Evaluating Indicators for Use in Setting the Countercyclical Capital Buffer*

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The European Systemic Risk Board (ESRB) recently issued a recommendation on the use of early warning indicators in macroprudential decisions involving the countercyclical capital buffer (Basel III framework). In addition to a primary indicator, deviation in the credit-to-GDP ratio from long-term trend, the ESRB advises the use of supplemental indicators to measure private-sector credit developments and debt burden, overvaluation of property prices, external imbalances, mispricing of risk, and strength of bank balance sheets. Based on empirical analysis of data for European Union countries, a large assortment of potential indicators, and comprehensive robustness checks, we propose specific suitable early warning indicators for each of the six risk categories set forth by the ESRB.

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1. Introduction

The purpose of the countercyclical capital buffer proposed by the Basel Committee on Banking Supervision (BCBS 2011) is to

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mitigate credit booms and related procyclicality in the financial system. When there are signs of excessive credit growth and emerging vulnerabilities related to the credit cycle, the BCBS advises monetary authorities to raise bank capital requirements. The buffer requirement, which is intended to improve bank resilience against future losses, may also slow credit growth as capital requirements are adjusted to a higher level.[1] To properly time adjustments in the countercyclical capital buffer level, policymakers must have some certainty that they have correctly identified the emergence of cyclical vulnerabilities.

The countercyclical capital buffer requirement was implemented under the European Union's (EU's) 2013 Capital Requirements Directive.[2] In determining appropriate buffer requirements, national authorities are advised to follow the BCBS harmonized buffer guide[3] and the European Systemic Risk Board (ESRB) guidance and official recommendations,[4] as well as to take into consideration domestic conditions relevant to cyclical vulnerabilities. The ESRB's official recommendation (ESRB 2014), based on the results of the empirical study by Detken et al. (2014), instructs policymakers to use a set of indicators that encompasses six risk categories: credit developments, potential overvaluation of property prices, private-sector debt burden, external imbalances, potential mispricing of risk, and strength of bank balance sheets. Beyond that, however, there is little guidance on the specific indicators to apply in each of these risk categories. Given the tangible economic consequences of capital requirements

[1]There are not yet many empirical impact studies on the countercyclical capital buffer due to the limited amount of data on policy decisions. See Akinci and Olmstead-Rumsey (2015), Cerutti, Claessens, and Laeven (2017), and Cerutti et al. (2016) for some early empirical evidence.

[2]CRD IV 2013/36/EU.

[3]The buffer guide is based on the deviation of the ratio of credit to GDP from its long-term trend calculated following the methodology of the BCBS with a one-sided Hodrick-Prescott filter and smoothing parameter $\lambda = 400{,}000$ (i.e., credit-to-GDP gap). When this trend gap is below (above) or equal to 2 percent (10 percent), the buffer guide suggests a 0 percent (2.5 percent) countercyclical capital buffer. Within the gap band, the countercyclical capital buffer would depend linearly on the trend gap.

[4]Although characterized as recommendations, they are not taken lightly by national policymakers. Compliance is monitored via an "act or explain" mechanism.

(Van den Heuvel 2008) and the economic impacts of such indicators in decisionmaking, it would be valuable for policymakers to have the clearest possible grasp of these state-of-the-art indicators in each category before issuing a buffer rate decision.

This empirical work continues that of Detken et al. (2014) with the aim of identifying informative warning indicators for the six risk categories. Using an unbalanced quarterly panel of twenty-eight EU countries for the period 1970 to 2012 as our data set, we consider roughly fifty conceptually varied indicators from national accounts, financial accounts, balance of payments, financial markets, and bank balance sheets. When all transformations are included, the number of considered indicators rises to nearly 400. Our indicator set brings together indicators identified in earlier studies and examines them in a consistent setup. We also include several theoretically motivated indicators that, to our knowledge, have never been studied in this context: the VIX index, the ratio of cross-border loans to GDP or assets, the spread between high-yield and investment-grade corporate bonds, benchmark government bond yields, household interest expense burden, and balance sheet indicators based on liquidity and short-term funding.

Indicator performance is assessed with standard measures from the early warning literature. We apply receiver operating characteristic (ROC) and relative usefulness analyses, which are both based on the relative numbers of type I (false positive) and type II (false negative) errors of the warning signals. The indicators are examined using most parsimonious non-parametric and parametric methods full sample and out of sample in a large panel of countries. Different crisis-prediction horizons and alternative financial crisis data sets are considered.

This work contributes to the current policy discussion on the EU legislative framework for countercyclical capital buffers. Due to the huge diversity of possible indicators in the six risk categories, we are compelled to investigate simultaneously a set of indicators larger than in any previous study. Our common evaluation setup facilitates thorough robustness checks and equal treatment of predictor performance that would otherwise be difficult to compare among existing findings. While the earlier literature has shown that combining multiple indicators into a composite indicator can improve signaling power, we focus mainly on individual indicators in order to identify specific robust indicators for each prescribed category.[5]

In line with the earlier literature (see the literature review in section 2.2), we find that measures of credit developments, especially those based on the credit-to-GDP ratio, are historically among the best predictors of financial crises. We further note that measures of private-sector debt burden and overvaluation of property prices (e.g., debt-service ratios and relative house prices) are highly useful. To our best knowledge, this is also the first study to identify the VIX index, the high-yield corporate bond spread, and benchmark government bond yields as useful indicators in this context. We report evidence of statistically significant predictive power of many indicators in the external imbalances, mispricing of risk, and bank balance sheet categories, including the ratio of current account to GDP, the ratio of cross-border loans to GDP, various measures based on stock market prices, the leverage ratio, and the ratio of total bank assets to GDP. Drawing on these findings, we recommend a practical set of indicators that appear to be relatively good predictors of financial crises and that meet the provisions of the ESRB recommendation.

The robustness checks with the alternative prediction horizons reveal that the indicators have no unique ranking in terms of performance. Instead, the predictors work optimally at different prediction horizons, a feature that could be quite valuable in policy decisions. Moreover, changing the crisis data set sometimes has a large impact on evaluated performance, underscoring the challenge of predicting financial crises without a clear definition of what constitutes a crisis.

The paper is organized as follows. Section 2 discusses the operationalization of the countercyclical capital buffer (2.1), along with the early warning indicator literature and our list of potential indicators to be considered in each of the ESRB's proposed categories (2.2). The data and empirical techniques are discussed in section 3, which presents the data sources and transformations (3.1–3.2), and reviews the concepts of signal extraction (3.3) as well as ROC analysis, usefulness measures, and the evaluation process (3.4–3.5). Section 4 presents the main results and our recommended set of indicators (4.1), results with alternative crisis-prediction horizons (4.2),

[5] Aikman et al. (2014) suggest that simple indicators often outperform more complex alternatives when there is uncertainty.

and alternative crisis data sets (4.3). Section 4.4 discusses various frameworks on how indicators might be interpreted or embedded in a monitoring framework. Section 5 concludes.

2. Early Warning Indicators Identified in the Previous Literature

In this section, we review the ESRB recommendation on operationalizing the countercyclical capital buffer and recent literature seeking a similar goal to ours, i.e., identification of indicators to be considered when setting the countercyclical capital buffer.[6] We next discuss, based on empirical evidence presented in the literature or conceptual relevance, each indicator category and potential indicators to be analyzed in the empirical part of this work.

2.1 Operationalizing the Countercyclical Capital Buffer

The ESRB recommendation (ESRB 2014) says that level adjustments of the countercyclical capital buffer should be based primarily on deviation of the private-sector credit-to-GDP ratio from its long-term trend (credit-to-GDP gap). Indeed, a number of empirical studies support the view that the credit-to-GDP gap is the best single indicator in predicting a banking crisis.[7] However, as there are potentially large uncertainties for the signals given by any single indicator, the ESRB recommends that authorities base their decisions on a wide set of information that captures the vulnerabilities caused by excessive credit growth and note six categories of risk usually associated with excessive credit growth.[8]

[6]Kauko (2014) provides a comprehensive literature survey on early warning indicators.

[7]See, e.g., Babecký et al. (2014), Behn et al. (2013), Bonfim and Monteiro (2013), Detken et al. (2014), Drehmann, Borio, and Tsatsaronis (2011), Drehmann et al. (2010), and Drehmann and Juselius (2014). For criticism, see, e.g., Repullo and Saurina (2011).

[8]The ESRB recommendation has a seventh category of indicators that includes indicators that combine information on the credit-to-GDP gap and indicators from the six alternative indicator categories. We do not consider these seventh-category indicators in our empirical analysis for two reasons. First, selection of these indicators only occurs after the suitable indicators for the other six categories have been determined. Second, the ESRB recommendation provides no guidance on calculation or public disclosure of seventh-category indicators.

In addition to the credit-to-GDP gap, the recommendation calls on authorities to monitor and publicly disclose at least one other indicator per category to accompany a countercyclical capital buffer adjustment. The six indicator categories are measures of

(i) credit developments,
(ii) private-sector debt burden,
(iii) potential overvaluation of property prices,
(iv) external imbalances,
(v) potential mispricing of risk, and
(vi) strength of bank balance sheets.

With respect to the actual indicators that describe these six categories, the ESRB only offers suggestions based on an empirical analysis by Detken et al. (2014). It does not provide specific recommendations, and thus leaves the decision on which specific indicators to use to the national authorities.

2.2 The Literature and Candidate Indicators for the Six Categories

We provide an extensive survey table of early warning indicators studied in earlier empirical works (see table 1). We make an attempt to incorporate most of the published research articles and some relevant unpublished works that evaluate early warning indicators of banking crises using panel data. Studies that rely on data on a single country are not included. Due to disparate approaches of the papers, it is not possible to incorporate much detail or to do full justice to earlier findings.

Within the voluminous literature of financial crises, there are several recent studies that focus on identifying indicators for guiding decisions on the countercyclical capital buffer.

In addition to the above-mentioned study of Detken et al. (2014), Behn et al. (2013) evaluate a wide set of macrofinancial and banking-sector indicators using data for EU member states. In addition to domestic factors such as credit developments and equity and house prices, they suggest that global variables on house prices and credit

Table 1. Survey of Early Warning Indicators

	Ferrari and Pirovano (2015)	Holopainen and Sarlin (2015)	Jordà, Schularick, and Taylor (2015)	Detken et al. (2014)	Anundsen, Gerdrup, and Hansen (2014)	Babecký et al. (2014)	Drehmann and Juselius (2014)	Lainà, Nyholm, and Sarlin (2014)	Behn et al. (2013)	Bonfim and Monteiro (2013)	Hahm, Shin, and Shin (2013)	Lo Duca and Peltonen (2013)	Bordo and Meissner (2012)	Kauko (2012a)	Kauko (2012b)	Roy and Kemme (2012)	Schularick and Taylor (2012)	Alessi and Detken (2011)	Drehmann, Borio, and Tsatsaronis (2011)	Barrell et al. (2010)	Bunda and Ca' Zorzi (2010)	Büyükkarabacak and Valev (2010)	Joyce (2011)	Borio and Drehmann (2009)	Davis and Karim (2008)	Von Hagen and Ho (2007)	Domaç and Peria (2003)	Demirgüç-Kunt and Detragiache (2000)	Kaminsky and Reinhart (1999)	Hardy and Pazarbaşıoğlu (1998)
Crisis Data Set / Target Variable:	B	L	C	D	C	B	L	C	B	D	O	FSI	C	NPL	NPL	R	C	O	C	L	R	C	CK	C	C	O	DD	DD	R	LI
No. of Countries:	15	15	17	28	16	40	26	11	23	9	30	28	14	25	34	14	14	18	36	14	76	37	20	18	105	47	88	34	20	38
1. Credit Developments																														
Total Credit to Private Sector		x	x	x	x	x	x	x	x	x		o	x			x	x		x	x		x			~	o	x	x		x
Bank Credit to Private Sector				x											x							x								
Household Credit						~		x														x								
Mortgage Loans								x														x								
Corporate Credit				x																		x								
Public Credit										x																				
Global Credit									x									x												
Credit-to-GDP Ratio	x	x		x	x		x	x	x	x	x								x		x			x	o	o	o		x	
Bank Credit-to-GDP Ratio	x			x													x						x							
Household Credit-to-GDP Ratio	x			x	x																									
Mortgage Loans-to-GDP Ratio								x																						
Corporate Credit-to-GDP Ratio					x																									
Public Credit-to-GDP Ratio		x		x		x				x						o					x									
Global Credit-to-GDP Ratio					o	o			x																					
Differenced Relative Total Credit		o		x											x															
Loans-to-Income Ratio																														
2. Private-Sector Debt Burden																														
Real Mortgage Interest Rate		x								x																				
Debt-Service Ratio			x		x				x																					
Household Debt-Service Ratio					x																									
Corporate Debt-Service Ratio					o																									

(continued)

Table 1. (Continued)

	Ferrari and Pirovano (2015)	Holopainen and Sarlin (2015)	Jordà, Schularick, and Taylor (2015)	Detken et al. (2014)	Anundsen, Gerdrup, and Hansen (2014)	Babecký et al. (2014)	Drehmann and Juselius (2014)	Lainà, Nyholm, and Sarlin (2014)	Behn et al. (2013)	Bonfim and Monteiro (2013)	Hahm, Shin, and Shin (2013)	Lo Duca and Peltonen (2013)	Bordo and Meissner (2012)	Kauko (2012a)	Kauko (2012b)	Roy and Kemme (2012)	Schularick and Taylor (2012)	Alessi and Detken (2011)	Drehmann, Borio, and Tsatsaronis (2011)	Barrell et al. (2010)	Bunda and Ca' Zorzi (2010)	Büyükkarabacak and Valev (2010)	Joyce (2011)	Borio and Drehmann (2009)	Davis and Karim (2008)	Von Hagen and Ho (2007)	Domaç and Peria (2003)	Demirgüç-Kunt and Detragiache (2000)	Kaminsky and Reinhart (1999)	Hardy and Pazarbaşıoğlu (1998)
Crisis Data Set / Target Variable:	**B**	**L**	**C**	**D**	**C**	**B**	**L**	**C**	**B**	**D**	**O**	**FSI**	**C**	**NPL**	**NPL**	**R**	**C**	**O**	**C**	**L**	**R**	**C**	**CK**	**C**	**C**	**O**	**DD**	**DD**	**R**	**LI**
No. of Countries:	**15**	**15**	**17**	**28**	**16**	**40**	**26**	**11**	**23**	**9**	**30**	**28**	**14**	**25**	**34**	**14**	**14**	**18**	**36**	**14**	**76**	**37**	**20**	**18**	**105**	**47**	**88**	**34**	**20**	**38**
3. Potential Overvaluation of Property Prices																														
House Price	x	x	x	x		o	x	x	x	x						x			x	x	x			x						
House Price / Income	x	x		x	x																									
House Price / Rent	x			x																										
Global House Prices									x																					
Global House Price / Income					x																									
Commercial Real Estate Price				x																										
4. External Imbalances																														
Current Account / GDP		x		x		x		x		x		x	o		x	x					x									o
Trade Balance						o																	o							
Trade / GDP						x																								
Exports															o														x	
Imports															o														x	x
Capital Flows / GDP																											o			
Foreign Assets																							o							
Foreign Liabilities																							x							x
Foreign Liabilities / Foreign Assets																											o			
Foreign Direct Investment (Decrease)																							x							
Foreign Portfolio Investment (Decrease)																							x							
Terms of Trade						x																o			x		o	o	x	o

(*continued*)

Table 1. (Continued)

	Ferrari and Pirovano (2015)	Holopainen and Sarlin (2015)	Jordà, Schularick, and Taylor (2015)	Detken et al. (2014)	Anundsen, Gerdrup, and Hansen (2014)	Babecký et al. (2014)	Drehmann and Juselius (2014)	Lainà, Nyholm, and Sarlin (2014)	Behn et al. (2013)	Bonfim and Monteiro (2013)	Hahm, Shin, and Shin (2013)	Lo Duca and Peltonen (2013)	Bordo and Meissner (2012)	Kauko (2012a)	Kauko (2012b)	Roy and Kemme (2012)	Schularick and Taylor (2012)	Alessi and Detken (2011)	Drehmann, Borio, and Tsatsaronis (2011)	Barrell et al. (2010)	Bunda and Ca' Zorzi (2010)	Büyükkarabacak and Valev (2010)	Joyce (2011)	Borio and Drehmann (2009)	Davis and Karim (2008)	Von Hagen and Ho (2007)	Domaç and Peria (2003)	Demirgüç-Kunt and Detragiache (2000)	Kaminsky and Reinhart (1999)	Hardy and Pazarbaşıoğlu (1998)
Crisis Data Set / Target Variable:	**B**	**L**	**C**	**D**	**C**	**B**	**L**	**C**	**B**	**D**	**O**	**FSI**	**C**	**NPL**	**NPL**	**R**	**C**	**O**	**C**	**L**	**R**	**C**	**CK**	**C**	**C**	**O**	**DD**	**DD**	**R**	**LI**
No. of Countries:	**15**	**15**	**17**	**28**	**16**	**40**	**26**	**11**	**23**	**9**	**30**	**28**	**14**	**25**	**34**	**14**	**14**	**18**	**36**	**14**	**76**	**37**	**20**	**18**	**105**	**47**	**88**	**34**	**20**	**38**
Exchange Rate	x			o		o						o				o					x				o	~		o	x	x
Foreign Exchange Reserves																														o
5. Potential Mispricing of Risk																														
Short-Term Interest Rate	x			x		x			x		o		~					x												
Long-Term Interest Rate	x	x		x					o	x																				
Yield Curve						x																								
Lending Rate / Deposit Rate																													x	
Stock Returns	x	x	~	x		~	o		o	x		x				x	o	x	x					x		o			x	
Global Stock Returns									x																					
Aggregate Asset Prices																		x						x						
LIBOR-OIS Spread																			x											
Corporate Bond Spread						x													o											
6. Strength of Bank Balance Sheets																														
Leverage Ratio				o	x				x			x								x										
Bank Profits									x										o											
Bank Deposits																													x	x
Loan / Deposits								x																						
Non-Core Liabilities					x		x				x																			
Banks Net Foreign Assets																														o
Bank Reserves / Assets																						o								
Bank Liquidiity															o					x						o	o			

(continued)

Table 1. (Continued)

	Ferrari and Pirovano (2015)	Holopainen and Sarlin (2015)	Jordà, Schularick, and Taylor (2015)	Detken et al. (2014)	Anundsen, Gerdrup, and Hansen (2014)	Babecký et al. (2014)	Drehmann and Juselius (2014)	Lainà, Nyholm, and Sarlin (2014)	Behn et al. (2013)	Bonfim and Monteiro (2013)	Hahm, Shin, and Shin (2013)	Lo Duca and Peltonen (2013)	Bordo and Meissner (2012)	Kauko (2012a)	Kauko (2012b)	Roy and Kemme (2012)	Schularick and Taylor (2012)	Alessi and Detken (2011)	Drehmann, Borio, and Tsatsaronis (2011)	Barrell et al. (2010)	Bunda and Ca' Zorzi (2010)	Büyükkarabacak and Valev (2010)	Joyce (2011)	Borio and Drehmann (2009)	Davis and Karim (2008)	Von Hagen and Ho (2007)	Domaç and Peria (2003)	Demirgüç-Kunt and Detragiache (2000)	Kaminsky and Reinhart (1999)	Hardy and Pazarbaşıoğlu (1998)
Crisis Data Set / Target Variable:	**B**	**L**	**C**	**D**	**C**	**B**	**L**	**C**	**B**	**D**	**O**	**FSI**	**C**	**NPL**	**NPL**	**R**	**C**	**O**	**C**	**L**	**R**	**C**	**CK**	**C**	**C**	**O**	**DD**	**DD**	**R**	**LI**
No. of Countries:	**15**	**15**	**17**	**28**	**16**	**40**	**26**	**11**	**23**	**9**	**30**	**28**	**14**	**25**	**34**	**14**	**14**	**18**	**36**	**14**	**76**	**37**	**20**	**18**	**105**	**47**	**88**	**34**	**20**	**38**
Banking-Sector CDS Spread																			x											
Financial-Sector Size																	x													
7. Real Economy Variables																														
GDP	o	x		x			o		o	o		x	~		o	x		x	x	o	o	o	x		x	x	o	x		x
Global GDP						x			o		o																			
Real GDP per Capita															x							x			~	o	o	o		
Output Gap					x																									
Unemployment				x						o																				
Industrial Production						x																							x	
Industry Share of GDP						x																								
Consumption						o												x												x
Investment						o					o							x												o
Capital / Output																														o
Government Consumption						o																								
Fiscal Deficit										~					o					o					o	x	o	o	x	
Net National Savings						o																								
Global Trade						o																								
8. Monetary Aggregates																														
Reserves																													x	o
M1						o				x								x								o			x	
Global M1																		x												
M2																			x											
M2 / Reserves																x				o		x	o		o		x	x	x	
M3					x	x									o															

(*continued*)

Table 1. (Continued)

	Ferrari and Pirovano (2015)	Holopainen and Sarlin (2015)	Jordà, Schularick, and Taylor (2015)	Detken et al. (2014)	Anundsen, Gerdrup, and Hansen (2014)	Babecký et al. (2014)	Drehmann and Juselius (2014)	Lainà, Nyholm, and Sarlin (2014)	Behn et al. (2013)	Bonfim and Monteiro (2013)	Hahm, Shin, and Shin (2013)	Lo Duca and Peltonen (2013)	Bordo and Meissner (2012)	Kauko (2012a)	Kauko (2012b)	Roy and Kemme (2012)	Schularick and Taylor (2012)	Alessi and Detken (2011)	Drehmann, Borio, and Tsatsaronis (2011)	Barrell et al. (2010)	Bunda and Ca' Zorzi (2010)	Büyükkarabacak and Valev (2010)	Joyce (2011)	Borio and Drehmann (2009)	Davis and Karim (2008)	Von Hagen and Ho (2007)	Domaç and Peria (2003)	Demirgüç-Kunt and Detragiache (2000)	Kaminsky and Reinhart (1999)	Hardy and Pazarbaşıoğlu (1998)
Crisis Data Set / Target Variable:	**B**	**L**	**C**	**D**	**C**	**B**	**L**	**C**	**B**	**D**	**O**	**FSI**	**C**	**NPL**	**NPL**	**R**	**C**	**O**	**C**	**L**	**R**	**C**	**CK**	**C**	**C**	**O**	**DD**	**DD**	**R**	**LI**
No. of Countries:	**15**	**15**	**17**	**28**	**16**	**40**	**26**	**11**	**23**	**9**	**30**	**28**	**14**	**25**	**34**	**14**	**14**	**18**	**36**	**14**	**76**	**37**	**20**	**18**	**105**	**47**	**88**	**34**	**20**	**38**
9. Inflation Variables																														
Commodity Prices						o																								
Inflation	o	x		x		o		x	~	o		x			o					o		~	x		~	o	x	x		x
Global Inflation						o																								
Real Interest Rate	x			o												x				o		x			~	x	o	x	x	o
10. Other Variables																														
Income Inequality													o			x														
Deposit Insurance Scheme																										x				
Finanical Deregulation																							x			o	x			
Capital Requirement																							x							
Contagion																							x							
Fixed Exchange Rate																							x				x			
Tax Burden						x																								

Notes: B = Babecký et al. (2014), C = compilation of various crisis databases, CK = Caprio and Klingebiel (1996), D = Detken et al. (2014), DD = Demirgüç-Kunt and Detragiache (1998), FSI = financial stress index as target variable, L = Laeven and Valencia (2012), LI = Lindgren et al. (1996), NPL = NPL ratio as target variable, O = author's own setup, R = Reinhart and Rogoff (2009). o = No significant predictive performance; x = At least some predictive performance; ~ = Ambiguous predictive performance. Few studies consider the significance of individual indicator variables. For studies that only present multivariate regressions, we have sought to identify whether the relevant predictor tends to be a statistically significant predictor of banking crises. However, due to disparate methods taken by different authors, the predictive performance is not comparable across their works. This may result in inconsistencies in the survey table. Even so, the information about where different types of indicators have been considered should be helpful in itself. In order to keep the number of different indicators feasible, first, we do not distinguish between different transformations of the same underlying variable, and second, we typically merge real and nominal variables into a single line.

developments have good forecasting properties.[9] Importantly, their multivariate approach provides superior crisis prediction relative to the traditional univariate approach, i.e., policymakers are likely to benefit from using a wide range of indicators in setting the countercyclical buffer rate.

Following Behn et al. (2013), Anundsen, Gerdrup, and Hansen (2014) propose a set of multivariate early warning models to guide policymakers in adjustment of the countercyclical capital buffer. They find that indicators on household credit developments predict crises better than those of non-financial corporations and that global housing market imbalances may be useful in signaling a crisis. They also propose a novel measure of housing and credit market exuberance based on the time-series methods proposed by Phillips, Shi, and Yu (2013).

Bonfim and Monteiro (2013) discuss suitable indicators for implementation of the countercyclical capital buffer. Their empirical analysis of nine European countries suggests that policymakers need to carefully monitor indicators on house and stock prices and credit developments.

In addition, a number of authorities have published single-country studies to justify their choice of indicators. Using Spanish data, Castro, Estrada, and Martinez (2014) analyze a group of potential additional indicators. In their analysis of the United Kingdom, Giese et al. (2014) suggest several complementary indicators for use alongside the credit-to-GDP gap.

In the following subsections, we continue this literature review beyond the studies focused explicitly on application to countercyclical capital buffer indicator and propose candidate indicators for each of the six categories in the ESRB recommendation. Detailed data definitions are provided in section 3.1.

2.2.1 Credit Developments

Credit growth is probably the most-analyzed indicator measuring credit developments. It has been found to be a statistically significant

[9]They remind us that the success of these variables might at least partly be explained by the global financial crisis, which causes a strong clustering of crisis episodes in the data.

predictor of banking crises in numerous studies (see, e.g., Schularick and Taylor 2012 and the references in table 1).

Nevertheless, other potential indicators should not be ruled out. For starters, we should consider the scope of credit indicators. Do we define credit as total credit that incorporates all credit regardless of the creditor or just the credit provided by the banks? Do we consider long-term growth rates such as three-year growth or absolute changes in credit levels in lieu of yearly growth rates? Do we acknowledge that private-sector, household, and non-financial corporation credit growth may each possess different signaling power with respect to an emerging banking crisis?[10]

There are also indicators that are quite similar to the benchmark indicator (credit-to-GDP gap calculated with a one-sided Hodrick-Prescott (HP) filter) that may contain additional relevant information helpful in predicting crises. For example, the credit-to-GDP gap could be analyzed separately for households and non-financial corporations. These indicators can be seen as augmenting credit-to-GDP gap information with detailed information on what underlies the primary indicator signal.

A well-known weakness of the credit-to-GDP gap is that it tends to increase when GDP declines (Repullo and Saurina 2011). In a slowing real economy, it may even be counterproductive to raise buffers. Indeed, if credit growth has already come to a halt, higher capital requirements could induce a large negative shock to the economy. Kauko (2012a) proposes two credit development measures that compare the one-year change in credit to the five-year moving average of GDP. The first measure is

$$X_{1,t} = \frac{5L_t}{\sum_{i=0}^{4} Y_{t-i}} - \frac{5L_{t-1}}{\sum_{i=1}^{5} Y_{t-i}}, \tag{1}$$

where L_t is the outstanding debt and Y_t is the GDP in year t. The second measure is such that the differencing is applied only to the debt variable,

[10]For example, Anundsen, Gerdrup, and Hansen (2014), Büyükkarabacak and Valev (2010), and Detken et al. (2014) all find that indicators of household credit developments are better at predicting banking crises than indicators of non-financial corporations.

$$X_{2,t} = \frac{5(L_t - L_{t-1})}{\sum_{i=0}^{4} Y_{t-i}}. \tag{2}$$

Kauko (2012a) argues that using a five-year moving average of GDP instead of yearly GDP addresses the problem of large short-term declines in GDP that hamper the use of the benchmark indicator. Detken et al. (2014) confirm that the indicator in which the credit change is divided by the one-year moving average of the GDP is among the best indicators for describing credit developments that foreshadow systemic financial crises.

For measuring credit developments, we consider the real credit and credit-to-GDP ratios. In each case, we consider four definitions of credit: total credit to non-financial private sector, total credit to households, total credit to non-financial corporations, and bank credit to private non-financial sector. Total credit includes loans and debt securities, irrespective of the creditor sector as reported in the financial accounts. Bank credit only includes credit where the creditor belongs to the banking sector.

2.2.2 Private-Sector Debt Burden

Private-sector indebtedness is unsustainable when borrowers can no longer meet their debt-servicing obligations. High private-sector indebtedness generates credit risk for banks and may depress consumption and investment throughout the economy. Indeed, both the debt-to-income ratio and the debt-service ratio have been found useful in signaling financial crises (e.g., Detken et al. 2014; Drehmann and Juselius 2014; Giese et al. 2014).[11] Adverse trends in the household debt burden may matter more for financial stability than the debt burden trends of non-financial corporations. Detken et al. (2014) conclude that the non-financial corporate debt-service ratio has no predictive power for banking crises.

Public data sources do not typically provide data on debt-servicing ratios.[12] Here, we use the data set collected for Detken et al. (2014). We also construct proxy indicators of the interest expense

[11]The debt-service ratio measures the interest rate and amortization costs of the debt relative to income.

[12]The Bank for International Settlements (BIS) recently began to post debt-service ratio data on its website.

burden without amortization costs. The constructed indicators are relevant in countries where mortgages have floating rates that move with market interest rates.[13] The first indicator is calculated by multiplying the household credit-to-GDP ratio by the three-month money market rate. The second indicator is calculated similarly, but the ten-year government bond interest rate replaces the three-month money market rate.

2.2.3 Potential Overvaluation of Property Prices

Variables related to developments in the real estate sector have been found useful in predicting banking crises (e.g., Jordà, Schularick, and Taylor 2015; see table 1). In particular, the combination of strong credit growth and rising house prices has been identified as threatening to financial stability (Barrel et al. 2011; Behn et al. 2013; Borio and Drehmann 2009; Jordà, Schularick, and Taylor 2015).

Credit and house prices tend to move hand-in-hand. House purchases are typically financed with loans, and house value affects the decision to grant a loan through the collateral process. Mortgages also typically make up a large share of household and bank balance sheets, making both vulnerable to swings in housing prices. In a downturn, the substantial losses to banks caused by defaults on household mortgages and loans to construction companies may be exacerbated by losses on other corporate lending caused by contractions in output and consumption. Many banks use mortgages to secure their own market-based funding, so a sharp negative correction in house prices may also increase costs of funding for troubled banks.

The state of the housing market can be assessed by comparing house prices with household income or housing rents. Relative developments in house prices and income reflect the affordability of housing from the buyer's point of view, while the relationship between housing prices and rents is conceptually identical to the stock market price-to-earnings ratio. Detken et al. (2014) find that

[13] In Finland, for example, mortgage interest rates are typically tied to EURIBOR rates (plus a fixed spread). Prime rates of European banks also typically track EURIBOR rates.

relative house price measures perform better in crisis prediction than other market- or real economy-based indicators.

For measuring potential overvaluation of property prices, we consider real residential property prices, the residential property price-to-rent ratio, the residential property price-to-income ratio, and commercial real estate prices.

2.2.4 External Imbalances

Indicators that measure excessive credit growth indirectly have been found useful in predicting banking crises. It is well known that when credit growth is much higher than GDP growth, domestic savings are typically insufficient to finance the credit expansion and indebtedness is financed with foreign money. Excessive foreign borrowing appears as a deficit in the current account. Many studies have found a link between large external imbalances and the frequency of financial crises. For example, Laeven and Valencia (2008) found that out of forty-one banking crisis around the world, thirty-nine countries ran current account deficits in the year preceding the crisis. There are also several studies that find a statistically significant relationship between the current account deficit and the likelihood of a banking crisis (see table 1). Joyce (2011) studies banking crises in emerging countries and concludes that an increase in foreign debt liabilities contributes to an increase in the incidence of crises, but foreign direct investment and portfolio equity liabilities have the opposite effect.

It has been argued in the literature that money originating from abroad, especially portfolio investment, provides a less stable credit source than money from domestic providers. In other words, heavy foreign borrowing may constitute a vulnerability to the financial system. Kim and Wei (2002) suggest that part of this vulnerability stems from the difficulties foreign investors have in evaluating risks in another country. This low-information condition leads to herding behavior that may trigger panicked pull-outs if risks materialize. Such investor flight may also drive up external imbalances (Kim and Wei 2002).

A number of studies consider trade- and currency-related variables such as exports, terms of trade, and exchange rate overvaluation, which are sometimes found to be statistically significant predictors (see table 1). We did not examine such variables in this study in order to steer away from the currency crises literature, which is beyond the scope of this paper.

Hence, we consider the current account deficit (ratio of current account to GDP), capital account deficit, ratio of portfolio investments to GDP, and other investment-to-GDP ratios as indicators for external imbalances. We also consider separately cross-border loans in foreign currency and domestic currency (divided by GDP) coming from abroad.

2.2.5 Potential Mispricing of Risk

Credit and asset price booms are typically associated with times of positive economic developments. During long periods of good times, agents may become oblivious to certain types of risk, which may be reflected as banks loosening their credit standards or investors demanding lower risk premia for risky securities.

In the securities markets, one might look for trends in the stock and bond markets. Rapid price increases on the stock market or high stock valuations (e.g., share prices relative to dividend yields, i.e., price-earnings (P/E) ratios) or a rapid decrease in the required risk premiums between safe and risky corporate bonds might reflect increased risk appetite among investors that leads to a mispricing of risk. Moreover, low levels of asset return volatility typically lead to increased risk-taking, i.e., in times of low volatility, investors seek out riskier assets to get the same returns as in times of higher volatility. The results of the previous literature on equity market indicators are mixed. Some studies find a link between stock market trends and banking crises, while others do not (see table 1).

As for the bond market, it is difficult to find sufficiently long time series of country-specific corporate bond data. Since corporate bond risk premiums have significant correlations across European countries (Krylova 2016), however, it may be sufficient here to use an international corporate bond risk premium for all countries.[14]

[14]Babecký et al. (2014) use the U.S. BAA corporate bond spread and find it to be one of the best predictors of banking crisis within a nine- to twelve-quarter horizon.

Several studies suggest that global indicators such as global equity price growth (Behn et al. 2013), global liquidity measures, or the global credit gap (Alessi and Detken 2011) are useful in predicting local crises.

A potential indicator that banks are mispricing risk may be seen in changes in the interest rate margin banks require for loans to households or corporations. A rapid drop in margins on new bank loans could indicate that banks are mispricing risk, e.g., due to increased competition. Risk-management tools of banks such as the value-at-risk metric may also tolerate higher risk-taking in periods of low volatility.

For measuring potential mispricing of risk, we consider the following indicators: local stock market index and local bank stock index, stock market volatility, dividend yield, P/E ratio, price-to-book (P/B) ratio, VIX index, high-yield corporate bond risk premiums, long- and short-term interest rates of two major economies (the United States and Germany), lending margin of household loans, and lending margin of corporate loans.

2.2.6 Strength of Bank Balance Sheets

Although it is quite clear that the causes of a banking crisis are at least partly manifested in vulnerabilities in bank balance sheets, the identification of reliable warning indicators contained in bank balance sheets is rare (see table 1). This likely relates to data issues. Bank aggregate balance sheets tend to be short and published on a yearly basis. They may also contain structural breaks due to changes in the banking industry and accounting standards.

Detken et al. (2014) consider and reject the leverage ratio as a predictor for systemic banking crises, as it lacks predictive power. Behn et al. (2013) find that higher aggregate banking-sector capitalization decreases the probability of banking crisis, while higher banking-sector profits may lead to excessive risk-taking and tend to precede banking crises.

There is some empirical evidence that the indicators of a bank's funding structure might work as predictors. Bank funding can be divided into core liabilities (stable deposits) and non-core liabilities (e.g., unstable short-term wholesale funding). During periods of rapid lending growth, banks may finance their increased lending with market funding. While deposit guarantee schemes have generally made traditional bank deposit runs extremely rare, market-based funding can face a bank run if the bank's prospects deteriorate. Hence, a higher share of more unstable market funding makes banks more vulnerable. Kamin and DeMarco (2012) and Lainà, Nyholm, and Sarlin (2015) note evidence that a larger share of deposit funding has a stabilizing effect for the financial system. Betz et al. (2013) and Hahm, Shin, and Shin (2013), similarly, show that a high share of non-core liabilities is a good predictor of an impending banking crisis.

For measuring the strength of the bank balance sheet, we consider the following indicators: ratio of total assets to GDP, leverage ratio, loans-to-deposits ratio, ratio of non-core liabilities to total assets or GDP, (short-term liabilities – liquid assets)/total assets, and short-term liabilities/liquid assets.

3. Empirical Analysis

3.1 Indicator Data and Transformations

We compile quarterly indicator data from central banks, international organizations, and commercial data sources. Table 2 provides the full list of the examined indicators together with definitions, and data sources.

The unbalanced panel data cover twenty-eight EU member states for the period 1970 to 2012. The length and availability of economic time series still varies across EU countries (e.g., available data are scarce for new EU member states). Table 3 shows the descriptive statistics, where the number of countries, number of observations, and number of financial crises is highlighted for each indicator.

We consider various transformations of indicators such as differences, growth rates, and trend gaps for each indicator. This is because the indicator as such may be non-stationary—an undesirable feature for a good indicator. Indeed, Kauko, Vauhkonen, and Topi (2014) argue that if an indicator lacks an equilibrium level to which it tends to return, interpretation of the indicator becomes a non-trivial task. In any case, the application of transformations solves potential non-stationarity problems.

Table 2. List of Indicators and Data Sources

Indicator	Definition	Transformations	Data Source
1. Credit Developments			
1.1. Real Total Credit	Total credit to private non-financial sectors by all sectors divided by CPI.	Growth rates, trend gaps	BIS (credit), IMF (CPI)
1.2. Real Total Bank Credit	Credit to private non-financial sectors by domestic banks divided by CPI.	Growth rates, trend gaps	BIS (credit), IMF (CPI)
1.3. Real Household Credit	Total credit to households and non-profit institutions serving households by all sectors divided by CPI.	Growth rates, trend gaps	BIS (credit), IMF (CPI)
1.4. Real Corporate Credit	Total credit to non-financial corporations by all sectors divided by CPI.	Growth rates, trend gaps	BIS (credit), IMF (CPI)
1.5. Total Credit / GDP	Total credit to private non-financial sectors by all sectors divided by GDP.	Growth rates, differences, trend gaps	BIS
1.6. Total Bank Credit / GDP	Credit to private non-financial sectors by domestic banks divided by GDP.	Growth rates, differences, trend gaps	BIS
1.7. Total Household Credit / GDP	Total credit to households and non-profit institutions serving households by all sectors divided by GDP.	Growth rates, differences, trend gaps	BIS
1.8. Total Corporate Credit / GDP	Total credit to non-financial corporations by all sectors divided by GDP.	Growth rates, differences, trend gaps	BIS
2. Private-Sector Debt Burden			
2.1. Debt-Service Ratio	Ratio of interest payments plus amortizations divided by income; includes households and non-financial corporations. See ESRB (2015).	Growth rates, differences, trend gaps	ESRB
2.2. Corporate Debt-Service Ratio	Ratio of interest payments plus amortizations divided by income; includes non-financial corporations.	Growth rates, differences, trend gaps	ESRB

(*continued*)

Table 2. (Continued)

Indicator	Definition	Transformations	Data Source
2.3. Household Debt-Service Ratio	Ratio of interest payments plus amortizations divided by income; includes households and non-profit institutions serving households.	Growth rates, differences, trend gaps	ESRB
2.4. Total HH Credit × 10y Rate / GDP	Total HH credit / GDP indicator multiplied by the country-specific ten-year government bond yield.	Growth rates, differences, trend gaps	Bloomberg (rate), BIS
2.5. Total HH Credit × 3m Rate / GDP	Total HH credit / GDP indicator multiplied by the country-specific three-month money market rate.	Growth rates, differences, trend gaps	Bloomberg (rate), BIS
3. Potential Overvaluation of Property Prices			
3.1. Real House Price	Deflated using the private consumption deflator from the national account statistics.	Growth rates, trend gaps	OECD
3.2. House Price / Rent	Nominal house index divided by rent price index.	Growth rates, differences, trend gaps	OECD
3.3. House Price / Income	Nominal house price divided by nominal disposable income per head.	Growth rates, differences, trend gaps	OECD
3.4. Real Commercial Real Estate Price	Commercial real estate appraisal index divided by CPI.	Growth rates, trend gaps	ECB
4. External Imbalances			
4.1. CurrentAccount / GDP	Current account balance divided by GDP.	Growth rates, differences	ECB BOP
4.2. Capital Account / GDP	Capital account balance divided by GDP.	Growth rates, differences	ECB BOP
4.3. Portfolio Investments / GDP	Portfolio investments part of the financial account divided by GDP. Unadjusted amount at the end of period.	Growth rates, differences	ECB BOP
4.4. Other Investments / GDP	Other investments part of the financial account divided by GDP. Unadjusted amount at the end of period.	Growth rates, differences	ECB BOP

(*continued*)

Table 2. (Continued)

Indicator	Definition	Transformations	Data Source
4.5. Foreign Currency Cross-Border Loans / GDP	All foreign currency cross-border loans extended to foreign countries divided by GDP.	Growth rates, differences, trend gaps	ECB BSI
4.6. Own Currency Cross-Border Loans / GDP	All own currency cross-border loans extended to foreign countries divided by GDP.	Growth rates, differences, trend gaps	ECB BSI
5. Potential Mispricing of Risk			
5.1. Stock Market Volatility	Average quarterly volatility of the main national stock market index.	Growth rates, differences	Bloomberg
5.2. Stock Market Index	Level of the main national stock market index.	Growth rates	Bloomberg
5.3. Bank Stock Index	Level of the index formed by the domestic listed banks.	Growth rates	Bloomberg
5.4. Stock Market P/E Ratio	Price-to-earnings ratio of the main national stock market index.	Growth rates, differences	Bloomberg
5.5. Stock Market P/B Ratio	Price-to-book value ratio of the main national stock market index.	Growth rates, differences	Bloomberg
5.6. Stock Market Dividend Yield	Dividend yield of the main national stock market index.	Growth rates, differences	Bloomberg
5.7. Household Lending Spread	The average rate at which banks issue new loans to households and non-profit institutions serving households. Unconsolidated.	Growth rates, differences	ECB MIR
5.8. Corporate Lending Spread	The average rate at which banks issue new loans to non-financial corporations.	Growth rates, differences	ECB MIR
5.9. High-Yield Spread	Difference between the Bank of America Merrill Lynch euro non-financial high-yield bond index (HNE0) and euro non-financial investment-grade bond index (EN00).	Growth rates, differences, trend gaps	Bloomberg
5.10. VIX Index	Measure of market expectations of near-term volatility conveyed by S&P 500 stock index option prices.	Growth rates, differences, trend gaps	Chicago Board Options Exchange

(continued)

Table 2. (Continued)

Indicator	Definition	Transformations	Data Source
5.11. German 10y Bund	Yield of German ten-year bund.	Growth rates, differences, trend gaps.	Bloomberg
5.12. German 1y Bill	Yield of German one-year bill.	Growth rates, differences, trend gaps	Bloomberg
5.13. German 1m Bill	Yield of German one-month bill.	Growth rates, differences, trend gaps	Bloomberg
5.14. U.S. 10y T-Note	Yield of U.S. ten-year Treasury note.	Groth rates, differences, trend gaps	Bloomberg
5.15. U.S. 1y T-Bill	Yield of U.S. one-year Treasury bill.	Growth rates, differences, trend gaps	Bloomberg
5.16. U.S. 1m T-Bill	Yield of U.S. one-month Treasury bill.	Growth rates, differences, trend gaps	Bloomberg
6. Strength of Bank Balance Sheets			
6.1. Leverage Ratio	Total equity divided by total assets.	Growth rates, differences	ECB CBD2
6.2. Loans / Deposits	Bank loans to private non-financial sector divided by bank deposits from the private non-financial sector.	Growth rates, differences	ECB CBD2
6.3. Total Assets / GDP	Total assets divided by GDP.	Growth rates, differences	ECB CBD2
6.4. Non-core Liabilities / GDP	Non-core liabilities = Total assets – Deposits – Capital and reserves.	Growth rates, differences	ECB BSI
6.5. Non-core Liabilities / Total Assets	See above.	Growth rates, differences	ECB BSI
6.6. Net ST Liabilities Ratio = (ST Liabilities – Liquid Assets) / Total Assets	Short-term liabilities include debt securities issued with maturity less than one year, short-term deposits (euro-area private sector, non-euro-area and euro-area other general government), inter-MFI deposits. Liquid assets include holdings of cash, MMF shares, euro-area private-sector debt securities with maturity below one year, inter-MFI loans, and government debt securities.	Growth rates, differences	ECB BSI
6.7. ST Liabilities / Liquid Assets	Ratio of short-term liabilities and liquid assets. The components are defined as above.	Growth rates, differences	ECB BSI

Notes: ECB data are for all resident monetary financial institutions (MFIs), excluding money market funds (MMF). ECB balance sheet items (BSI), and MFI interest rates (MIR) statistics are reported on an unconsolidated basis. ECB Consolidated Banking Statistics (CBD2) is consolidated. BOP = balance of payments. HH = household.

Table 3. Descriptive Statistics

Indicator	$\bar{X}$	Sd(x)	Min.	p_{25}	p_{50}	p_{75}	Max.	N	N_c	N_f
1. Credit Developments										
1.1. Real Total Credit	10.48	12.56	0.27	1.90	5.25	15.83	80.46	1735	15	15
1.2. Real Total Bank Credit	6.64	7.61	0.17	1.11	2.55	10.61	42.83	1716	15	15
1.3. Real Household Credit	4.69	5.04	0.05	1.04	2.16	6.99	26.35	1434	15	15
1.4. Real Corporate Credit	7.67	8.47	0.36	1.80	5.12	11.31	54.72	1434	15	15
1.5. Total Credit / GDP	0.93	0.82	0.005	0.33	0.71	1.27	5.20	2746	18	22
1.6. Total Bank Credit / GDP	0.55	0.43	0.004	0.22	0.45	0.80	2.20	2715	18	22
1.7. Total Household Credit / GDP	0.41	0.32	0.01	0.16	0.35	0.59	1.60	2022	18	20
1.8. Total Corporate Credit / GDP	0.73	0.61	0.04	0.35	0.59	0.90	4.47	1998	18	19
2. Private-Sector Debt Burden										
2.1. Debt-Service Ratio	0.19	0.16	0.01	0.12	0.15	0.19	1.08	2899	27	27
2.2. Corporate Debt-Service Ratio	0.37	0.21	0.10	0.25	0.32	0.44	1.77	1713	26	19
2.3. Household Debt-Service Ratio	0.12	0.06	0.02	0.08	0.11	0.14	0.36	1701	26	19
2.4. Total HH Credit × 10y Interest Rate / GDP	2.93	1.67	0.38	1.80	2.56	3.67	12.83	1451	20	17
2.5. Total HH Credit × 3m Interest Rate / GDP	2.19	1.73	0.06	0.91	1.75	2.96	11.90	1923	25	21
3. Potential Overvaluation of Property Prices										
3.1. Real House Price	81.88	29.07	23.18	58.98	79.28	100.8	178.6	2241	21	22
3.2. House Price / Rent	82.98	27.81	23.88	61.35	81.71	101.1	178.6	2071	20	21
3.3. House Price / Income	86.63	25.49	32.75	66.93	87.89	100.9	189.4	2070	21	21
3.4. Real Commercial Real Estate Price	97.03	37.18	37.54	73.60	94.97	108.4	255.7	1209	15	14
4. External Imbalances										
4.1. Current Account / GDP	–0.33	1.74	–13.82	–1.07	–0.21	0.66	9.53	2472	26	16
4.2. Capital Account / GDP	0.001	0.003	–0.02	0	0	0.001	0.04	1491	21	16
4.3. Portfolio Investments / GDP	–0.46	2.00	–19.89	–0.30	–0.10	–0.01	0.90	1024	21	14
4.4. Other Investments / GDP	–0.46	2.00	–19.89	–0.30	–0.10	–0.01	0.90	1024	21	14
4.5. F.C. Cross-Border Loans / GDP	0.14	0.45	0	0.01	0.01	0.05	2.67	1303	15	12
4.6. D.C. Cross-Border Loans / GDP	0.10	0.34	0	0.004	0.01	0.04	2.13	1303	15	12

(*continued*)

Table 3. (Continued)

Indicator	$\bar{X}$	Sd(x)	Min.	p_{25}	p_{50}	p_{75}	Max.	N	N_c	N_f
5. Potential Mispricing of Risk										
5.1. Stock Market Volatility	0.18	0.11	0	0.11	0.15	0.22	1.19	3180	28	27
5.2. Stock Market Index	3869	6149	47.67	714.4	2017	4477	47803	1584	14	14
5.3. Bank Stock Index	1050	1544	11.66	185.7	434.7	1134	9288	1632	13	17
5.4. Stock Market P/E Ratio	41.81	337.01	0.32	11.66	15.12	21.19	9377	1350	23	15
5.5. Stock Market P/B Ratio	1.65	0.62	0.32	1.18	1.54	2.07	3.25	494	14	9
5.6. Stock Market Dividend Yield	3.33	1.33	0.89	2.44	3.12	3.99	10.95	720	14	9
5.7. Household Lending Spread	1.95	1.17	–5.36	1.20	1.85	2.61	8.32	1112	28	14
5.8. Corporate Lending Spread	1.92	0.84	0.03	1.26	1.76	2.47	5.51	1070	27	13
5.9. High-Yield Spread*	576.6	347.8	164.2	335.4	486.3	715.9	1744	1596	28	30
5.10. VIX Index*	21.39	6.97	12.50	14.73	20.91	25.92	40.60	2632	28	17
5.11. German 10y Bund*	6.06	2.33	0.77	4.24	6.17	7.93	11.10	5040	28	33
5.12. German 1y Bill*	4.37	2.43	0.33	2.36	4.09	5.65	9.90	3696	28	31
5.13. German 1m Bill*	4.44	2.84	0.01	2.62	3.95	5.68	12.38	4144	28	31
5.14. U.S. 10y T-Note*	6.95	2.81	1.61	4.85	6.75	8.32	15.32	4816	28	31
5.15. U.S. 1y T-Bill*	5.60	3.19	0.93	3.18	5.57	7.50	15.51	3472	28	31
5.16. U.S. 1m T-Bill*	6.01	4.07	0.30	3.21	5.62	8.26	20.58	3920	28	31
6. Strength of Bank Balance Sheets										
6.1. Leverage Ratio	8.80	3.39	2.54	6.21	8.38	10.53	21.33	1348	28	14
6.2. Loans / Deposits	134.0	52.3	47.1	100.9	123.9	151.6	327.1	1101	28	13
6.3. Total Assets / GDP	3.76	6.67	0.001	0.90	2.26	3.42	39.75	1274	21	14
6.4. Non-core Liabilities / GDP	2.54	5.61	0.001	0.30	1.13	1.94	33.92	844	20	10
6.5. Non-core Liabilities / Total Assets	0.48	0.15	0.17	0.35	0.50	0.58	0.82	1031	27	12
6.6. (ST Liabilities – Liquid Assets) / Total Assets	0.19	0.14	–0.03	0.06	0.20	0.31	0.48	554	13	7
6.7. Short-Term Liabilities / Liquid Assets	1.72	0.57	0.92	1.17	1.62	2.15	3.62	554	13	7

Notes: The sample statistics are calculated for the full sample, 1970–2012. $\bar{X}$ and Sd(x) are the sample mean and sample standard deviation. p_{25}, p_{50}, and p_{75} denote the first, second, and third quartiles, respectively. N, N_c, and N_f are the number of observations, countries, and financial crises, respectively. F.C. and D.C. refer to foreign currency and domestic currency, respectively. Indicators marked by * are understood as global indicators, so the data are repeated for each country.

The simplest transformations are the growth and difference. *n-year growth* is calculated as

$$100\frac{x_t - x_{t-4n}}{x_{t-4n}}. \tag{3}$$

n-year difference is calculated as

$$x_t - x_{t-4n}. \tag{4}$$

We simply apply the rates of growth and differences $n = 1$ (year) and $n = 3$ (years) that correspond to typical choices used by practitioners when monitoring macroeconomic and financial developments. Why do we consider both differences and rates of growth? Note that in the panel setup, the level values of some indicators (such as house price index or real credit stock) may not lead to an economically sensible model. In such cases, it is more appropriate to use relative measures such as rates of growth and relative trend gap (defined below).

Additionally, we consider four alternative trend gaps. Two alternative trend gaps utilize the trend calculated with a one-sided HP filter with smoothing parameter $\lambda = 400{,}000$. "One-sided" here means that the trend at time t is calculated using only values up to time t. Once the trend component is estimated, we form the trend gap (denoted *trend gap* in the tables) as

$$x_t - trend_t, \tag{5}$$

and the relative trend gap (denoted *relative gap*) as

$$100\left(\frac{x_t}{trend_t} - 1\right), \tag{6}$$

respectively. Because the one-sided trend makes little sense for the first few observations of the time series, the trend gaps are calculated only after the time series has five years of historical data. Hence, the trend-gap-transformed indicators have somewhat lower number of observations than the original series. Finally, we consider two more alternative definitions of the trend. First, a trend that is the historical average of the original indicator x_t is calculated as

$$average_t = \sum_{s=t_0}^{t} \frac{x_s}{t - t_0 + 1}. \tag{7}$$

Second, a trend that is the five-year moving average of the original indicator x_t is calculated as

$$5y\ ma_t = \sum_{s=0}^{19} \frac{x_{t-s}}{20}. \tag{8}$$

The corresponding trend gaps are denoted *ave. gap,* calculated as

$$x_t - average_t, \tag{9}$$

and *5y M.A. gap,* calculated as

$$\text{and } x_t - 5y\ ma_t. \tag{10}$$

As with the one-sided HP-filtered trends, these trend gaps are only calculated after five years of historical data are available.

3.2 Banking Crisis Variable

Our main results are reported for the systemic financial crisis variable published by Detken et al. (2014). At the time of writing, this was the most recent available financial crisis database. As our work extends that of Detken et al. (2014), their crisis data set (henceforth labeled Detken's) is a natural starting point. However, a variety of banking crisis data sets are provided in the earlier literature, with Babecký et al. (2014) and Laeven and Valencia (2012) among the newest (henceforth labeled Babecký's and Laeven's crisis data sets).[15]

The data sets use different definitions as to what constitutes a banking crisis. Therefore, table 4 lays out these alternative crisis definitions. Detken's data set, which is based on Babecký's data set, includes numerous modifications to align crisis episodes with policymakers' objectives. Crises that were not systemic banking crises or not associated with a domestic credit cycle are excluded, while

[15] Table 1 shows the crisis data sets used in some earlier studies. In addition to Babecký's, Detken's, and Laeven's crisis data sets, crisis dating of, e.g., Caprio and Klingebiel (1996), Demirgüç-Kunt and Detragiache (1998), Lindgren, Garcia, and Saal (1996), and Reinhart and Rogoff (2009) have been used.

Table 4. Information about Alternative Banking Crisis Data Sets: Banking Crisis Definitions

Label	Source	Banking Crisis Definition
Babecký's	Babecký et al. (2014)	They collect information about crisis occurrence from ten influential papers. They validate the coding of crises with the help of a comprehensive survey among country experts.
Detken's	Detken et al. (2014)	They amend Babecky's data set with the following changes: Non-systemic banking crises and crises not associated with the credit cycle are excluded. "Would-be crises" (i.e., periods where domestic developments related to the credit cycle could have caused a systemic banking crisis had it not been for policy action or an external event that dampened the financial cycle) are added.
Laeven's	Laeven and Valencia (2012)	A banking crisis is defined as systemic if two conditions are met: (i) significant signs of financial distress in the banking system (as indicated by significant bank runs, losses in the banking system, and/or bank liquidations) and (ii) significant banking policy intervention measures in response to significant losses in the banking system.

periods where domestic developments related to the credit cycle that likely would have led to a systemic banking crisis in the absence of policy intervention or an external event that dampened the credit cycle are added.

As the differences can be quite significant, we consider the three separate crisis data sets, and provide a summary of our key findings with each alternative crisis data set.[16] The crisis periods for the three financial crisis data sets considered in this work are summarized in table 5.

3.3 Extracting Early Warning Signals

We follow a common approach to extracting warning signals from early warning indicators—the *signaling* approach. Basically, it is a non-parametric model suitable for single-variable warning indicators (Alessi and Detken 2011; Borio and Drehmann 2009; Borio and Lowe 2002; Drehmann, Borio, and Tsatsaronis 2011; Drehmann et al. 2010). The earlier literature considers other approaches to extract early warning signals, such as the discrete choice model (Barrell et al. 2010; Behn at al. 2013; Davis and Karim 2008; Demirgüç-Kunt and Detragiache 2000; Frankel and Rose 1996; Hardy and Pazarbaşıoğlu 1998; Lo Duca and Peltonen 2013; and Lund-Jensen 2012), decision trees, and machine-learning techniques (Holopainen and Sarlin 2015). For our work, the primary advantages of the signaling method are its transparency and ease of interpretation relative to the other, more complex techniques. It helps us keep the focus on identifying informative indicators rather than useful methods.

The idea of the signaling approach is simple. Below or above some *signaling threshold*, a warning signal of increased vulnerability is issued when that threshold is crossed. For example, a warning signal might be issued if one-year growth in real household credit exceeds 6 percent.

The rationale for specifying the thresholds is closely related to the performance evaluation of the warning indicators. If the threshold is too insensitive, so that it rarely gives alarms, the number of false alarms is likely to be low, but the indicator may also fail to warn on the cusp of most crises. Conversely, if the threshold is overly sensitive, false alarms are frequent, but few crises are missed.

3.4 Evaluating Early Warning Indicators

We use two early warning indicator evaluation statistics—area under the receiver operating characteristic (ROC) curve (this area is

[16]The full set of results calculated with alternative data sets is available from the authors on request.

Table 5. Information about Alternative Banking Crisis Data Sets: Crisis Periods in EU Countries for Different Data Sets

Country	Babecký's	Detken's	Laeven's
Austria	2008:Q1–2008:Q4		2008:M9–2010
Belgium	2008:Q1–2008:Q4		2008:M9–2010
Bulgaria	1971:Q1–1971:Q2		
	1994:Q1–1997:Q4	1995:Q2–1997:Q4	1996:M1–1997
		2004:Q4–2007:Q2*	
Croatia		1998:Q1–2000:Q2	1998:M3–1999
Cyprus		2012:Q2–2012:Q4	
Czech Republic	1991:Q1–1991:Q4		
	1994:Q1–2000:Q4	1998:Q1–2002:Q2	1996:M6–2000
Denmark	1987:Q1–1993:Q4	1987:Q1–1993:Q4	
	2008:Q1–2010:Q4	2008:Q3–2012:Q4	2008:M9–2010
Estonia	1992:Q1–1995:Q4		1992:M11–1994
	1998:Q1–1998:Q4	1998:Q2–1998:Q4	
Finland	1991:Q1–1995:Q4	1991:Q3–1995:Q4	1991:M9–1995
France	1994:Q1–1995:Q4	1993:Q3–1995:Q4	
	2008:Q1–2009:Q4	2008:Q3–2012:Q4	2008:M9–2010
Germany	1974:Q2–1974:Q4		
	1977:Q1–1979:Q4		
		2000:Q1–2003:Q4	
	2008:Q1–2008:Q4		2008:M9–2010
Greece	1991:Q1–1995:Q4		
	2008:Q1–2010:Q4	2008:Q1–2012:Q4	2008:M8–2010
Hungary	1991:Q1–1995:Q4		1991:M9–1995
	2008:Q1–2009:Q2	2008:Q3–2012:Q4	2008:M9–2010
Ireland	1985:Q1–1985:Q1		
	2007:Q1–2010:Q4	2008:Q3–2012:Q4	2008:M9–2010
Italy	1990:Q1–1995:Q4	1994:Q1–1995:Q4	
			2008:M9–2010
Latvia	1995:Q1–2003:Q4		1995:M4–1996
	2008:Q1–2008:Q4	2008:Q4–2010:Q3	2008:M9–2010
Lithuania	1995:Q1–1996:Q4	1995:Q1–1996:Q4	1995:M12–1996
	2009:Q1–2009:Q4	2008:Q4–2010:Q4	
Luxembourg	2008:Q1–2010:Q4		2008:M9–2010
Netherlands		2002:Q1–2003:Q4*	
	2008:Q1–2008:Q4	2008:Q3–2012:Q4	2008:M9–2010
Poland	1991:Q1–1994:Q4		1992–94
Portugal		1999:Q1–2000:Q1*	
	2008:Q1–2008:Q4	2008:Q4–2012:Q4	2008:M9–2010
Romania	1990:Q1–1999:Q4		1990–92
		1997:Q2–1999:Q1	

(*continued*)

Table 5. (Continued)

Country	Babecký's	Detken's	Laeven's
Slovak Republic	1991:Q1–2002:Q4		1998–2002
Slovenia	1992:Q1–1994:Q4	1992:Q1–1994:Q4	1992–92
	2008:Q1–2008:Q4	2008:Q1–2012:Q4	2008:M9–2010
Spain	1977:Q1–1985:Q4	1978:Q1–1985:Q3	1977–81
	2008:Q1–2008:Q4	2009:Q2–2012:Q4	2008:M9–2010
Sweden	1990:Q3–1995:Q4	1990:Q3–1993:Q4	1991:M9–1995
	2008:Q1–2008:Q4	2008:Q3–2010:Q4	2008:M9–2010
United Kingdom	1974:Q1–1976:Q4	1973:Q4–1975:Q4	
	1984:Q1–1984:Q4		
	1991:Q1–1995:Q4	1990:Q3–1994:Q2	
	2007:Q1–2007:Q4	2007:Q3–2012:Q4	2007:M9–2010

Note: For Detken's data set, the three events marked by * are not actual realized crises but domestic developments related to the credit cycle that could well have caused a systemic banking crisis had it not been for policy action or an external event that dampened the credit cycle.

henceforth denoted AUC) and relative usefulness (U_r). Both evaluation statistics have been quite popular in recent banking crisis early warning literature.[17] We provide only a short introduction to the methods, as detailed expositions of the measures are available elsewhere.[18]

Both AUC and relative usefulness consider the relative amounts of type I and type II errors produced by the early warning indicator (see figure 1A). The measures can be applied more generally to any situation where there is a trade-off between type I and type II errors. In our case, a type I error (false positive) corresponds to a false alarm, i.e., the indicator issues an early warning signal, but no crisis follows within the specified prediction horizon. A type II

[17] AUC is used in, e.g., Bonfim and Monteiro (2013), Buchholst and Rangvid (2013), Comelli (2014), and Drehmann and Juselius (2014). Both statistics are applied in Behn et al. (2013), Betz et al. (2013), and Detken et al. (2014). Relative usefulness is found in Alessi and Detken (2011), Babecký et al. (2014), Lainà, Nyholm, and Sarlin (2015), and Lo Duca and Peltonen (2013).

[18] See, e.g., Drehmann and Juselius (2014) and Sarlin (2013) for AUC and usefulness, respectively.

Figure 1. Correspondence of the Generic Confusion Matrix with the Early Warning Exercise

A. Generic Confusion Matrix

		True condition: Condition positive	True condition: Condition negative
Predicted condition	Predicted condition positive	True positive	False positive (Type I error)
Predicted condition	Predicted condition negative	False negative (Type II error)	True negative

B. Confusion Matrix for the Early Warning Exercise

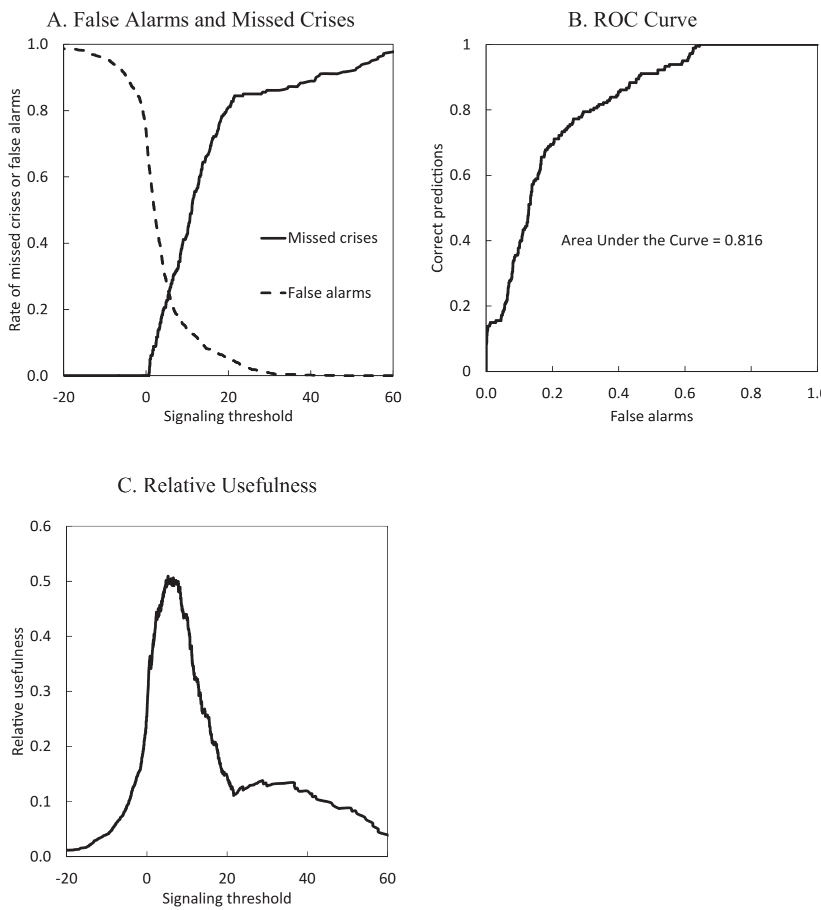
		True condition: Crisis	True condition: No crisis
Predicted condition	Signal	Correct alarm (A)	False alarm (B)
Predicted condition	No signal	Missed crisis (C)	Correctly no alarm (D)

error (false negative) corresponds to a missed crisis, i.e., the indicator does not give a signal, but a banking crisis occurs within the specified prediction horizon.

Figure 2A illustrates the tradeoff between false alarms and missed crises for the total credit-to-GDP trend gap indicator. If the signaling threshold is below the trend gap of 0 percent, there will be no missed crises, but the number of false alarms will be quite high. In contrast, if the threshold is above the trend gap of 20 percent, the share of missed crises is quite high, but the false alarm rate is very low. Thus, the policy-relevant threshold likely lies somewhere between 0 and 20 percent (the actual BCBS benchmark buffer guide applied in the EU legislation has triggers in the range of 2 to 10 percent of the trend gap).

In specifying the horizon for crisis prediction, we follow the conventions in Detken et al. (2014) and set the crisis-prediction horizon to three years. If the time to crisis is less than a year, the policymaker lacks sufficient lead time to react. Hence, we do not include in the evaluation observations that take place when the distance to the banking crisis is less than one year. A publication lag of one

Figure 2. False Alarms and Missed Crises for Different Signaling Thresholds, ROC Curve, and Relative Usefulness for Different Signaling Thresholds



quarter is applied to all indicators. As a robustness check and to gain further insight on the lead-lag structure of different indicators, i.e., when different indicators are expected to give signals, we also consider prediction horizons from six months to five years.

The ROC curve is the visual curve that shows the tradeoff between type I and type II errors. This is illustrated for the credit-to-GDP gap indicator in figure 2B. For a given rate of type I errors on the horizontal axis (false alarms), it would be desirable for the rate of correct alarms (vertical axis) to be as close to 1 as possible. Broadly speaking, the larger the area under the ROC curve (AUC), the better the indicator. For a completely uninformative indicator, AUC = 0.5, while for a perfect indicator AUC = 1. Thus, to be an informative indicator, we need AUC > 0.5. In our credit-to-GDP gap example, AUC = 0.82 would make it a very good indicator in this context.

The *relative usefulness* statistic uses a loss function that accounts for type I and type II errors. The weights of the loss function reflect the presumed preferences for the errors. The methodology goes back to the policy loss functions of Bussière and Fratzscher (2008) and Demirgüc-Kunt and Detragiache (2000), and the usefulness measure proposed by Alessi and Detken (2011) and later supplemented by Sarlin (2013).

The loss function of Alessi and Detken (2011) is defined as follows:

$$L_{AD}(\theta) = \theta T_2 + (1-\theta) T_1 = \theta \frac{C}{A+C} + (1-\theta) \frac{B}{B+D}, \qquad (11)$$

where the right-hand side is a weighted average of type I and type II error rates, T_1 and T_2, respectively.[19] The correspondence of the right-hand-side alphabetic letters with the generic confusion matrix is illustrated in figure 1B. A is the number of periods in which an indicator provides a correct signal (crisis starts within one to three years of issuing the signal), and B is the number of periods in which a wrong signal is issued. C is the number of periods in which a signal is not provided although the crisis is starting within a reasonable number of periods (one to three years). At last, D denotes the number of periods in which correctly no signal is provided. In other words, $A = TP$, number of true positives; $B = FP$, number of false positives; $C = FN$, number of false negatives; and $D = TN$, number

[19]In the formula, the order of T_1 and T_2 differs from some of the earlier literature. It is just a matter of convention for forming the null hypothesis. Type I error (or false positive) is the incorrect rejection of a true null hypothesis H_0. We set the H_0: "no crisis within the next three years" so that a false positive means a false alarm. Type II error (false negative) is incorrectly retaining a false null hypothesis so that in our case false negative means failure to detect a crisis.

of true negatives. θ is the parameter revealing the policymaker's relative risk aversion to type I and type II errors. A higher parameter value θ means that the policymaker is more averse to missing a crisis than getting a false alarm.

Sarlin (2013) augments the loss function with the unconditional crisis probability such that

$$L_S(\mu) = \mu P T_2 + (1-\mu)(1-P)T_1, \tag{12}$$

where $P = \frac{A+C}{A+B+C+D}$ is the unconditional crisis probability as estimated from the sample. The advantage of the augmented loss function is that it is explicit with respect to the relative frequency of situations when type I or type II errors can occur. Yet, for each μ there exists θ such that the two alternative loss functions lead to equivalent policies.

For either loss function, the relative usefulness statistics is defined as

$$U_r = \frac{\omega - L}{\omega}, \tag{13}$$

where for Alessi and Detken (2011) $\omega = \min(\theta, 1-\theta)$ and for Sarlin (2013) $\omega = \min(\mu P, 1-\mu P)$. The normalization parameter α ensures that the maximum value of relative usefulness is 1, i.e. a perfect warning indicator. In theory, any indicator is useful to a policymaker if its usefulness is larger than 0 (the higher the better), and useless if usefulness is less than 0 (all useless indicators are equally useless). In practice, indicators with low positive usefulness would likely be ignored by a policymaker with access to more useful indicators.

We set $\theta = 0.5$ as the point at which the policymaker is indifferent to type I and type II errors. In our data the probability of crisis is $P = 0.1$, so our choice of θ is equivalent to our choice of $\mu = 0.9$. Whether these are the correct values for μ or θ is up to the policymaker's actual preferences. In any case, both parameter values are close to those previously used in the literature.[20]

[20]Babecký et al. (2014) and Lo Duca and Peltonen (2013) both use $\theta = 0.5$. For example, Detken et al. (2014) use $\theta = 0.5/0.6/0.7$. Behn et al. (2013) use $\mu = 0.9$ and Betz et al. also use $\mu = 0.9$ as the benchmark case.

Figure 2C illustrates the relative usefulness for credit-to-GDP gap for different signaling thresholds. As expected from previous discussion, the credit-to-GDP gap indicator is most useful for signaling thresholds between 0 percent and 20 percent. Following the curve from left to right, usefulness initially increases as the rate of false alarms goes down rapidly, while the rate of missed crises increases at a relatively slow pace (see figure 2A). At the peak of the usefulness curve, the rate of change of false alarms is exactly opposite to the rate of change of missed crises. From this point onwards, usefulness starts to decrease as the improvement in false alarms no longer offsets the increase in the missed crisis rate.

Note that it is possible in principle that both high and low indicator values might signal increased vulnerability. This turned out not to be much of an issue for the indicators considered in this paper, however.[21] Hence, we report the evaluation results for each indicator using the single directionality, which is based on economic reasoning and earlier literature discussed in section 2.2. The hypothesized directionality is indicated for each indicator together with the evaluation results. If the observed data goes against the hypothesized direction, the resulting usefulness values are expected to be low or negative and the AUC statistic below 0.5. Additionally, the tables in an online appendix (available at http://www.ijcb.org) report the statistical significance for the logit model coefficient β_1 for the model

$$\Pr(precrisis = 1) = F(\beta_0 + \beta_1 indicator), \tag{14}$$

where $F(z) = e^z/(1 + e^z)$ is the cumulative logistic distribution, and the binary dependent variable is 1 for the pre-crisis quarters (one to three years before onset of crisis) and for the normal quarters (more than three years before crisis).[22] As is evident in the tables in the online appendix, with rare exceptions the logit coefficient either has the hypothesized sign or is not statistically significant.

[21] We initially evaluated the usefulness of each indicator in both directions—the direction hypothesized based on economic reasoning, and the opposite direction. Generally the opposite direction was not useful, but in a handful of cases the opposite direction was more useful than the hypothesized direction. These cases were the weakly performing indicators 4.1.4., 4.2.4., 4.3.4., 5.4.2., and 5.4.4.

[22] Note that late pre-crisis quarters (less than one year before crisis) and crisis quarters are excluded from all the evaluations because we are looking for *early* warning signals.

3.5 Full-Sample and Out-of-Sample Evaluation

We perform two types of performance evaluations for the indicators—full-sample and out-of-sample evaluation—following an approach which is by now common in the literature (see, e.g., Holopainen and Sarlin 2015). In our *full-sample* evaluation, the data extend from 1970 to 2012. While we have the data after 2012, it is excluded because our crisis-prediction horizon extends to three years, so we cannot say if signals after 2012 are correct or wrong. In the full-sample evaluation, the policymaker's choices are based on the same signaling threshold throughout all time periods. The full-sample usefulness statistics are then based on this threshold. The AUC measure is only reported for the full sample, as the methodology does not naturally accommodate a changing threshold.

For the relative usefulness metric, we also perform an *out-of-sample* evaluation. The out-of-sample evaluation is a recursive simulation for the period 2000 to 2012. In 2000:Q1, the policymaker uses information about a crisis data set for the periods 1970:Q1–1999:Q4 and about the previous indicator values. Because the policymaker does not yet know whether 1997:Q1–1999:Q4 are tranquil or pre-crisis periods, only the data within the period 1970:Q1–1996:Q4 are usable. The policymaker determines what is the optimal signaling threshold based on this history (and the policy parameter $\theta = 0.5$). This, combined with the indicator value for 2000:Q1, determines whether or not there is a warning signal in 2000:Q1. The signal is compared with the ex post information about 2000:Q1, and we record a true positive, false positive, true negative, or false negative. The same procedure is repeated for the next quarter 2000:Q2 (i.e., the signaling threshold now depends on the data for 1970:Q1–1997:Q1), and so on. This process continues until we reach 2012:Q4, our last evaluated quarter. The resulting out-of-sample relative usefulness is denoted $U_{r,o}$.

4. Results of the Empirical Analysis

4.1 The Set of Recommended Indicators

Recall that our objective is to identify a set of indicators that satisfies the criteria of high information content, simplicity, and robustness, and that we seek indicators relevant to each of the ESRB's six risk categories (credit developments, private-sector debt burden, overvaluation of property prices, external imbalances, mispricing of risk, and strength of bank balance sheets). The main result of the paper, of course, is the indicator set we present in table 6. The AUC and relative usefulness measures in table 6 are based on Detken's crisis data set,[23] with the crisis-prediction horizon set to one to three years. In subsequent subsections, we discuss how our results change as the prediction horizon or crisis definition is altered. The detailed performance numbers for the full set of indicators and transformation are available in the online appendix (tables A1–A7). Below we summarize the main findings from table 6 for each risk category (blocks 1–6).

4.1.1 Credit Developments

In line with findings of previous literature, we find that the ratio of credit to GDP (1.5.5.) tends to be more informative than credit alone (1.1.1.); see the first block in table 6. The result remains intact regardless of the definition of credit used. Alternative definitions include total private-sector credit (which includes, e.g., bank credit and market-based funding), total bank credit to private sector, total credit to households, and total credit to non-financial corporations. The *benchmark indicator* proposed by the Basel Committee, the total credit-to-GDP trend gap (1.5.5.) calculated using the broadest definition of credit, is clearly among the top-performing indicators in this category. However, various alternative transformations and credit concepts are found to be at least as informative. Using total bank credit to private sector or total credit to households in the numerator (1.6.5., 1.7.5.) generally leads to a slightly better AUC and higher full-sample and out-of-sample relative usefulness than the benchmark indicator. In contrast, calculating the trend gap using the prescribed HP filter does not seem to lead to improvement over the more practical transformations such as three-year difference or deviation from the five-year moving average (see table A1 in the online appendix for detailed results for the alternative transformations). The indicators proposed by Kauko (2012a) that relate credit to a

[23]Recall from section 3.2 our labeling of banking crisis data sets.

Table 6. Summary of the Recommended Indicators for Each Category

Indicator	Transformation	Sign	Full Sample							Out of Sample					
			AUC	U_r	FNR	FPR	N	N_c	N_f	$U_{r,o}$	FNR	FPR	N	N_c	N_f
1. Credit Developments															
1.1.1. Real Total Credit	1y Growth	+	0.69^{***}	0.30	0.07	0.63	1262	15	14	0.24	0.01	0.75	471	15	9
1.2.1. Real Total Bank Credit	1y Growth	+	0.71^{***}	0.37	0.14	0.49	1243	15	14	0.33	0.09	0.58	471	15	9
1.3.1. Real Household Credit	1y Growth	+	0.66^{***}	0.27	0.23	0.50	961	15	14	0.17	0.03	0.81	450	15	9
1.4.1. Real Corporate Credit	1y Growth	+	0.69^{***}	0.29	0.29	0.43	961	15	14	0.21	0.08	0.71	450	15	9
1.5.5. Total Credit / GDP	Trend Gap	+	0.82^{***}	0.53	0.24	0.23	1787	18	20	0.32	0.07	0.61	558	18	11
1.5.8. Total Credit / GDP	KK_1	+	0.80^{***}	0.53	0.31	0.16	2042	18	22	0.31	0.00	0.69	573	18	11
1.6.5. Total Bank Credit / GDP	Trend Gap	+	0.83^{***}	0.55	0.26	0.19	1755	18	20	0.29	0.31	0.41	558	18	11
1.6.8. Total Bank Credit / GDP	KK_1	+	0.80^{***}	0.55	0.22	0.24	2010	18	22	0.38	0.08	0.53	573	18	11
1.7.5. Total Household Credit / GDP	Trend Gap	+	0.83^{***}	0.57	0.19	0.23	1135	17	18	0.42	0.03	0.54	516	17	11
1.7.8. Total Household Credit / GDP	KK_1	+	0.82^{***}	0.55	0.29	0.16	1368	18	20	0.47	0.03	0.50	552	18	11
1.8.5. Total Corporate Credit / GDP	Trend Gap	+	0.66^{***}	0.28	0.29	0.42	1115	17	18	0.11	0.33	0.56	516	17	11
1.8.8. Total Corporate Credit / GDP	KK_1	+	0.77^{***}	0.42	0.20	0.39	1356	18	19	0.30	0.16	0.54	552	18	11
2. Private-Sector Debt Burden															
2.1.1. Debt-Service Ratio	1y Difference	+	0.78^{***}	0.42	0.36	0.22	2161	26	26	0.26	0.09	0.65	764	26	16
2.2.1. Corporate Debt-Service Ratio	1y Difference	+	0.73^{***}	0.39	0.28	0.33	967	25	17	0.20	0.03	0.77	599	25	13
2.3.1. Household Debt-Service Ratio	1y Difference	+	0.75^{***}	0.37	0.29	0.34	952	25	18	0.21	0.00	0.79	599	25	13
2.4. HH Credit × 10y Rate / GDP		+	0.66^{***}	0.33	0.35	0.32	951	18	17	0.41	0.42	0.17	539	18	11
2.4.2. HH Credit × 10y Rate / GDP	3y Difference	+	0.68^{***}	0.34	0.28	0.38	788	17	14	0.23	0.34	0.44	481	17	11
2.5. HH Credit × 3m Rate / GDP		+	0.60^{**}	0.20	0.27	0.52	1328	25	21	0.23	0.54	0.24	738	25	15
2.5.1. HH Credit × 3m Rate / GDP	1y Difference	+	0.71^{***}	0.29	0.26	0.45	1240	25	21	0.14	0.06	0.81	696	25	15
3. Potential Overvaluation of Property Prices															
3.1.2. Real House Price	3y Growth	+	0.67^{***}	0.30	0.43	0.27	1429	16	20	0.14	0.42	0.44	465	16	11
3.2.1. House Price / Rent	1y Difference	+	0.64^{**}	0.27	0.57	0.16	1428	17	21	0.09	0.52	0.39	526	17	12
3.2.2. House Price / Rent	3y Difference	+	0.70^{***}	0.34	0.42	0.24	1286	17	20	0.16	0.37	0.47	483	17	12
3.2.8. House Price / Rent	Avg. Gap	+	0.74^{***}	0.45	0.38	0.16	1174	16	20	0.25	0.15	0.60	448	16	12
3.3.1. House Price / Income	1y Difference	+	0.69^{***}	0.33	0.50	0.18	1410	20	21	0.30	0.44	0.26	563	20	12
3.3.2. House Price / Income	3y Difference	+	0.77^{***}	0.45	0.38	0.18	1260	18	19	0.26	0.27	0.47	512	18	12
3.3.8. House Price / Income	Avg. Gap	+	0.81^{***}	0.52	0.30	0.18	1148	17	19	0.31	0.09	0.61	470	17	12
3.4.1. Real Commercial Real Estate Price	1y Growth	+	0.73^{***}	0.39	0.21	0.40	718	15	14	0.39	0.35	0.26	391	15	10

(*continued*)

Table 6. (Continued)

Indicator	Transformation	Sign	Full Sample AUC	U_r	FNR	FPR	N	N_c	N_f	Out of Sample $U_{r,o}$	FNR	FPR	N	N_c	N_f
4. External Imbalances															
4.1. Current Account / GDP		–	0.64*	0.30	0.45	0.25	1159	19	16	0.14	0.4	0.5	601	19	12
4.1.8. Current Account / GDP	Avg. Gap	–	0.70**	0.41	0.35	0.24	792	19	13	0.29	0.43	0.28	410	19	11
4.5.2. F.C. Cross-Border Loans / GDP	3y Difference	+	0.56	0.24	0.53	0.23	698	13	11	0.22	0.31	0.47	389	13	7
4.6.2. D.C. Cross-Border Loans / GDP	3y Difference	+	0.52	0.19	0.43	0.38	698	13	11	0.18	0.19	0.63	389	13	7
5. Potential Mispricing of Risk															
5.1. Stock Market Volatility		–	0.56*	0.13	0.44	0.43	2274	28	27	0.16	0.21	0.63	933	28	16
5.2.1. Stock Market Index	1y Growth	+	0.60***	0.28	0.16	0.57	1062	14	14	0.41	0.16	0.44	458	14	9
5.2.2. Stock Market Index	3y Growth	+	0.65***	0.33	0.21	0.47	958	14	14	0.34	0.22	0.44	453	14	9
5.9. VIX Index		–	0.71***	0.35	0.33	0.32	2205	28	30	0.51	0.13	0.36	947	28	16
5.10. High-Yield Spread		–	0.79***	0.49	0.17	0.33	1043	28	17	0.42	0.12	0.46	947	28	16
5.15.1. U.S. 1y T-Bill	1y Difference	+	0.63***	0.25	0.30	0.45	2612	28	31	0.21	0.19	0.61	947	28	16
5.15.2. U.S. 1y T-Bill	3y Difference	+	0.71***	0.39	0.38	0.24	2396	28	31	0.52	0.16	0.32	947	28	16
5.16.1. U.S. 1m T-Bill	1y Difference	+	0.63***	0.25	0.28	0.48	3044	28	31	0.23	0.06	0.71	947	28	16
5.16.2. U.S. 1m T-Bill	3y Difference	+	0.67***	0.35	0.37	0.28	2828	28	31	0.48	0.15	0.37	947	28	16
6. Strength of Bank Balance Sheets															
6.1.1. Leverage Ratio	1y Difference	–	0.61**	0.21	0.46	0.33	605	26	14	0.36	0.17	0.47	605	26	14
6.1.2. Leverage Ratio	3y Difference	–	0.67***	0.33	0.16	0.50	422	24	12	−0.02	0.85	0.17	422	24	12
6.3.1. Total Assets / GDP	1y Difference	+	0.64**	0.22	0.26	0.52	658	21	13	0.22	0.41	0.37	589	21	12
6.3.2. Total Assets / GDP	3y Difference	+	0.57	0.19	0.53	0.28	507	19	11	0.18	0.63	0.19	504	19	11

Notes: Sign + (–) indicates that larger (smaller) values of indicator signal a financial crisis. *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent significance level, respectively, based on clustered bootstrap estimation. AUC($\leq$1) is area under the ROC curve; larger AUC is better. U_r and $U_{r,o}$($\leq$1) are the full-sample and out-of-sample relative usefulness with policy preference $\theta = 0.5$ (or equivalently $\mu = 0.9$); larger U_r is better. FNR and FPR are the false negative rate and false positive rate, respectively. N, N_c, and N_f are the number of observations, countries, and financial crises, respectively. Full-sample results are for 1970–2012; out-of-sample results are for 2000–12. All indicators are quasi-real time with a one-quarter publication lag. Detken's crisis data set is used; prediction horizon is one to three years. F.C. and D.C. refer to foreign currency and domestic currency, respectively. KK_1 is one of the indicators proposed Kauko (2012a); see equation (1) in section 2.2.

moving average of GDP perform very well. For space reasons, we only include the first version of the indicator (i.e., version that takes the ratio first, then the difference, KK_1, e.g., 1.5.8.). Even if the real credit growth rates (any definition of credit) and the corporate credit-to-GDP gap (1.8.5.) appear historically to be slightly worse predictors than other credit-to-GDP gaps, the authorities might benefit from using a broad range of credit development indicators such as those included in the table.

4.1.2 Private-Sector Debt Burden

Ratios that measure debt-servicing expenses relative to income are highly informative predictors of financial crises; see the second block in table 6. Furthermore, they are informative regardless of whether restricted to household or corporate debt-servicing costs. Our results indicate that authorities should make a special effort to monitor yearly changes in the debt-service ratio (2.1.1.). The approximations for interest rate burden (2.4., 2.4.2., 2.5., 2.5.2.), while informative, have slightly lower full-sample performance than the debt-service ratios. The difference disappears in the out-of-sample analysis.

4.1.3 Potential Overvaluation of Property Price

While all the indicators in this category are informative, the ratio of house price to rent (3.2.*) and the ratio of house price to income (3.3.*) generally outperform real house prices alone (3.1.2.); see the third block in table 6. Relating the house price to income rather than to rents apparently produces better signaling quality for the predictor. In both cases, the deviation from the long-term average and three-year differences were the highest-performing transformations. We also find evidence that growth in deflated commercial real estate prices (3.4.1.) increases the risk of a financial crisis.

4.1.4 External Imbalances

We find the ratio of current account to GDP (4.1) to be robust in full sample and out of sample; see the fourth block in table 6. Its deviation from the long-term average (4.1.8.) emerged as the most informative transformation. None of the other accounts in the balance of payments is particularly informative even full sample (details are available in table A4 in the online appendix). Changes in domestic and foreign currency cross-border loans-to-GDP ratios (4.5.2., 4.6.2.) are useful in the full sample and sometimes out of sample, but they still failed to produce statistically significant AUC with Detken's crisis data set. They perform better, however, with the alternative crisis data sets (see table 9). Given the paucity of indicators for external imbalances, we conclude that these cross-border loan ratios are worth monitoring.

4.1.5 Mispricing of Risk

Stock market volatility (5.1.) and growth in domestic stock price indexes (5.2.1., 5.2.2.) are informative predictors of risk of financial crises; see the fifth block in table 6. As global stock markets are highly interconnected, it is hardly surprising that the VIX index (5.9.) performs as well as or better than domestic stock market-based measures. We also find evidence of low (and subsequently increasing) interest rates (5.15.*, 5.16.*) and pricing of credit risk as an indicator of heightened risk of crisis. The lower spread between European high-yield and investment-grade corporate bonds (5.10.) shows very good performance in the full sample and out of sample, even when compared with the indicators in the credit developments category. Finally, both full-sample and out-of-sample metrics give some support to the predictive ability of lower household and corporate borrowing rate spreads. However, their usefulness values are quite low. For the high-yield spread, it is the lower value of interest rate spread that signals the risk. We also find that a rise in short-term U.S. interest rates (e.g., one-month and one-year maturities) signals increased vulnerability with high performance in the full sample and out of sample. These findings help explain why financial crises tend to cluster in time and affect multiple countries simultaneously.

4.1.6 Strength of Bank Balance Sheets

As noted above, the data series for bank balance sheets are generally quite short compared with our other indicator categories. We find that the leverage ratio (6.1.*) and the total assets-to-GDP ratio (6.3.*) are the only two indicators that have relatively robust performance both in the full sample and out of sample; see the last block in table 6. Using the leverage ratio in countercyclical capital buffer decisions could, however, prove problematic. We see that in the most recent financial crisis, banks built up excessive leverage while maintaining risk-based capital ratios. As a result, Basel III introduces a minimum requirement for bank leverage ratios to be implemented on January 1, 2017. Hence, it may be superfluous to use the current capital positions of banks in deciding whether banks need more capital or not. Also, due to the changes in the legislation, it is likely that this indicator will not work as well as it does here in the future. Regarding other bank balance sheet measures, we find evidence in the full sample that a large net short-term liabilities ratio,[24] large non-core-liabilities, and a large loans-to-deposits ratio signal increased risk of a financial crisis (see table A7 in the online appendix for details). None of these findings, however, extend to the out-of-sample evaluation (possibly due to short length of the data series).

As a general remark regarding the relationship among the performance measures in table 6, the observed AUC and relative usefulness have very high correlation (0.97). The out-of-sample relative usefulness has somewhat higher correlation with the full-sample relative usefulness (0.41) than with the AUC (0.29).

4.2 Robustness to Alternative Prediction Horizons

We now consider whether the choice of prediction horizon affects the quality of indicator warning signal. For example, some indicators might signal a banking crisis only six months before the onset of the crisis, while other indicators could be informative at longer prediction horizons. We follow the approach of Drehmann and Juselius (2014) and investigate the signaling quality when the prediction horizon is fixed at lengths extending from six months to five years. Similar to Drehmann and Juselius (2014), we focus here only on the AUC statistics because, as noted earlier, they are highly correlated with the relative usefulness statistics. Drehmann and Juselius

[24]Recall from table 1 that Net ST liabilities ratio = (Short-term liabilities – Liquid assets) / Total assets.

(2014) impose two additional stability conditions on policy-relevant indicators:

- interpretation of the signal should not reverse during the policy-relevant horizon,[25] and
- signaling quality should improve as the forecast horizon shortens.

Table 7 shows the AUC statistics at different prediction horizons for the recommended set of indicators introduced in the preceding subsection. We also highlight the interpretation of each indicator with a (+) sign if higher values of the indicator signal the crisis, and with a (–) sign if lower values of the indicator signal the crisis.

The recommended indicators generally satisfy the stability criteria of Drehmann and Juselius (2014) at the policy-relevant horizon, and most indicators become more informative as the crisis nears; see table 7. Two exceptions are the cross-border loans indicators (4.5.2., 4.6.2.) and the leverage ratio indicator (6.1.1.–6.1.2.). If the relevant policy horizon extends beyond three years, the cross-border loans indicators fail the first condition, as they have a reverse interpretation or are not informative at horizons longer than three years. The leverage ratio fulfills the first condition but fails to meet the second condition, as its signaling quality does not improve when the forecast horizon shortens. As noted by Behn et al. (2013), it may be that banks tend to be highly profitable in the years immediately preceding a financial crisis.

Indicators based on the credit-to-GDP ratio appear to signal crises from up to three and even five years; see the first block in table 7. Like other indicators with GDP in the denominator (e.g., current account to GDP, 4.1., and total assets to GDP, 6.3.1.), they are particularly informative in the late pre-crisis period (one or two quarters before the crisis); see the first, second, fourth, and sixth block in table 7. This is because a slowdown in GDP growth often precedes (and certainly follows) a financial crisis. Unfortunately, at

[25] In Drehmann and Juselius (2014), the relevant horizon for policy considerations is more than a year and less than five years. However, we assume the upper limit for countercyclical capital buffer considerations is only three years, as in Detken et al. (2014).

Table 7. AUC Statistics for Specific Prediction Horizons

Indicator	Transformation	Sign	Distance to Crisis (in Quarters)									
			2	4	6	8	10	12	14	16	18	20	Lag
1. Credit Developments													
1.1.1. Real Total Credit	1y Growth	+	0.65	0.72	0.69	0.68	0.69	0.66	0.58	0.57	0.58	0.52	8.7
1.2.1. Real Total Bank Credit	1y Growth	+	0.68	0.67	0.68	0.73	0.78	0.73	0.66	0.62	0.61	0.59	10.0
1.3.1. Real Household Credit	1y Growth	+	0.57	0.55	0.66	0.71	0.76	0.74	0.69	0.69	0.72	0.71	12.4
1.4.1. Real Corporate Credit	1y Growth	+	0.67	0.81	0.71	0.64	0.60	0.57	0.45	0.37	0.40	0.40	5.8
1.5.5. Total Credit / GDP	Trend Gap	+	0.86	0.89	0.86	0.85	0.84	0.82	0.79	0.77	0.78	0.81	10.4
1.5.8. Total Credit / GDP	KK_1	+	0.84	0.86	0.84	0.82	0.84	0.84	0.76	0.68	0.67	0.62	9.5
1.6.5. Total Bank Credit / GDP	Trend Gap	+	0.86	0.86	0.86	0.88	0.86	0.82	0.78	0.77	0.78	0.77	10.3
1.6.8. Total Bank Credit / GDP	KK_1	+	0.83	0.78	0.83	0.84	0.85	0.87	0.82	0.74	0.71	0.70	10.3
1.7.5. Total Household Credit / GDP	Trend Gap	+	0.80	0.85	0.88	0.88	0.87	0.85	0.82	0.79	0.77	0.79	10.6
1.7.8. Total Household Credit / GDP	KK_1	+	0.79	0.79	0.87	0.90	0.91	0.89	0.85	0.85	0.82	0.83	11.1
1.8.5. Total Corporate Credit / GDP	Trend Gap	+	0.79	0.81	0.69	0.66	0.60	0.57	0.53	0.55	0.58	0.68	8.5
1.8.8. Total Corporate Credit / GDP	KK_1	+	0.80	0.87	0.79	0.77	0.73	0.67	0.54	0.45	0.49	0.46	6.5
2. Private-Sector Debt Burden													
2.1.1. Debt-Service Ratio	1y Difference	+	0.82	0.86	0.83	0.81	0.78	0.69	0.64	0.60	0.61	0.56	8.3
2.2.1. Corporate Debt-Service Ratio	1y Difference	+	0.77	0.81	0.78	0.75	0.65	0.61	0.54	0.53	0.47	0.39	6.5
2.3.1. Household Debt-Service Ratio	1y Difference	+	0.59	0.71	0.80	0.81	0.76	0.75	0.65	0.65	0.67	0.64	10.5
2.4. HH Credit × 10y Rate / GDP		+	0.72	0.73	0.72	0.69	0.63	0.61	0.63	0.62	0.60	0.58	9.1
2.4.2. HH Credit × 10y Rate / GDP	3y Difference	+	0.79	0.76	0.74	0.76	0.60	0.54	0.61	0.64	0.60	0.61	8.7
2.5. HH Credit × 3m Rate / GDP		+	0.74	0.73	0.67	0.60	0.51	0.50	0.54	0.52	0.52	0.51	5.7
2.5.1. HH Credit × 3m Rate / GDP	1y Difference	+	0.77	0.83	0.82	0.74	0.57	0.55	0.55	0.48	0.47	0.36	5.8
3. Potential Overvaluation of Property Prices													
3.1.2. Real House Price	3y Growth	+	0.63	0.66	0.68	0.70	0.69	0.66	0.63	0.59	0.59	0.60	10.0
3.2.1. House Price / Rent	1y Difference	+	0.47	0.59	0.56	0.65	0.74	0.69	0.69	0.62	0.56	0.58	11.7
3.2.2. House Price / Rent	3y Difference	+	0.66	0.71	0.72	0.74	0.71	0.68	0.65	0.62	0.61	0.61	9.9
3.2.8. House Price / Rent	Avg. Gap	+	0.78	0.79	0.78	0.76	0.74	0.72	0.71	0.67	0.64	0.59	9.4
3.3.1. House Price / Income	1y Difference	+	0.43	0.60	0.64	0.74	0.75	0.76	0.74	0.60	0.52	0.67	11.5
3.3.2. House Price / Income	3y Difference	+	0.71	0.79	0.81	0.81	0.77	0.76	0.74	0.72	0.69	0.69	10.4
3.3.8 House Price / Income	Avg. Gap	+	0.83	0.85	0.84	0.84	0.82	0.81	0.77	0.74	0.71	0.69	10.0
3.4.1 Real Commercial Real Estate Price	1y Growth	+	0.53	0.67	0.77	0.76	0.69	0.64	0.52	0.39	0.33	0.33	7.7

(*continued*)

Table 7. (Continued)

Indicator	Transformation	Sign	Distance to Crisis (in Quarters)										
			2	4	6	8	10	12	14	16	18	20	Lag
4. External Imbalances													
4.1. Current Account / GDP		–	0.71	0.68	0.64	0.64	0.63	0.61	0.58	0.55	0.56	0.57	8.6
4.1.8. Current Account / GDP	Avg. Gap	–	0.79	0.77	0.73	0.70	0.69	0.69	0.65	0.58	0.57	0.62	8.9
4.5.2. F.C. Cross-Border Loans / GDP	3y Difference	+	0.62	0.63	0.57	0.57	0.51	0.45	0.40	0.39	0.42	0.42	4.6
4.6.2. D.C. Cross-Border Loans / GDP	3y Difference	+	0.62	0.61	0.55	0.51	0.47	0.42	0.42	0.41	0.42	0.40	3.7
5. Potential Mispricing of Risk													
5.1. Stock Market Volatility		–	0.38	0.52	0.59	0.56	0.55	0.57	0.60	0.58	0.63	0.52	12.7
5.2.1. Stock Market Index	1y Growth	+	0.43	0.58	0.64	0.64	0.58	0.60	0.65	0.68	0.50	0.29	10.6
5.2.2. Stock Market Index	3y Growth	+	0.55	0.64	0.69	0.71	0.59	0.41	0.38	0.30	0.22	0.21	6.4
5.9. VIX Index		–	0.64	0.72	0.73	0.72	0.69	0.68	0.65	0.62	0.53	0.39	8.7
5.10. High-Yield Spread		–	0.66	0.82	0.87	0.80	0.74	0.69	0.79	0.74	0.72	0.62	10.3
5.15.1. U.S. 1y T-Bill	1y Difference	+	0.46	0.54	0.59	0.64	0.70	0.69	0.65	0.62	0.54	0.42	11.2
5.15.2. U.S. 1y T-Bill	3y Difference	+	0.62	0.70	0.73	0.75	0.70	0.63	0.56	0.44	0.33	0.29	7.4
5.16.1. U.S. 1m T-Bill	1y Difference	+	0.46	0.55	0.59	0.64	0.68	0.66	0.58	0.55	0.51	0.40	10.1
5.16.2. U.S. 1m T-Bill	3y Difference	+	0.64	0.70	0.70	0.71	0.66	0.58	0.54	0.42	0.36	0.32	6.9
6. Strength of Bank Balance Sheets													
6.1.1. Leverage Ratio	1y Difference	–	0.49	0.51	0.58	0.59	0.69	0.74	0.69	0.55	0.50	0.57	11.8
6.1.2. Leverage Ratio	3y Difference	–	0.64	0.67	0.69	0.65	0.73	0.75	0.69	0.61	0.67	0.59	10.6
6.3.1. Total Assets / GDP	1y Difference	+	0.71	0.69	0.65	0.63	0.61	0.59	0.53	0.48	0.46	0.49	6.3
6.3.2. Total Assets / GDP	3y Difference	+	0.66	0.64	0.59	0.54	0.54	0.51	0.48	0.53	0.54	0.59	8.2

Notes: Sign + (–) indicates that larger (smaller) values of indicator signal a financial crisis. AUC($\leq$1) is area under the ROC curve; larger AUC is better. All indicators are quasi-real time with a one-quarter publication lag. The time period is 1970–2012. Detken's crisis data set is used. F.C. and D.C. refer to foreign currency and domestic currency, respectively. KK_1 is one of the indicators proposed Kauko (2012a); see equation (1) in section 2.2. Lag is the weighted-average prediction horizon (in quarters) where the indicator is useful, and it is calculated as $Lag = \sum_{l=2}^{20} l * \max\ (AUC(l) - 0.5, 0) / \sum_{(k=2)}^{20} \max\ (AUC(k) - 0.5, 0)$.

that point it is likely too late for the policymaker to increase the countercyclical buffer without risking doing more damage than good.

The debt-service ratio (2.1.1., 2.2.1.) and interest burden indicators (2.4., 2.4.2., 2.5., 2.5.1.) are especially good in the short horizon; see the second block in table 7. In addition to the decline in income in the denominator of this ratio, the numerator of the debt-service ratio typically catches the rise in the interest rate that often triggers the recession in the economy.

Indicators based on asset prices such as stock index growth (5.2.1., 5.2.2.), real commercial real estate prices (3.4.1.), and the one-year change in the house price-to-income ratio (3.3.1.) typically start to fall already before the onset of a crisis; see the third and fifth block in table 7. Whether a decline in asset prices triggers the crisis or asset prices actually anticipate the future downturn may not matter, as these indicators are prone to change before the onset of a financial crisis.

The key take-away here is that policymakers should take into account the fact that the relevance of different indicators may depend on the remoteness from the crisis. Table 8 conveys the information in table 7 in a more practical format that could be useful for policymakers.[26] The recommended set of indicators are categorized into three categories according to the relevant policy horizon for that particular indicator. Short-term (one to two years) indicators tend to signal relatively late, giving the policymaker little time to react; see the first column in table 8. The medium-term indicators work best two to three years before the crisis. A few indicators, including some credit-based measures and low stock market volatility, appear informative even in the longer term (four to five years). Many indicators fall into several categories at the same time.

4.3 Robustness to Alternative Crisis Data Sets

The financial crisis data sets made available by various authors are of great benefit to early warning study, yet the definition of what constitutes a crisis colors every data set. This leads to considerable differences across the alternative crisis data sets. To fill the gap in

[26] In this categorization, we do not consider prediction horizons of less than a year, as the policymaker would essentially have no time to react.

Table 8. Summary Table of the Most Relevant Crisis-Prediction Horizons for Recommended Indicators

Indicator	Short Term 1–2 Years	Medium Term 2–3 Years	Long Term 4–5 Years
1. Credit Developments			
1.1. Real Total Credit		X	
1.2. Real Total Bank Credit		X	
1.3. Real Household Credit		X	X
1.4. Real Corporate Credit	X		
1.5. Total Credit / GDP	X	X	X
1.6. Total Bank Credit / GDP	X	X	X
1.7. Total Household Credit / GDP	X	X	X
1.8. Total Corporate Credit / GDP	X		
2. Private-Sector Debt Burden			
2.1. Debt-Service Ratio	X	X	
2.2. Corporate Debt-Service Ratio	X	X	
2.3. Household Debt-Service Ratio		X	
2.4. Total HH Credit × 10y Rate / GDP	X		
2.5. Total HH Credit × 3m Rate / GDP	X		
3. Potential Overvaluation of Property Prices			
3.1. Real House Price		X	
3.2. House Price / Rent	X	X	
3.3. House Price / Income	X	X	
3.4. Real Commercial Real Estate Price		X	
4. External Imbalances			
4.1. Current Account / GDP	X	X	
4.5. F.C. Cross-Border Loans / GDP	X		
4.6. D.C. Cross-Border Loans / GDP	X		
5. Potential Mispricing of Risk			
5.1. Stock Market Volatility		X	X
5.2. Stock Market Index		X	
5.9. VIX Index	X	X	
5.10. High-Yield Spread	X	X	
5.15. U.S. 1y T-Bill	X		
5.16. U.S. 1m T-Bill	X		
6. Strength of Bank Balance Sheets			
6.1. Leverage Ratio		X	
6.3. Total Assets / GDP	X	X	

Notes: Categorization is based on the AUC statistics for different prediction horizons reported in table 7. The prediction horizons where the indicator has relatively high performance, i.e., relative to its own performance at different prediction horizons, are marked with X.

the literature and further examine the stability of the indicators, we reproduce the performance measures in table 6 for the two additional (Babecký's and Laeven's) crisis data sets. The results of this robustness exercise are shown in table 9.

While all predictors remain informative, their rankings change depending on the crisis data set used. On average, the performance measures are significantly higher for Detken's and Laeven's data set compared with Babecký's data set, while there is on average no difference between Detken's and Laeven's data set.

The result that the crises in Detken's and Laeven's data sets are relatively easier to predict than the crises in Babecký's data set may derive from the fact that the two former data sets aim to include only systemic banking crises while the latter aims to include all banking crises. It is plausible that systemic banking crises emerge from larger economic imbalances than smaller banking crises, and the larger imbalances are then easier to detect with the early warning indicators.

In terms of average full-sample measures (AUC and U_r), the various credit-to-GDP measures are the best predictors only with Detken's data set; see the first block in table 9.[27] Using Babecký's data set, some measures of the overvaluation of property prices and mispricing of risk categories have better full-sample metrics and similar or better out-of-sample metrics; see the third block in table 9. Measures for the mispricing of risk also rank high using Laeven's data set (by any measure). The VIX index and U.S. Treasury bills perform especially good out of sample; see the fifth block in table 9. In contrast, the high-yield spread has lower out-of-sample performance for the two alternative data sets—even if its full-sample performance attains the highest numbers of all (AUC 0.88 and 0.89, U_r 0.71 and 0.70). As noted before, due to short length of time series, the indicators classified as strength of bank balance sheets have low

[27]The construction of Detken's data set from Babecký's data set implies that the improved performance of credit development indicators could result from the policy-oriented adjustments of crisis episodes that have been performed in deriving Detken's data set (see section 3.2 for the adjustments made). However, the near-identical successful performance of credit-related indicators for both Detken's and Laeven's data sets supports the notion that these indicators are good at predicting systemic banking crises (as opposed to non-systemic crises).

Table 9. Robustness of the Predictors against Alternative Crisis Variables

Indicator	Transformation	Sign	Babecký's Crisis Scheme			Detken's Crisis Scheme			Laeven's Crisis Scheme		
			AUC	U_r	$U_{r,o}$	AUC	U_r	$U_{r,o}$	AUC	U_r	$U_{r,o}$
1. Credit Developments											
1.1.1. Real Total Credit	1y Growth	+	0.50	0.11	0.17	0.69***	0.30	0.24	0.65***	0.29	0.03
1.2.1. Real Total Bank Credit	1y Growth	+	0.54	0.12	0.18	0.71***	0.37	0.33	0.68***	0.32	0.03
1.3.1. Real Household Credit	1y Growth	+	0.56	0.20	0.14	0.66***	0.27	0.17	0.64**	0.33	0.00
1.4.1. Real Corporate Credit	1y Growth	+	0.48	0.04	−0.05	0.69***	0.29	0.21	0.63***	0.22	0.05
1.5.5. Total Credit / GDP	Trend Gap	+	0.70***	0.32	0.20	0.82***	0.53	0.32	0.78***	0.53	0.25
1.5.8. Total Credit / GDP	KK_1	+	0.66***	0.35	0.24	0.80***	0.53	0.31	0.83***	0.64	0.35
1.6.5. Total Bank Credit / GDP	Trend Gap	+	0.66***	0.28	0.16	0.83***	0.55	0.29	0.74***	0.42	0.14
1.6.8. Total Bank Credit / GDP	KK_1	+	0.67***	0.36	0.25	0.80***	0.55	0.38	0.81***	0.56	0.30
1.7.5. Total Household Credit / GDP	Trend Gap	+	0.71***	0.39	0.25	0.83***	0.57	0.42	0.80***	0.53	0.31
1.7.8. Total Household Credit / GDP	KK_1	+	0.72***	0.42	0.35	0.82***	0.55	0.47	0.83***	0.62	0.27
1.8.5. Total Corporate Credit / GDP	Trend Gap	+	0.53	0.11	−0.12	0.66***	0.28	0.11	0.61*	0.25	0.04
1.8.8. Total Corporate Credit / GDP	KK_1	+	0.60**	0.20	0.28	0.77***	0.42	0.30	0.77***	0.46	0.21
2. Private-Sector Debt Burden											
2.1.1. Debt-Service Ratio	1y Difference	+	0.60**	0.24	0.12	0.78***	0.42	0.26	0.74***	0.40	0.15
2.2.1. Corporate Debt-Service Ratio	1y Difference	+	0.63***	0.25	0.09	0.73***	0.39	0.20	0.72***	0.38	0.13
2.3.1. Household Debt-Service Ratio	1y Difference	+	0.72***	0.36	0.13	0.75***	0.37	0.21	0.76***	0.45	0.12
2.4. HH Credit × 10y Rate / GDP		+	0.55	0.15	0.06	0.66***	0.33	0.41	0.51	0.12	−0.02
2.4.2. HH Credit × 10y Rate / GDP	3y Difference	+	0.54	0.12	−0.13	0.68***	0.34	0.23	0.62***	0.23	−0.03
2.5. HH Credit × 3m Rate / GDP		+	0.52	0.13	−0.03	0.60**	0.20	0.23	0.54	0.15	0.05
2.5.1. HH Credit × 3m Rate / GDP	1y Difference	+	0.70***	0.35	−0.07	0.71***	0.29	0.14	0.79***	0.45	0.32
3. Potential Overvaluation of Property Prices											
3.1.2. Real House Price	3y Growth	+	0.66***	0.32	0.18	0.67***	0.30	0.14	0.70***	0.38	0.08
3.2.1. House Price / Rent	1y Difference	+	0.67***	0.33	0.13	0.64**	0.27	0.09	0.68***	0.30	0.12
3.2.2. House Price / Rent	3y Difference	+	0.68***	0.32	0.19	0.70***	0.34	0.16	0.72***	0.42	0.12
3.2.8. House Price / Rent	Avg. Gap	+	0.71***	0.39	0.07	0.74***	0.45	0.25	0.79***	0.53	0.03
3.3.1. House Price / Income	1y Difference	+	0.69***	0.36	0.29	0.69***	0.33	0.30	0.70***	0.32	0.11
3.3.2. House Price / Income	3y Difference	+	0.71***	0.38	0.33	0.77***	0.45	0.26	0.75***	0.47	0.25
3.3.8 House Price / Income	Avg. Gap	+	0.77***	0.45	0.02	0.81***	0.52	0.31	0.80***	0.57	0.14
3.4.1 Real Commercial Real Estate Price	1y Growth	+	0.61**	0.20	0.07	0.73***	0.39	0.39	0.61**	0.19	0.11

(continued)

Table 9. (Continued)

Indicator	Transformation	Sign	Babecký's Crisis Scheme			Detken's Crisis Scheme			Laeven's Crisis Scheme		
			AUC	U_r	$U_{r,o}$	AUC	U_r	$U_{r,o}$	AUC	U_r	$U_{r,o}$
4. External Imbalances											
4.1. Current Account / GDP		–	0.51	0.14	−0.11	0.64*	0.30	0.14	0.52	0.17	−0.05
4.1.8. Current Account / GDP	Avg. Gap	–	0.56	0.21	0.10	0.70**	0.41	0.29	0.60	0.32	0.20
4.5.2. F.C. Cross-Border Loans / GDP	3y Difference	+	0.59	0.29	0.09	0.56	0.24	0.22	0.75***	0.48	0.25
4.6.2. D.C. Cross-Border Loans / GDP	3y Difference	+	0.60	0.29	0.06	0.52	0.19	0.18	0.75***	0.46	0.17
5. Potential Mispricing of Risk											
5.1. Stock Market Volatility		–	0.61***	0.21	0.29	0.56*	0.13	0.16	0.64***	0.25	0.28
5.2.1. Stock Market Index	1y Growth	+	0.61***	0.28	0.37	0.60***	0.28	0.41	0.66***	0.38	0.25
5.2.2. Stock Market Index	3y Growth	+	0.54	0.13	0.30	0.65***	0.33	0.34	0.67***	0.38	0.45
5.9. VIX Index		–	0.70***	0.38	0.45	0.71***	0.35	0.51	0.81***	0.52	0.67
5.10. High-Yield Spread		–	0.88***	0.71	0.06	0.79***	0.49	0.42	0.89***	0.70	0.08
5.15.1. U.S. 1y T-Bill	1y Difference	+	0.70***	0.38	0.61	0.63***	0.25	0.21	0.69***	0.36	0.14
5.15.2. U.S. 1y T-Bill	3y Difference	+	0.71***	0.40	0.39	0.71***	0.39	0.52	0.80***	0.55	0.64
5.16.1. U.S. 1m T-Bill	1y Difference	+	0.67***	0.38	0.62	0.63***	0.25	0.23	0.70***	0.37	0.30
5.16.2. U.S. 1m T-Bill	3y Difference	+	0.66***	0.35	0.29	0.67***	0.35	0.48	0.76***	0.52	0.66
6. Strength of Bank Balance Sheets											
6.1.1. Leverage Ratio	1y Difference	–	0.57*	0.20	−0.09	0.61**	0.21	0.36	0.51	0.07	−0.04
6.1.2. Leverage Ratio	3y Difference	–	0.58*	0.20	−0.18	0.67***	0.33	−0.02	0.51	0.14	−0.15
6.3.1. Total Assets / GDP	1y Difference	+	0.63***	0.23	−0.03	0.64**	0.22	0.22	0.66***	0.27	0.00
6.3.2. Total Assets / GDP	3y Difference	+	0.59*	0.22	−0.06	0.57	0.19	0.18	0.66**	0.29	0.04

Notes: Sign + (–) indicates that larger (smaller) values of indicator signal a financial crisis. *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent significance level, respectively, based on clustered bootstrap estimation. AUC($\leq$1) is area under the ROC curve; larger AUC is better. U_r and $U_{r,o}$($\leq$1) are the full-sample and out-of-sample relative usefulness with policy preference $\theta = 0.5$ (or equivalently $\mu = 0.9$); larger U_r is better. Time period is 1970–2012. Full-sample results are for 1970–2012; out-of-sample results are for 2000–12. All indicators are quasi-real time with a one-quarter publication lag. F.C. and D.C. refer to foreign currency and domestic currency, respectively. KK_1 is one of the indicators proposed Kauko (2012a); see equation (1) in section 2.2. See section 3.2 for crisis data set labeling.

out-of-sample performance across the alternative crisis data sets; see the sixth block in table 9.

4.4 Interpreting Indicators for Policy Guidance

So far, we have identified indicators the policymaker should monitor to detect increased vulnerability ahead of a systemic banking crisis. Unfortunately, the policymaker must also correctly interpret signals or lack thereof from these indicators. While the interpretation ultimately depends on the policymaker's overall perception of financial stability and economic outlook, we offer some quantitative insights that may be helpful.

For most of these indicators, interpretation is straightforward in the sense that the higher (or lower) the value of the indicator, the more likely the risk of financial crisis. However, the policymaker also has to decide at which point the indicators have moved sufficiently to justify policy action. Within the EU, national policymakers consider the appropriateness of the countercyclical capital buffer every three months. If they find a need, for example, to raise the countercyclical capital buffer level, they can increase it gradually from 0 percent to the maximum 2.5 percent over a period of several years. The process involves a number of decisions that take place at different levels of the indicators. While the benchmark buffer guide readily suggests a value for the countercyclical buffer,[28] it is necessary for the policymaker to judge whether other relevant indicators comport with the benchmark story. While a comprehensive analysis of these issues is beyond the scope of the current paper, such comparison could at its simplest be achieved via descriptive analysis of historical values of indicators using, say, a logit or probit model to estimate the correspondence between crisis probabilities and indicator values.

In the online appendix, we report the statistical significance of logit-model coefficients as an additional robustness check for the warning indicators (see tables A1–A7 in the online appendix). Here, while we are reluctant to attach a specific crisis probability to a given value of the indicators, we offer a few insights that can be drawn from

[28]The benchmark buffer guide maps the value of the total credit-to-GDP trend gap into a value of countercyclical capital buffer.

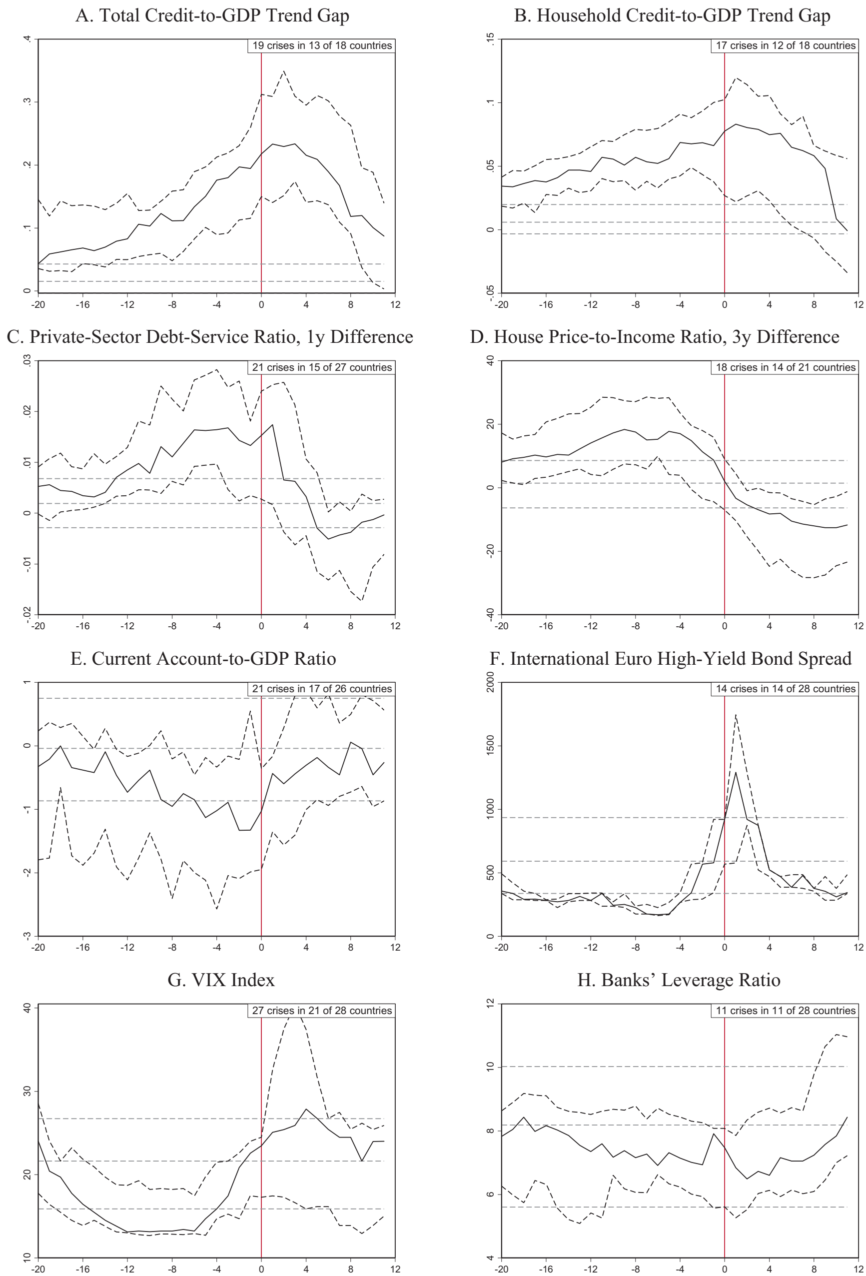
the logit estimates.[29] Regarding the credit-to-GDP trend gaps, we conclude that the crisis probability is more sensitive to the trend gap of total credit to households divided by GDP than the respective trend gaps that use total corporate credit or total credit. For example, if a 4 percent total credit-to-GDP trend gap corresponds to some probability of banking crisis, a 1 percent household credit-to-GDP trend gap would yield the same crisis probability. Regarding the new mispricing of risk indicators, VIX index values below 20 are associated with a significantly heightened probability of financial crisis. For the high-yield spread, values below 400 basis points are similarly associated with significantly heightened crisis probability.

Figure 3 visually draws out some of the top-performing indicators in each category. The horizontal axis shows the time to crisis such that negative values take place before the crisis, and zero, highlighted with a vertical line, corresponds to the first quarter of a financial crisis. The data are aggregated over all financial crises for which the indicator data is available for the five-year window prior to the crisis. The curves show first through third quartiles of the indicator data during this period and also during tranquil periods (the horizontal lines) for comparison.

If the aim is a specific threshold, perhaps the most common way of identifying threshold values for warning indicators is to derive them based on policymakers' preferences with respect to false alarms and missed crises (e.g., Alessi and Detken 2011; Behn et al. 2013; Detken et al. 2014; Drehmann, Borio, and Tsatsaronis 2011; Drehmann et al. 2010). In these methods, one makes an assumption about the preferences of policymakers in setting thresholds, e.g., the optimal noise-to-signal ratio or a specific formula for the policymaker's loss function with respect to missed crises and false alarms. Thus, it is not only difficult to assess the expected costs and

[29] As the logit model does not provide a good fit for some indicators, these insights are limited in scope. Also, due to sensitivity of the estimates to the data set at hand, the cited probabilities should not be treated unconditionally but conditionally on the given data set and the crisis variable used. Hence we seek to emphasize features that could remain robust in the wider context. Drehmann and Juselius (2014) note that a logit model can be employed to estimate the probabilities, but they emphasize that statistical properties of binary regression models are largely unknown under the high levels of persistency in their indicator variables.

Figure 3. Illustrations of Some Early Warning Indicators around Crisis Dates



Notes: Crisis dates are from Detken et al. (2014). The vertical line denotes the onset of crisis. First, second, and third quartile of indicator values are shown. The dashed horizontal lines show the first through third quartile of indicator values during tranquil periods. Only those crisis events for which the indicator data spans the whole thirty-two quarter period are included in the graphs. "19 crises in 13 of 18 countries" in the legend means that the corresponding graph is based on 19 crises that occurred in 13 countries, and the quartiles for tranquil periods employ data on 5 additional countries that did not have a crisis.

benefits of macroprudential policy, but about as daunting to specify an optimal trade-off. Hence, assumptions made about policymakers' preferences can be seen as somewhat arbitrary. To address this issue, Ferrari and Pirovano (2015) present a methodology for determining thresholds that is based on moments of an indicator's statistical distributions conditional on crisis periods and tranquil periods. Thresholds could also be country specific, as Ferrari and Pirovano (2015) show that their method works better when taking into account the country specificities. More complex methods try to derive thresholds based on multivariate models. Detken et al. (2014) show that this might be complicated, as there can be timing mismatch between different indicators and the data availability varies.

Given that there are significant uncertainties related to every potential method of determining thresholds, one should use them with care. Perhaps it would be wise to aim for a wider interpretation of the indicators than to aim for a single set of thresholds. One could use different methods to get a comprehensive picture of the information provided by various indicators.

5. Conclusions

The goal of this study has been to identify empirically a set of early warning indicators of banking crises that satisfy the policy requirements laid down in the EU legal framework. Specifically, we sought to identify suitable warning indicators for the ESRB's six categories for indicator measures: credit developments, private-sector debt burden, potential overvaluation of property prices, external imbalances, mispricing of risk, and strength of bank balance sheets. The results in general confirm earlier findings, but they also identify several new, highly useful predictors.

For the three most-studied categories (credit developments, private-sector debt burden, and potential overvaluation of property prices), we basically confirm earlier findings. Measures of credit-to-GDP, debt-service ratios, and measures of house price valuation and commercial real estate prices are all very good predictors of banking crises.

The previous literature reports mixed evidence for the remaining three categories (mispricing of risk, external imbalances, and strength of bank balance sheets). We propose several new predictors and subsequently report strong predictive performance for the following indicators in the category measures of potential mispricing of risk: the VIX index, the international credit spread between high-yield and investment-grade corporate bonds, and benchmark government bond yields. Our results hold firm in the full sample and out of sample, and for alternative crisis-prediction horizons and data sets. In addition, in agreement with Drehmann and Juselius (2014), we report some predictive success measures based on stock market price and stock market volatility.

In the external imbalances category, we find evidence in favor of the ratio of current account to GDP. None of the other examined items in the balance-of-payments accounts appear useful. We also propose a new predictor—the cross-border loans-to-GDP ratio—which shows some limited predictive performance.

Few of the bank balance sheet variables were robust predictors. This may have been hampered by the short time span of the available data. The strongest predictors, total banking assets-to-GDP ratio and leverage ratio, were statistically significant but otherwise showed weak performances. Several other indicators—such as a large net stable funding ratio, large non-core liabilities, and large loans-to-deposit ratios—are useful in the full sample, but that usefulness did not carry over to the out-of-sample results.

Our results contribute to the early warning literature of financial crisis and should help policymakers in selecting indicators for monitoring and making informed decisions on the countercyclical capital buffer. Our robustness checks are extensive compared with the earlier literature; we consider full-sample and out-of-sample estimations, many different transformations of the indicators, a range of prediction horizons, and three alternative financial crisis data sets. To the best of our knowledge, our robust findings on the informativeness of the VIX index and high-yield spread in predicting banking crises are new to literature.

A number of issues should be kept in mind when applying our results. First, we have selected the indicators based on evidence for the *average of all* countries.[30] Due to institutional or other country-specific features, some indicators might not work as well for some

[30]History shows that banking crises are caused by a group of fairly similar factors (Kauko 2014).

countries as others. Therefore, it might be optimal for some countries to select indicators other than those we propose when there is reason to believe that this country is not represented well in this average set of countries. Second, given that our aim has been to analyze data for as many countries as possible, we have relied mainly on public data sets. The national authorities monitoring these indicators in their own countries should avail themselves of the best available data. Nevertheless, we believe that our results hold for the indicators computed with different time series as long as they measure the same economic concepts.

References

Aikman, D., M. Galesic, G. Gigerenzer, S. Kapadia, K. Katsikopolous, A. Kothiyal, E. Murphy, and T. Neumann. 2014. "Taking Uncertainty Seriously: Simplicity versus Complexity in Financial Regulation." Financial Stability Paper No. 28, Bank of England.

Akinci, O., and J. Olmstead-Rumsey. 2015. "How Effective are Macroprudential Policies? An Empirical Investigation." International Finance Discussion Paper No. 2015-1136, Board of Governors of the Federal Reserve System.

Alessi, L., and K. 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* 27 (3): 520–33.

Anundsen, A., K. Gerdrup, and F. Hansen. 2014. "Bubbles and Crises: House Prices, Credit and Financial Market Turbulence." Mimeo.

Babecký, J., T. Havránek, J. Matěju, M. Rusnák, K. Šmídková, and B. Vašíček. 2014. "Banking, Debt, and Currency Crises in Developed Countries: Stylized Facts and Early Warning Indicators." *Journal of Financial Stability* 15 (December): 1–17.

Barrell, R., E. P. Davis, D. Karim, and L. Liadze. 2010. "Bank Regulation, Property Prices and Early Warning Systems for Banking Crises in OECD Countries." *Journal of Banking and Finance* 34 (9): 2255–64.

———. 2011. "How Idiosyncratic Are Banking Crises in OECD Countries?" *National Institute Economic Review* 216 (1): R53–R58.

Basel Committee on Banking Supervision. 2011. "Basel III: A Global Regulatory Framework for More Resilient Banks and Banking Systems — Revised Version." (June). Bank for International Settlements.

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 No. 1604.

Betz, F., S. Oprică, T. Peltonen, and P. Sarlin. 2013. "Predicting Distress in European Banks." ECB Working Paper No. 1597 (October).

Bonfim, D., and N. Monteiro. 2013. "The Implementation of the Countercyclical Capital Buffer: Rules versus Discretion." In *Financial Stability Report* (November): 87–110. Banco de Portugal.

Bordo, M. D., and C. M. Meissner. 2012. "Does Inequality Lead to a Financial Crisis?" *Journal of International Money and Finance* 31 (8): 2147–61.

Borio, C., and M. Drehmann. 2009. "Assessing the Risk of Banking Crises — Revisited." *BIS Quarterly Review* (March): 29–46.

Borio, C., and P. Lowe. 2002. "Assessing the Risk of Banking Crises." *BIS Quarterly Review* (December): 43–54.

Buchholst, B. V., and J. Rangvid. 2013. "Leading Indicators of Distress in Danish Banks in the Period 2008–12." Working Paper No. 85, Danmarks Nationalbank.

Bunda, I., and M. Ca' Zorzi. 2010. "Signals from Housing and Lending Booms." *Emerging Markets Review* 11 (1): 1–20.

Bussière, M., and M. Fratzscher. 2008. "Low Probability, High Impact: Policy Making and Extreme Events." *Journal of Policy Modeling* 30 (1): 111–21.

Büyükkarabacak, B., and N. T. Valev. 2010. "The Role of Household and Business Credit in Banking Crises." *Journal of Banking and Finance* 34 (6): 1247–56.

Caprio, G., and D. Klingebiel. 1996. "Bank Insolvencies: Cross-Country Experience." Policy Research Working Paper No. 1620, World Bank.

Castro, C., Á. Estrada, and J. Martínez. 2014. "The Countercyclical Capital Buffer in Spain: An Exploratory Analysis of Key Guiding Indicators." *Financial Stability Journal* (Bank of Spain) 27 (November): 31–59.

Cerutti, E. M., S. Claessens, and L. Laeven. 2017. "The Use and Effectiveness of Macroprudential Policies: New Evidence." *Journal of Financial Stability* 28 (February): 203–24.

Cerutti, E. M., R. Correa, E. Fiorentino, and E. Segalla. 2016. "Changes in Prudential Policy Instruments — A New Cross-Country Database." IMF Working Paper No. 16/110.

Comelli, F., 2014. "Comparing the Performance of Logit and Probit Early Warning Systems for Currency Crises in Emerging Market Economies." IMF Working Paper No. 14/65.

Davis, E. P., and D. Karim. 2008. "Comparing Early Warning Systems for Banking Crises." *Journal of Financial Stability* 4 (2): 89–120.

Demirgüc-Kunt, A., and E. Detragiache. 1998. "The Determinants of Banking Crises in Developed Countries." *IMF Staff Papers* 45 (1): 81–109.

———. 2000. "Monitoring Banking Sector Fragility: A Multivariate Logit Approach." *World Bank Economic Review* 14 (2): 287–307.

Detken. K, O. Weeken, L. Alessi, D. Bonfim, M. Boucinha, C. Castro, S. Frontczak, G. Giordana, J. Giese, N. Jahn, J. Kakes, B. Klaus, J. Lang, N. Puzanova, and P. Welz. 2014. "Operationalising the Countercyclical Capital Buffer: Indicator Selection, Threshold Identification and Calibration Options." ESRB Occasional Paper No. 5 (June).

Domaç, I., and M. S. Martinez Peria. 2003. "Banking Crises and Exchange Rate Regimes: Is There a Link? *Journal of International Economics* 61 (1): 41–72.

Drehmann, M., C. Borio, L. Gambacorta, G. Jiminez, and C. Trucharte. 2010. "Countercyclical Capital Buffers: Exploring Options." BIS Working Paper No. 317.

Drehmann, M., C. Borio, and K. Tsatsaronis. 2011. "Anchoring Countercyclical Capital Buffers: The Role of Credit Aggregates." *International Journal of Central Banking* 7 (4, December): 189–240.

Drehmann, M., and M. Juselius. 2014. "Evaluating Early Warning Indicators of Banking Crises: Satisfying Policy Requirements." *International Journal of Forecasting* 30 (3): 759–80.

European Systemic Risk Board. 2014. "Recommendation of the ESRB on Guidance for Setting Countercyclical Buffer Rates." Available at https://www.esrb.europa.eu/pub/pdf/recommendations/2014/140630_ESRB_Recommendation.en.pdf.

Ferrari, S., and M. Pirovano. 2015. "Early Warning Indicators for Banking Crises: A Conditional Moments Approach." MPRA Paper No. 62406.

Frankel, J., and A. Rose. 1996. "Currency Crashes in Emerging Markets: An Empirical Treatment." International Finance Discussion Paper No. 534, Board of Governors of the Federal Reserve System.

Giese, J., H. Andersen, O. Bush, C. Castro, M. Farag, and S. Kapadia. 2014. "The Credit-to-GDP Gap and Complementary Indicators for Macroprudential Policy: Evidence from the UK." *International Journal of Finance and Economics* 19 (1): 25–47.

Hahm, J.-H., H. S. Shin, and K. Shin. 2013. Noncore Bank Liabilities and Financial Vulnerability." *Journal of Money, Credit and Banking* 45 (s1): 3–36.

Hardy, D., and C. Pazarbaşıoğlu. 1998. "Leading Indicators of Banking Crises: Was Asia Different?" IMF Working Paper No. 98/91.

Holopainen, M., and P. Sarlin. 2015. "Toward Robust Early Warning Models: A Horse Race, Ensembles and Model Uncertainty." Discussion Paper No. 6, Bank of Finland.

Jordà, Ò., O. Schularick, and A. M. Taylor. 2015. "Leveraged Bubbles." *Journal of Monetary Economics* 76 (Supplement): S1–S20.

Joyce, J. 2011. "Financial Globalization and Banking Crises in Emerging Markets." *Open Economies Review* 22 (5): 875–95.

Kamin, S., and L. DeMarco. 2012. "How Did a Domestic Housing Slump Turn into a Global Financial Crisis?" *Journal of International Money and Finance* 31 (1): 10–41.

Kaminsky, G., and C. Reinhart. 1999. "The Twin Crises: The Causes of Banking and Balance-of-Payments Problems." *American Economic Review* 89 (3): 473–500.

Kauko, K. 2012a. "Triggers for Countercyclical Capital Buffers." *BoF Online* 7 (2012).

———. 2012b. "External Deficits and Non-performing Loans in the Recent Financial Crisis. *Economics Letters* 115 (2): 196–99.

———. 2014. "How to Foresee Banking Crises? A Survey of the Empirical Literature." *Economic Systems* 38 (3): 289–308.

Kauko, K., J. Vauhkonen, and J. Topi. 2014. "How Should the Countercyclical Capital Buffer Requirement Be Applied?" *Bank of Finland Bulletin* 2 (2014): 57–67.

Kim, W., and S.-J Wei. 2002. "Foreign Portfolio Investors Before and During a Crisis." *Journal of International Economics* 56 (1): 77–96.

Krylova, E., 2016. "Determinants of Euro-Denominated Corporate Bond Spreads." ECB Working Paper No. 1912 (June).

Laeven, L., and F. Valencia. 2008. "Systemic Banking Crises: A New Database." IMF Working Paper No. 08/224.

———. 2012. "Systemic Banking Crises Database: An Update." IMF Working Paper No. 12/163.

Lainà, P., J. Nyholm, and P. Sarlin. 2015. "Leading Indicators of Systemic Banking Crises: Finland in a Panel of EU Countries." *Review of Financial Economics* 24 (January): 18–35.

Lindgren, C.-J., G. Garcia, and M. I. Saal, eds. 1996. *Bank Soundness and Macroeconomic Policy.* International Monetary Fund.

Lo Duca, M., and T. Peltonen. 2013. "Assessing Systemic Risks and Predicting Systemic Events." *Journal of Banking and Finance* 37 (7): 2183–95.

Lund-Jensen, K. 2012. "Monitoring Systemic Risk Based on Dynamic Thresholds." IMF Working Paper No. 12/159.

Phillips, P. C. B., S. Shi, and J. Yu. 2013. "Testing for Multiple Bubbles: Historical Episodes of Exuberance and Collapse in the S&P 500." Discussion Paper No. 1914, Cowles Foundation.

Reinhart, C. M., and K. S. Rogoff. 2009. *This Time is Different: Eight Centuries of Financial Folly.* Princeton University Press.

Repullo, R., and J. Saurina. 2011. "The Countercyclical Capital Buffer of Basel III: A Critical Assessment." CEPR Discussion Paper No. 8304.

Roy, S., and D. M. Kemme. 2012. "Causes of Banking Crises: Deregulation, Credit Booms and Asset Bubbles, Then and Now." *International Review of Economics and Finance* 24 (October): 270–94.