulation of the loss function differs from the one in Alessi and Detken (2011), which has also been widely used in the literature, by weighting the two types of errors by the unconditional probabilities P and (1-P). The loss function proposed by Sarlin (2013) and employed in this paper is closer in spirit to the seminal contribution of Demirgüc-Kunt and Detragiache (2000). They show that the expected loss of a policymaker does not only depend on the costs of missing crises versus the costs of taking pre-emptive policy action when no crisis materialises, but also on the relative frequencies of the two events. Since crises are rare events (i.e. the unconditional probability of a crisis is low), the frequency of false alarms and hence of incurring unnecessary costs of pre-emptive policy action is potentially high. By accounting for the unconditional probabilities Sarlin's loss function has the advantage that differences in the frequency between crises (rare events) and normal periods (frequent events) are explicitly taken into account. The preference parameter θ can then be exclusively interpreted as the relative costs of missing crises versus costs of false alarms.
5. The optimisation procedure was run using a grid search over the percentile of an indicator's distribution range [0,100] with incremental steps of 5.
6. The results for lower values of the preference parameter are available in the working paper version of this article.
7. This is corroborated by (unreported) results based on a sample that excludes the great recession (the "in-sample" results mentioned below). The global risk indicators are also in this shorter sample among the best performing early warning indicators.
8. We use the in-sample unconditional probability of a severe recession to compute the usefulness criterion out-of-sample as in Sarlin (2013).
9. We also tested if our results are robust when we exclude the 1970s from the sample. The reason is that financial liberalisation took off in the 1980s and hence countries became more intertwined and the type of shocks countries have faced may have changed. The results change very little when the 1970s are excluded from the sample and are therefore not reported here but are available in the working paper version of this article.

Bibliography

Ahrend, R. and A. Goujard (2012), "International Capital Mobility and Financial Fragility – Part 1. Drivers of Systemic Banking Crises: The Role of Bank-Balance-Sheet Contagion and Financial Account Structure", *OECD Economics Department Working Papers*, No. 902, OECD Publishing, *http://dx.doi.org/10.1787/5kg3k8ksgglw-en*.

Alessi, L. and C. Detken (2014), "Identifying excessive credit growth and leverage", *ECB Working Paper Series*, No. 1723, *www.ecb.europa.eu/pub/pdf/scpwps/ecbwp1723.pdf*.

Alessi, L. and C. Detken (2011), "Quasi real time early warning indicators for costly asset price boom/bust cycles: A role for global liquidity", *European Journal of Political Economy*, Vol. 27/3, pp. 520-533, *http://dx.doi.org/10.1016/j.ejpoleco.2011.01.003*.

Babecký, J. et al. (2014), "Banking, debt, and currency crises in developed countries: Stylized facts and early warning indicators", *Journal of Financial Stability*, Vol. 15, pp. 1-17, *http://dx.doi.org/10.1016/j.jfs.2014.07.001*.

المنارة للاستشارات

www.manaraa.com

Behn, M., C. Detken, T. Peltonen and W. Schudel (2013), "Setting Countercyclical Capital Buffers Based On Early Warning Models: Would it Work?", *ECB Working Paper Series*, No. 1604, *www.ecb.europa.eu/pub/pdf/scpwps/ecbwp1604.pdf*.

Benetrix, A., J. Shambaugh and P. Lane (2015), "International Currency Exposures, Valuation Effects and the Global Financial Crisis," *Journal of International Economics*, Vol. 96/1, pp. S98-S109, *http://dx.doi.org/10.1016/j.jinteco.2014.11.002*.

Berg, A. and C. Pattillo (1999), "Predicting Currency Crises: The Indicators Approach and an Alternative", *Journal of International Money and Finance*, Vol. 18/4, pp. 561-586, *http://dx.doi.org/10.1016/S0261-5606(99)00024-8*.

Borio, C. and Drehmann, M. (2009), "Assessing the Risk of Banking Crises – Revisited", *BIS Quarterly Review*, March 2009, pp. 29-46, *www.bis.org/publ/qtrpdf/r_qt0903e.pdf*.

Borio, C. and P. Lowe (2002), "Assessing the Risk of Banking Crisis", *BIS Quarterly Review*, December 2002, pp. 43-52, *www.bis.org/publ/qtrpdf/r_qt0212e.pdf*.

Bry, G. and C. Boschan (1971), *Cyclical Analysis of Time Series: Selected Procedures and Computer Programs*, National Bureau of Economic Research, New York.

Bussiere, M. and M. Fratzscher (2006), "Towards a New Early Warning System of Financial Crises", *Journal of International Money and Finance*, Vol. 25/6, pp. 953-973, *http://dx.doi.org/10.1016/10.1016/j.jimonfin.2006.07.007*.

Caldera Sánchez, A., M. Rasmussen and O. Röhn (2016), "Economic Resilience: What Role for Policies?" *Journal of International Commerce, Economics and Policy*, Vol. 07, No. 02.

Claessens, S., M. Kose and M.M. Terrones (2012), "How Do Business and Financial Cycles Interact?", *Journal of International Economics*, Vol. 87, pp. 178-190.

Demirgüc-Kunt, A. and E. Detragiache, (2000), Monitoring Banking Sector Fragility: A Multivariate Logit Approach", *The World Bank Economic Review*, Vol. 14, pp. 287-307.

Demirgüc-Kunt, A. and E. Detragiache (1998), "The Determinants of Banking Crises in Developing and Developed Countries", *IMF Staff Papers*, Vol. 45/1, *www.imf.org/external/Pubs/FT/staffp/1998/03-98/pdf/demirguc.pdf*.

Drehman, M. et al. (2010), "Countercyclical Capital Buffers: Exploring Options", *BIS Working Papers*, No. 317, *www.bis.org/publ/work317.pdf*.

Frankel, J. and G. Saravelos (2012), "Can leading indicators assess country vulnerability? Evidence from the 2008-09 global financial crisis", *Journal of International Economics*, Vol. 87/2, pp.216-231, *http://dx.doi.org/10.1016/j.jinteco.2011.12.009*.

Furceri, D., S. Guichard and E. Rusticelli (2011), "Episodes of Large Capital Inflows and the Likelihood of Banking and Currency Crises and Sudden Stops", *OECD Economics Department Working Papers*, No. 865, OECD Publishing.

Hermansen, M. and O. Röhn (2015), "Economic Resilience: The Usefulness of Early Warning Indicators in OECD Countries", *OECD Economics Department Working Papers*, No. 1250, OECD Publishing, *http://dx.doi.org/10.1787/5jrxhgfqx3mv-en*.

Jordà O., M. Schularick and A. Taylor (2011), "Financial Crises, Credit Booms, and External Imbalances: 140 Years of Lessons", *IMF Economic Review*, Vol. 59/2, pp. 340-378, *http://dx.doi.org/10.1057/imfer.2011.8*.

Jordà, O., M. Schularick and A.M. Taylor (2015), "Leveraged Bubbles", *Journal of Monetary Economics*, Vol. 76(S), p. S1-S20, *http://dx.doi.org/10.1016/j.jmoneco.2015.08.005*.

Kaminsky, G. and C. Reinhart (1999), "The Twin Crises: The Causes of Banking and Balance-of-Payments Problems", *American Economic Review*, Vol. 89/3, pp. 473-500, *http://dx.doi.org/10.1257/aer.89.3.473*.

Kaminsky, G., S. Lizondo and C. Reinhart (1998), "Leading Indicators of Currency Crises", *IMF Staff Papers*, Vol. 45, No. 1, *www.imf.org/external/Pubs/FT/staffp/1998/03-98/pdf/kaminsky.pdf*.

Keilis-Borok, V., J. Stock, A. Soloviev and P. Mikhalev (2000), "Pre-recession Pattern of Six Economic Indicators in the USA", *Journal of Forecasting*, Vol. 19/1, pp. 65-80, *http://dx.doi.org/10.1002/(SICI)1099-131X(200001)19:1<65::AID-FOR730>3.0.CO;2-U*.

Laeven L. and F. Valencia (2012), "Systemic Banking Crises Database: An Update", *IMF Working Paper*, No. 12/163, *www.palgrave-journals.com/imfer/journal/v61/n2/pdf/imfer201312a.pdf*.

Lo Duca, M. and T. Peltonen (2013), "Assessing Systemic Risks and Predicting Systemic Events", *Journal of Banking & Finance*, Vol. 37/7, pp. 2183-2195, *http://dx.doi.org/0.1016/j.jbankfin.2012.06.010*.

المنارة للاستشارات
www.manaraa.com

Ravn, M. and H. Uhlig (2002), "On adjusting the HP-filter for the frequency of observations", *Review of Economics and Statistics*, Vol. 84/2, pp. 371-376, *http://dx.doi.org/10.1162/003465302317411604*.

Reinhart, C. and K. Rogoff (2011), "From Financial Crash to Debt Crisis", *American Economic Review*, Vol. 101/5, pp. 1676-1706, *http://dx.doi.org/10.1257/aer.101.5.1676*.

Reinhart, C. and K. Rogoff (2013), "Banking Crisis: An Equal Opportunity Menace", *Journal of Banking and Finance*, Vol. 37/11, pp. 4557-4573, *http://dx.doi.org/10.1016/j.jbankfin.2013.03.005*.

Röhn, O., A. Caldera Sánchez, M. Hermansen and M. Rasmussen (2015), "Economic Resilience: A New Set of Vulnerability Indicators for OECD Countries", *OECD Economics Department Working Papers*, No. 1249, OECD Publishing, *http://dx.doi.org/10.1787/5jrxhgjw54r8-en*.

Romer, C. and D. Romer (2015), "New Evidence on the Impact of Financial Crises in Advanced Countries", *NBER Working Paper Series*, No. 21021, *http://dx.doi.org/10.3386/w21021*.

Rose, A. and M. Spiegel (2011), "Cross-country Causes and Consequences of the Crisis: An Update", Special Issue: Advances in International Macroeconomics: Lessons from the Crisis, *European Economic Review*, Vol. 55/3, pp. 309-324, *http://dx.doi.org/10.1016/j.euroecorev.2010.12.006*.

Sarlin, P. (2013), "On Policymakers' Loss Functions and the Evaluation of Early Warning Systems", *Economics Letters*, Vol. 119, pp.1-7.

Schularick, M. and A. Taylor (2012), "Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008", *American Economic Review*, 102, No. 2, pp. 1029-61, *http://dx.doi.org/10.1257/aer.102.2.1029*.

Taylor, A. (2012), "External Imbalances and Financial Crises", *NBER Working Paper Series*, No. 18606, *http://dx.doi.org/10.3386/w18606*.

المنارة للاستشارات

www.manaraa.com

Appendix

Table A1.1. **Crises and recessions by country**

	All recessions[1]	Severe recessions[1]	Crises[2]	Banking crises[2]	Currency crises[2]	Sovereign debt crises[2]
AUS	7	2	1	1	0	0
AUT	3	1	1	1	0	0
BEL	4	2	3	1	2	0
CAN	5	3	1	1	0	0
CHE	6	4	2	2	0	0
CHL	2	1	3	1	4	4
CZE	3	1	2	2	3	0
DEU	5	1	3	3	0	0
DNK	6	2	5	2	4	0
ESP	4	1	3	2	3	0
EST	3	1	2	2	1	0
FIN	5	3	4	1	4	0
FRA	5	1	2	2	0	0
GBR	5	3	4	4	1	0
GRC	7	5	5	2	3	1
HUN	3	1	5	2	0	4
IRL	4	1	4	2	2	1
ISL	6	4	6	3	4	0
ISR	6	2	2	1	4	0
ITA	4	2	3	1	4	0
JPN	5	2	1	1	0	0
KOR	3	3	3	3	1	0
LUX	5	4	2	1	1	0
LVA	2	1	3	2	1	0
MEX	5	4	3	2	3	2
NLD	5	4	1	1	0	0
NOR	3	2	4	2	6	0
NZL	5	4	4	2	2	0
POL	1	0	2	1	0	2
PRT	5	3	2	1	1	0
SVK	2	2	1	1	0	0
SVN	1	1	2	2	0	0
SWE	4	2	4	2	3	1
TUR	6	5	7	4	7	2
USA	4	3	2	2	0	0
Total	149	81	102	63	64	17

1. For the period 1970-2014, except for the following countries for which GDP series are not available for the full period: Chile (1986-), Czech Republic (1990-) Poland (1990-), Slovenia (1990-), Hungary (1991-), Slovak Republic (1993-), Estonia (1995-), and Latvia (1995-). Peak and trough dates in GDP per capita are identified using the Bry and Boschan (1971) algorithm. A severe recession is defined as a fall in GDP per capita from peak to trough exceeding the median fall, which is 3.4% of peak GDP per capita across the full country-year sample.
2. Over the period 1970-2010. A crisis can be a twin or triple crisis, which is why column 5-7 do not sum to column 4.

Source: Babecký et al. (2014) and authors' calculations.

المنارة للاستشارات
www.manaraa.com

Table A1.2. **Dataset**

Indicator	Description	Data Source	No. countries	Time coverage	Transformations
Non-financial sector imbalances					
Total private credit	Lending from all sectors (including foreign) to private non-financial sector in per cent of GDP.	BIS	27	1970Q4-2014Q2	Level, gap1-3, growth 1-3
Private bank credit	Lending from domestic bank sector to private non-financial sector in per cent of GDP.	BIS	27	1971Q2-2014Q2	Level, gap1-3, growth 1-3
Household credit	Lending from all sectors (including foreign) to households in per cent of GDP.	BIS	27	1994Q4-2014Q2	Level, gap1-3, growth 1-3
Corporate credit	Lending from all sectors (including foreign) to non-financial corporations in per cent of GDP.	BIS	27	1994Q4-2014Q2	Level, gap1-3, growth 1-3
Asset market imbalances					
Real house prices	Deflated by CPI. Indexed to 2010 = 100.	OECD	33	1988Q1-2014Q2	Gap1-3, growth 1-3
Price-to-disposable income ratio	Nominal house prices to nominal net household disposable income per capita. Indexed to 2010 = 100.	OECD	29	1995Q1-2014Q2	Level, gap1-3, growth 1-3
Price-to-rent ratio	Nominal house prices to rent prices. Indexed to 2010 = 100.	OECD	32	1991Q1-2014Q2	Level, gap1-3, growth 1-3
Residential investment as % of GDP	Gross fixed capital formation, housing, in per cent of GDP.	OECD	34	1970Q1-2014Q4	Level, gap1-3, growth 1-3
Real equity prices	Share price index deflated by CPI.	OECD	35	1981Q1-2014Q4	Gap1-3, growth 1-3
External imbalances					
Current account balance	In per cent of GDP.	OECD	35	1975Q1-2014Q4	Level
Foreign currency exposure index (fxagg)*	Index of the sensitivity of a country's portfolio to a uniform currency movement by which the domestic currency moves proportionally against all foreign currencies. Index between -1 (zero foreign-currency foreign assets and only foreign-currency foreign liabilities) and 1 (only foreign-currency foreign assets and only domestic-currency foreign liabilities).	Benetrix, Shambaugh and Lane (2015)	34	1990-2012	Level
Quantitative foreign currency exposure (netfx)*	Quantitative exposure to a uniform shift in the value of the domestic currency against all foreign currencies. It is calculated as the foreign currency exposure index (fxagg) multiplied by the sum of foreign assets and liabilities in % of GDP.	Benetrix, Shambaugh and Lane (2015)	34	1990-2012	Gap1-3, growth 1, 3
Foreign exchange reserves	In per cent of GDP.	IMF	35	1970Q1-2014Q4	Level, gap1-3, growth 1-3

المنارة للاستشارات
www.manaraa.com

Table A1.2. **Dataset** *(cont.)*

Indicator	Description	Data Source	No. countries	Time coverage	Transformations
Foreign exchange reserves*	In per cent of money supply M2.	World Bank	31	1970-2013	Gap1-3, growth 1,3
Real effective exchange rate	Competitiveness indicator. Relative consumer prices (CPI), overall weights based on exports of goods.	OECD	35	1970Q1-2014Q4	Gap1-3, growth 1-3
Real effective exchange rate	Competitiveness indicator. Relative unit labour costs (ULC) for overall economy and overall weights based on exports of goods.	OECD	35	1970Q1-2014Q4	Gap1-3, growth 1-3
Export performance	Exports of goods and services relative to export market for goods and services.	OECD	35	1975Q1-2014Q4	Gap1-3, growth 1-3
Spillovers, contagion and global risk					
Trade openness	Sum of exports and imports in per cent of GDP.	OECD	35	1970Q1-2014Q4	Level
Global total private credit (% of GDP)	Weighted average of total private credit-to-GDP ratios across countries for each quarter. Weights defined by nominal GDP at Purchasing Power Parity (PPP).	BIS	27	1970Q4-2014Q4	Level, gap1-3, growth 1-3
Global private bank credit (% of GDP)	Weighted average of private bank credit-to-GDP ratios across countries for each quarter. Weights defined by nominal GDP at PPP.	BIS	27	1971Q2-2014Q2	Level, gap1-3, growth 1-3
Global real equity prices	Weighted average of country share price indexes for each quarter. Weights defined by nominal GDP at PPP.	OECD	35	1981Q1-2014Q4	Gap1-3, growth 1-3
Global real house prices	Weighted average of country real house price indexes for each quarter. Weights defined by nominal GDP at PPP.	OECD	33	1988Q1-2014Q2	Gap1-3, growth 1-3
VIX	Implied volatility of the S&P 500 index over the next 30 days. Calculated using a range of options on the S&P 500 index. The VIX is quoted in percentage points and can roughly be interpreted as the expected movement in the S&P 500 index over the next 30-day period.	Datastream	-	1990Q2-2015Q1	Level, gap1-3, growth 1-3

Note: The indicators are measured on a quarterly frequency, except for indicators marked with *, which are measured on an annual frequency. Up to six different transformations have been tested for each indicator and only the best in terms of the relative usefulness criteria is reported. Gap1: deviation from a recursive, slowly-adjusting HP-filter with smoothing parameter $\lambda = 400000$ for quarterly series ($\lambda = 1600$ for annual series); gap2: deviation from a recursive, faster-adjusting HP-filter with smoothing parameter $\lambda = 26000$ for quarterly series ($\lambda = 100$ for annual series); gap3: deviations from a 20 quarter (5 year) moving average; gr1: year-on-year growth rates; gr2: quarter-on-quarter growth rates; gr3: cumulated growth rates over the preceding 6 quarters (4 years for annual series).

المنارة للاستشارات
www.manaraa.com

Table A1.3. **Correlations among vulnerability indicators**

	Total private credit	Private bank credit	Household credit	Corporate credit	Real house prices	Price-to-disposable income	Price-to-rent	Residential investment	Real equity prices	Current account balance	Foreign reserves	Real effective exchange rate (CPI)	Real effective exchange rate (ULC)	Export performance	Trade openness	Global private credit	Global private bank credit	VIX	Global share price index	Global real house price index
Total private credit	1.00																			
Private bank credit	0.76	1.00																		
Household credit	0.78	0.82	1.00																	
Corporate credit	0.92	0.52	0.47	1.00																
Real house prices	0.42	0.49	0.34	0.24	1.00															
Price-to-disposable income	0.16	0.27	0.09	0.08	0.80	1.00														
Price-to-rent	0.29	0.39	0.23	0.16	0.92	0.86	1.00													
Residential investment	-0.35	-0.27	-0.22	-0.23	-0.37	-0.09	-0.30	1.00												
Real equity prices	0.46	0.44	0.42	0.33	0.47	0.17	0.34	-0.17	1.00											
Current account balance	0.41	0.30	0.31	0.38	0.00	-0.01	0.05	-0.20	-0.14	1.00										
Foreign reserves	0.01	0.11	0.05	-0.04	0.11	0.00	0.04	-0.09	0.03	0.09	1.00									
Real effective exchange rate (CPI)	0.12	0.14	0.13	0.02	0.11	0.10	0.09	0.01	0.14	0.02	-0.18	1.00								
Real effective exchange rate (ULC)	0.15	0.16	0.16	0.02	0.31	0.29	0.31	-0.06	0.23	-0.04	-0.13	0.76	1.00							
Export performance	0.22	0.22	0.18	0.13	-0.14	-0.14	-0.01	-0.11	0.03	0.18	-0.02	0.01	-0.13	1.00						
Trade openness	0.51	0.20	0.18	0.64	0.10	-0.10	-0.01	-0.22	0.21	0.24	0.21	-0.07	-0.12	-0.06	1.00					
Global private credit	0.41	0.36	0.40	0.28	0.47	0.01	0.22	-0.40	0.53	0.12	0.13	-0.03	0.09	0.01	0.27	1.00				
Global private bank credit	0.47	0.41	0.45	0.34	0.50	0.04	0.25	-0.41	0.57	0.13	0.16	0.01	0.10	-0.03	0.32	0.94	1.00			
VIX	0.08	0.07	0.04	0.06	0.03	-0.01	0.02	-0.04	-0.06	-0.02	0.02	-0.02	0.00	0.00	0.02	0.14	0.16	1.00		
Global share price index	0.39	0.35	0.36	0.26	0.49	-0.01	0.25	-0.32	0.54	0.04	0.16	-0.04	-0.05	-0.07	0.36	0.89	0.88	-0.11	1.00	
Global real house price index	0.48	0.45	0.47	0.30	0.56	0.11	0.34	-0.37	0.52	0.03	0.14	0.06	0.08	-0.14	0.31	0.85	0.83	-0.21	0.85	1.00

Note: Pairwise correlations across all countries and time periods for untransformed indicators. The table only include indicators on quarterly frequency.
Source: Author's calculations.

المنارة للاستشارات

www.manaraa.com

Table A1.4. **Detailed full-sample performance of individual indicators**

	Transformation	No. crises episodes	No. observations	Direction to be safe	Thresh. percentile	Rel. usefulness	Usefulness	aNtS	Type I error	Type II error	Cond. prob.	Diff. prob	ALT
$\theta = 0.8$													
Global private bank credit (% of GDP)	gr3	65	3849	<	70	0.31	0.04	0.35	0.38	0.22	0.33	0.19	7.0
Global real equity prices	gap3	81	4488	<	75	0.30	0.04	0.35	0.43	0.20	0.35	0.19	6.7
Global real house prices	gap3	67	3670	<	65	0.27	0.03	0.43	0.35	0.28	0.30	0.14	7.0
Price-to-disposable income ratio	none	51	3140	<	80	0.26	0.03	0.29	0.54	0.13	0.36	0.22	5.9
VIX volatility index	gap2	55	3289	<	65	0.25	0.03	0.42	0.35	0.27	0.29	0.14	6.6
Price-to-rent ratio	none	65	3526	<	80	0.18	0.02	0.38	0.63	0.14	0.33	0.17	6.0
Global private credit (% of GDP)	gr1	67	3933	<	55	0.18	0.02	0.53	0.30	0.37	0.25	0.10	7.0
Real house prices	gap3	67	3670	<	85	0.15	0.02	0.39	0.69	0.12	0.32	0.17	5.8
Foreign reserves to M2 *	none	72	1072	>	15	0.14	0.02	0.48	0.72	0.13	0.34	0.14	1.3
Private bank credit (% of GDP)	gr3	65	3849	<	75	0.13	0.02	0.49	0.56	0.21	0.26	0.11	6.4
$\theta = 0.9$													
Global real equity prices	gap3	81	4488	<	50	0.27	0.02	0.51	0.19	0.42	0.27	0.11	7.0
Global real house prices	gap3	67	3670	<	55	0.24	0.02	0.48	0.23	0.37	0.27	0.12	6.9
VIX volatility index	gap2	55	3289	<	55	0.24	0.02	0.49	0.25	0.37	0.26	0.11	6.7
Global private bank credit (% of GDP)	gr3	65	3849	<	60	0.22	0.02	0.44	0.30	0.31	0.29	0.14	6.9
Global private credit (% of GDP)	gr3	66	3881	<	30	0.17	0.01	0.73	0.12	0.64	0.19	0.05	7.3
Price-to-disposable income ratio	none	51	3140	<	60	0.15	0.01	0.51	0.34	0.34	0.25	0.10	6.7
Price-to-rent ratio	gr3	61	3339	<	40	0.12	0.01	0.70	0.19	0.57	0.21	0.05	6.9
Corporate credit (% of GDP)	gap1	52	3118	<	25	0.09	0.01	0.82	0.12	0.72	0.18	0.03	7.4
Real house prices	gr3	63	3510	<	40	0.09	0.01	0.72	0.21	0.57	0.20	0.05	6.8
Real equity prices	gap3	81	4488	<	45	0.07	0.01	0.69	0.24	0.52	0.21	0.06	7.1

Note: The indicators are measured on a quarterly frequency, except for indicators marked with *, which are measured on an annual frequency. Relative usefulness measures the share of the usefulness of the indicator relative to a perfectly performing indicator (see section 3). Up to six different transformations have been tested for each indicator and only the best in terms of the relative usefulness criteria is reported. Gap1: deviation from a recursive, slowly-adjusting HP-filter with smoothing parameter $\lambda = 400000$ for quarterly series ($\lambda = 1600$ for annual series); gap2: deviation from a recursive, faster-adjusting HP-filter with smoothing parameter $\lambda = 26000$ for quarterly series ($\lambda = 100$ for annual series); gap3: deviations from a 20 quarter (5 year) moving average; gr1: year-on-year growth rates; gr2: quarter-on-quarter growth rates; gr3: cumulated growth rates over the preceding 6 quarters (4 years for annual series). aNtS stands for adjusted noise-to-signal ratio. ALT stands for average lead time and is measured as the number of quarters unless the indicator is indicated with a * in which case it is measured as the number of years. For the calculation of the statistics see section 3 in the main text.
Source: Authors' calculations.

المنارة للاستشارات

www.manaraa.com

Reproduced with permission of copyright owner. Further reproduction prohibited without permission.

www.manaraa.com