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Leading indicators of systemic banking crises:

Finland in a panel of EU countries

Macroprudential Research Network

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Abstract

This paper investigates leading indicators of systemic banking crises in a panel of 11 EU countries, with a particular focus on Finland. We use quarterly data from 1980Q1 to 2013Q2, in order to create a large number of macro-financial indicators, as well as their various transformations. We make use of univariate signal extraction and multivariate logit analysis to assess what factors lead the occurrence of a crisis and with what horizon the indicators lead a crisis. We find that loans-to-deposits and house price growth are the best leading indicators. Growth rates and trend deviations of loan stock variables also yield useful signals of impending crises. While the optimal lead horizon is three years, indicators generally perform well with lead times ranging from one to four years. We also tap into unique long time-series of the Finnish economy to perform historical explorations into macro-financial vulnerabilities.

Keywords: leading indicators, macro-financial indicators, banking crisis, signal extraction, logit analysis
JEL codes: E440, F300, G010, G150, C430

Non-technical summary

Macroprudential policies have an ultimate aim of preventing financial crises. Basel III and the EU's legislative acts CRD and CRR IV, among others, propose the implementation of macroprudential tools. These tools are designed for curbing booms in household, especially real estate, sectors through controlling the growth rate of private loan stocks and for restraining overall booms in the wider economy, as well as to strengthen the banking sector by enhancing its loss absorbing capacity and by reducing default probabilities and losses given default. Hence, this motivates further research on the identification of underlying vulnerabilities and risks through early-warning indicators that function as guidance for macroprudential policy.

This paper investigates macro-financial factors as leading indicators of systemic banking crises in Europe, and particularly reflects over the case of the Finnish economy. The investigated questions in this paper relate to what factors lead the occurrence of a crisis and with what horizon the indicators lead a crisis. Ultimately, the studied indicators aim at providing guidance for the activation of macroprudential tools, such as countercyclical capital buffers, loan-to-value caps and risk weights.

The previous literature has consistently found excessive growth in credit aggregates and asset prices to lead banking crises. Despite a large number of studies on leading indicators, only a few of them have a pure focus on European economies. While some studies only include Europe as an aggregate, those that include individual European countries also include economies from other continents, mainly covering OECD economies. Those studies that focus on distress in Europe have a different scope and aim. For instance, Betz et al. (2014) include country-level indicators, but aim at predicting distress at the level of banks in most European countries, whereas Behn et al. (2013) perform an exercise similar to building an early-warning model, but use it for setting countercyclical capital buffers. Accordingly, the latter study focuses mainly on the role of credit variables. Further, diverting from assessing core Europe, they also include Central and Eastern European transition or developing economies.

This paper investigates leading indicators of systemic banking crises in a panel of 11 EU countries, with a particular focus on Finland. To enable and support the analysis of Finland, we collect data on eleven developed European economies. Hence, rather than taking a pan-European or single-country perspective, we aim at collecting data on a possibly homogeneous set of economies. We use quarterly data from 1980Q1 to 2013Q2, in order to create a large number of macro-financial indicators, as well as various transformations. The considered indicators cover a range of asset, credit and macro variables, following the previous literature. For developed EU countries, this enables us to study not only patterns of pre-crisis, crisis and post-crisis dynamics, but also to rank leading indicators of systemic banking crises and their optimal signaling horizon. To serve this purpose, we make use of univariate signal extraction and multivariate logit analysis.

This paper contributes to the literature on systemic banking crisis determinants as follows. In terms of univariate signal extraction, we show that best-in-class indicators are the growth rates of loans-to-deposits and house prices. In addition, the growth rates and trend deviations of mortgages, household loans and private loans are also useful leading indicators. Besides real growth of GDP, we do not find much evidence of standard macroeconomic variables as good leading indicators. Accordingly, inflation, current account deficits and real interest rates do not perform well as leading indicators of crises. The results with multivariate logit analysis support the findings with the signal extraction analysis. With a three year lead time, statistical significance does not depend on whether we use trend deviations or growth rates. For the shorter lead time window, trend deviations of the loan stock variables are perform better than growth rates. Interestingly, the sign of house price growth reverts to negative when the time horizon is shortened, which indicates that rising house prices imply an impending crisis within three years, whereas one year prior to a crisis house prices have already reached their turnpoint. While the usefulness of loan stock variables as well as house price and GDP growth is in line with previous literature, we contrast earlier findings with two differences. We do not find any evidence on the usefulness of current account deficits and we find the growth rate of the loans-to-deposits ratio to be among the most useful leading indicators.

This paper also contributes to the technical derivation of early-warning indicators and models. When assessing different model specifications, we find that differences between absolute and relative trend deviations are only minor, where absolute trend deviations refer to an indicator value substracted from its HP trend and relative trend deviations divide the absolute trend deviation with its corresponding HP trend. Yet, we find that growth rates tend to be the most prominent transformation. If trend deviations of ratios are used, we propose to detrend GDP as a denominator to support persistence with respect to short-term variation in the real economy. Further, we propose the use of cumulative estimated probabilities of logit analysis over the entire historical forecast horizon, in addition to only assessing non-cumulative probabilities. We also investigate differences in indicators depending on lead times and transformations. The indicators show best performance with a lead time of three years, but generally perform well with up to a four-year lead time. Shortening the horizon impairs the quality of the signals. This provides input to policymakers in control of macroprudential tools, as indicators with a three-year lead time are early enough to support macroprudential tools with long activation times.

As a final exercise, we also tap into unique long time-series of the Finnish economy to perform historical explorations into macro-financial vulnerabilities. Beyond the current global financial crisis, Finland experienced three crises at the beginning of the 20th century, as well as a severe banking crisis in the 1990s, which was impacted by both a currency crisis and the collapse of the Soviet Union. Using the estimates on panel data, we correctly call most of the Finnish crises since the beginning of the 20th century. While the growth of the loans-to-deposits ratio was the best-in-class indicator by signaling within three years prior to each Finnish crisis, the growth rates of real house prices and real private loans and the private loans-to-GDP gap also signaled most of the crises since the beginning of the 20th century.

1. Introduction

This paper investigates macro-financial factors as leading indicators of systemic banking crises in Europe, and particularly reflects over the case of the Finnish economy. Our definition of a systemic banking crisis implies simultaneous failures in the banking sector that significantly impairs the capital of the banking system as a whole, which mostly results in large economic effects and government intervention. The investigated questions in this paper relate to what factors lead the occurrence of a crisis and with what horizon the indicators lead a crisis.

The implementation of macroprudential policies, particularly when being of discretionary nature, may exhibit challenges in tackling the vulnerability of the financial system to procyclicality. To this end, recent legislative initiatives provide a basis for the use of policy instruments. Basel III, the EU's legislative acts CRD and CRR IV and the Finnish Ministry of Finance (2012) all propose the implementation of macroprudential tools at the national level. These tools are designed for curbing booms in household, especially real estate, sectors through controlling the growth rate of private loan stocks. They are also meant to strengthen the banking sector by enhancing its loss absorbing capacity and by reducing default probabilities and losses given default. Other tools such as countercyclical capital buffers are intended for restraining booms in the wider economy. Although some discretion and judgment will inevitably be required, tying macroprudential instrument triggering to risk indicators via simple rules aids in overcoming resistance to countercyclical measures during booms (e.g., Agur and Sharma, 2013). Thus, before coupling risk indicators with precise policy instruments, an essential question is to investigate how and provide means for assessing whether risks are concentrated in a particular sector or whether they extend to a number of sectors. This paper studies indicators for rule-based guiding of the activation of countercyclical capital buffers, loan-to-value caps and risk weights, rather than overall discretion and judgment in decisions or the effects of these macroprudential tools.

Macroprudential instruments have an ultimate aim of preventing and mitigating the occurrence of financial crises. Yet, one key problem is that the implementation takes time. To launch the tools, policymakers need to be aware of risks and vulnerabilities building up at an early stage (e.g., CRD IV specifies a 12-month implementation period). By focusing on identifying underlying vulnerabilities and risks, this paper investigates indicators that function as early enough signals of an impending crisis. Another problem is that the implementation of these tools is costly, whereas implementation is sensible only if it will prevent a crisis. This motivates further research on leading indicators of financial crises, and their specific specification, including transformations and time horizon, as well as a balance between false alarms and missed crises. Eventually, one should still note that analytical tools for early identification of risks provide only guiding support, whereas direct early-warning signals are an output of internal investigations and thorough scrutiny.

The previous literature has consistently found excessive growth in credit aggregates and asset prices to lead banking crises. For instance, the signal extraction approach is used by Kaminsky and Reinhart (1999) to study the connection between financial and currency crises and by Alessi and Detken (2011) to investigate predictors of asset price booms with costly real economy consequences. Likewise, Borio and Lowe (2002) have found unusually rapid expansions in credit and asset prices, particularly deviation from their long-term trend, as useful leading indicators of wide-spread financial distress. Despite a large number of studies on crisis determinants, only a few of them have a pure focus on European economies. Accordingly, the traditional literature focuses on leading indicators in emerging markets (e.g., Frankel and Rose, 1996; Kaminsky et al., 1998) or both developed and developing economies (e.g., Demirgüç-Kunt and Detragiache, 1998). While some studies only include Europe as an aggregate (e.g., Lo Duca and Peltonen, 2013; Sarlin and Peltonen, 2013), those that include individual European countries also include economies from other continents. For instance, Reinhart and Rogoff (2009), Alessi and Detken (2011), Babecky et al. (2013) and Boissay et al. (2013) all focus on developed, mainly OECD, economies. Those studies that focus on distress in Europe have a different scope and aim. For instance, Betz et al. (2014) and Männasoo and Mayes (2009) include country-level indicators, but aim at predicting distress at the level of banks in most European and Eastern European transition countries, respectively, whereas Behn et al. (2013) perform an exercise similar to building an early-warning model, but use it for setting countercyclical capital buffers. Accordingly, Behn et al. (2013) focus mainly on the role of credit variables. Further, diverting from assessing core Europe, they also include Central and Eastern European transition or developing economies.

This paper assesses leading indicators of systemic banking crises in Europe, with a particular focus on the Finnish economy. To enable and support the analysis of Finland, we collect data on eleven developed European economies. Hence, rather than taking a pan-European or single-country perspective, we aim at collecting data on a possibly homogeneous set of economies. While the sample economies are partly chosen based upon data availability, we deliberately exclude transition economies, for which the trajectory of financial development has been of different nature compared to rest of Europe. The considered macro-financial indicators cover a range of asset, credit and macro variables, following the previous literature. For developed EU countries, this enables us to study not only patterns of pre-crisis, crisis and post-crisis dynamics, but also to perform a structured analysis and ranking of leading indicators of systemic banking crises and their optimal signaling horizons. Beyond this, we also test the impact of a number of model specifications on early-warning performance.

This paper contributes to the literature on banking crisis determinants as follows. We find strongest evidence on loans-to-deposit and house price growth as leading indicators of systemic banking crises. Loan stock variables – mortgages, household loans and private loans – also perform well as leading indicators. The indicators show best performance with a lead time of three years, but generally perform well with up to a four-year lead time. This provides input to policymakers in control of macroprudential tools, as indicators with a three-year lead time are early enough to support macroprudential tools with long activation times. Further, we also tap into unique long time-series of the Finnish economy to perform historical explorations into macro-financial vulnerabilities. Beyond the current global financial crisis, Finland experienced three crises at the beginning of the 20th century, as well as a severe banking crisis in the 1990s, which was impacted by both a currency crisis and the collapse of the Soviet Union. Using the estimates on panel data, we correctly call most of the Finnish crises since the beginning of the 20th century. This paper also contributes to the technical derivation of early-warning indicators and models. When assessing different model specifications, we find that differences between absolute and relative trend deviations are only minor and that growth rates tend to be the most prominent transformation. If trend deviations of ratios are used, we propose to detrend GDP as a denominator to support persistence with respect to short-term variation in the real economy. Further, we propose the use of cumulative estimated probabilities of logit analysis over the entire historical forecast horizon, in addition to only assessing non-cumulative probabilities.

This paper is organized as follows. Section 2 provides a review of indicators and method used in the literature, and presents those used in this paper. Section 3 presents descriptive statistics through measures of pre-crisis, crisis and post-crisis dynamics. In Section 4, we present the signal extraction results and discuss the usefulness of each indicator, whereafter we turn to an assessment of the indicators by means of multivariate logit analysis. Before concluding, Section 5 presents long time series for the Finnish economy in light of our previous findings. In addition, the indicators analyzed in this paper have been included in a supplementary interactive dashboard: http://risklab.fi/demo/lainaetal/.

2. Data and methods

This section briefly reviews previous works on early warning indicators and models, particularly with respect to used data and estimation methods. Next, we turn to a discussion of the collected data for this study and the methods that we use in this paper to assess leading indicators.

2.1. A review of indicators and methods

As above noted, a large number of studies have assessed leading and early-warning indicators of banking and financial crises overall. Herein, we briefly review previous works on early warning indicators and models, in order to support the subsequent choice of data and estimation methods. We have reviewed a large number of recent works on early-warning indicators and models, and assessed successful indicators in terms of broad categories of indicators. For instance, credit aggregates include mortgages, household loans, corporate loans and total loans, among others, whereas asset prices include equity indices, house prices and other property prices, as well as their various transformations.

Table 1 shows the performance (or significance) of proposed indicators in terms of broad indicator categories. It highlights the significance of indicators related to credit aggregates and asset prices, but also the lack of a direct consensus in the used indicators and their performance. This might be a consequence of variations in the analyzed economies, types of crises and time spans. Thus, it highlights the importance of a study focusing on a homogeneous set of economies, on a specific type of crisis and on the recent experience of turmoil.

Starting from credit variables, Table 1 shows that credit-related indicators have been included in all studies and most have also found one or several of them to be successful, such as credit-to-GDP gap by Borio and Lowe (2002) and similar global measures by Alessi and Detken (2011). Likewise, asset prices have been oftentimes both included in assessments and found significant, such as the deviation from trend of an aggregated asset price index by Borio and Lowe (2002) and deviation from trend of stockmarket capitalization to GDP by Lo Duca and Peltonen (2013) and Sarlin and Peltonen (2013). While financial regulation and financial sector size have been accounted in only a few studies, money aggregates have been used more frequently. For instance, Alessi and Detken (2011) find global M1 gap to be among the most useful indicators. Indicators related to interest rates and external imbalances like exchange rates and current account deficits have rarely been used or found significant. An exception is the current account deficit, which has indeed been significant in five studies, but these mostly involve emerging markets and/or focus on the identification of exchange-rate pressure. Moreover, measures related to GDP have been common, such as real GDP growth, but their significance has not been undisputed.

From the viewpoint of the applied methods, the studies have generally used signal extraction (also called the signaling approach) and multivariate logit or probit analysis. For instance, while Kaminsky and Reinhart (1999), Borio and Lowe (2002), Alessi and Detken (2011) and Lo Duca and Peltonen (2013) make use of signal extraction, whereas Schularick and Taylor (2012), Lo Duca and Peltonen (2013) and Sarlin and Peltonen (2013) use logit or probit analysis. Moreover, the set of studies in Table 1 also included Self-Organizing Maps (Sarlin and Peltonen, 2013), standard linear OLS regression (Kauko, 2012) and Bayesian Model Averaging (Babecky et al., 2013). Beyond the studies in the table, it is also worth noting that a number of studies have utilized classification and regression trees for the study of banking crises (e.g., Dattagupta and Cashin, 2011; Davis et al., 2011).

2.2. Data

The dataset used in this paper has been collected with the aim of covering as many European economies, particularly focusing on developed economies with long time series. While a narrow focus improves homogeneity in the sample, long time series are necessary for also including the previous wave of European systemic banking crises in the early 1990s. The data used in this paper are quarterly and span the period of 1980Q1 to 2013Q2. The sample is an unbalanced panel with 11 European Union countries: Austria, Belgium, Denmark, Finland, France, Germany, Italy, the Netherlands, Spain, Sweden and United Kingdom. In total, the sample includes 19 systemic banking crises. The dataset consists of two parts: crisis events and vulnerability indicators. In the following, we provide a more detailed description of the two parts.

The crisis events used in this paper are chosen as to cover country-level systemic stress in the banking sector. We define a systemic banking crisis as the occurrence of simultaneous failures in the banking sector, which significantly impairs the capital of the banking system as a whole, and accordingly a crisis mostly results in large economic effects and government intervention. Table 2 presents the crisis periods in the sample from 1980 to 2013. The main source of the events is the initiative by the European System of Central Banks (ESCB) Heads of Research Group, as reported in Babecky et al. (2013). The database includes banking, currency and debt crisis events for a global set of advanced economies from 1970 to 2012. The database is a compilation of crisis events from a large number of influential papers (e.g., Caprio and Klingebiel, 2003; Detragiache and Spilimbergo, 2001;

Table 1: Early-warning indicators and models.

Source	Credit	Asset Prices	Financial Regulation	Financial Sector Size	Money Aggregate	Interest Rate	Exchange Rate	Current Account	GDP
Demirgüç-Kunt & Detragiache (1998)	(x)		x		x	x	-		x
Kaminsky & Reinhart (1999)	x	(x)	x		x	(x)	x	x	x
Borio & Lowe (2002)	x	x					x		
Demirgüç-Kunt & Detragiache (2005)	x		x		x	x	-		x
Borio & Drehmann (2009)	x	x							
Reinhart & Rogoff (2009)	(x)	x	x		(x)		x	x	x
Büyükkarabacak & Valev (2010)	x			x	x	x			(x)
Alessi & Detken (2011)	x	x			x	x	(x)		x
Babecký et al (2013)	x	x			(x)	x	(x)	-	x
Claessens et al (2011)	x	x							
Crowe et al (2013)	x	x							
Drehmann et al (2011)	x	x			-				-
Lo Duca & Peltonen (2013)	x	x					-	x	(x)
Sarlin & Peltonen (2013)	x	x						x	x
CGFS (2012)	x	x							
Drehmann & Juselius (2012)	x								
Kauko (2012)	x				-			x	(x)
Schularick & Taylor (2012)	x	(x)		(x)	(x)				
Arregui et al (2013)	x	(x)							

x = significant

(x) = somewhat significant

- = non-significant

Kaminsky, 2006; Kaminsky and Reinhart, 1999; Laeven and Valencia, 2008, 2010, 2012; Levy-Yeyati and Panizza, 2011; and Reinhart and Rogoff, 2008, 2011), which have been complemented by ESCB Heads of Research based upon their domain expertise and judgment. We further cross-check and complement the crisis database using events in Caprio et al (2005), Freystätter and Mattila (2011), IMF (2010), Kindleberger and Aliber (2011), and Reinhart and Rogoff (2009). Using the above sources, we have tried to find consensus in the literature when choosing the crisis periods and their precise dates, particularly from the viewpoint of systemic stress in the banking sector. Even though the 2008 events may be argued not to always descend from a domestic systemic banking crisis, we have included them as they clearly exhibit periods of elevated stress in the financial sector and also involved a effects on the real economy.

The second part of the dataset consists of a number of country-level vulnerability and risk indicators. Generally, these cover a range of macro-financial imbalances. We include measures covering asset prices (e.g., house prices), credit aggregates and leverage (e.g., mortgages, private loans, household loans and real interest rate of the mortgage stock), business cycle indicators (e.g., GDP and inflation), external imbalances (e.g., current account deficits), and the banking sector (e.g., loans to deposits). The used measures partly coincide with macroeconomic and financial imbalances from the EU Alert Mechanism Report related to the EU Macroeconomic Imbalance Procedure. Further, to better proxy imbalances and vulnerabilities, we consider the following transformations: inflation adjustments, shares of GDP, growth rates, and absolute and relative trend deviations. We do not focus on global variables or any other aggregate beyond country-level measures, even though this has been commonly done in other studies (e.g., Lo Duca and Peltonen, 2013; Sarlin and Peltonen, 2013). In an increasingly integrated economy, their relevance is clear, particularly in the case of the crisis of 2007–2008. Yet, as they do not vary across countries, and most had a crisis in 2008, their usefulness is known already prior to any empirical exercise. Another weakness is that they do not serve as an input to some of the standard country-specific macroprudential tools, such as loan-to-value caps.

For detrending ratios of loan stock variables in relation to GDP and measures of house prices, the trend is extracted using the one-sided Hodrick–Prescott filter (HP filter). This means that each point of the trend line corresponds to the last point of the estimated trend line using data from the beginning

Table 2: Crisis periods between 1980 and 2013.

	Crisis periods		
Country	**1980s**	**1990s**	**2000s**
Austria			2008Q3–Q4
Belgium			2008Q3–Q4
Germany			2008Q3–Q4
Spain	1978Q1–1985Q4		2008Q3–Q4
Finland		1991Q3–95Q4	2008Q3–Q4
France		1994Q1–95Q4	2008Q3–09Q4
Italy		1990Q1–95Q4	2008Q3–Q4
Netherlands			2008Q3–Q4
Denmark	1987Q1–92Q4		2008Q3–10Q4
Great Britain	1984Q1–Q4	1990Q3–95Q4	2007Q3–Q4
Sweden		1991Q3–95Q4	2008Q3–Q4

up to this particular point. By doing this, we use the information set available to the policymaker at each point in time when calculating the trend. The smoothness parameter λ of the HP filter is specified to be 400,000, which assumes financial cycles to be four times longer than standard business cycles, as suggested by Drehmann et al. (2011). This captures long-term trends and has been suggested to appropriately capture the cyclical nature of credit aggregates and asset prices, particularly in quarterly data. Even though empirical measurement of a sustainable trend, or so-called equilibrium, is highly challenging, one could argue that the λ parameter assumption is appropriate as crises occur on average every 20–25 years in our sample. Growth rates are defined as annual rates, whereas the relative deviation from trend differs from the absolute by relating the deviation to the value of the trend. The rationale for measuring relative gaps is that levels of the ratios might be different (e.g., depending on the state of financial development), and particularly when measuring gaps on level variables like house prices. When assessing data in relation to GDP, the GDP series have been detrended with a similar one-sided HP filter as for the credit and asset price series. This supports the persistence of ratios with respect to short-term variation in the real economy.

2.3. Methods

To estimate leading indicators of, as well as trends and patterns around, crises, this paper uses a number of methods. Beyond simple descriptive statistics to assess univariate crisis dynamics, we use a both non-parametric and parametric methods to assess and evaluate leading indicators. In particular, we make use of univariate signal extraction and multivariate logit analysis.

Systemic banking crisis occurrences can be represented with a binary state variable for country i in period t: $I_{i,t}(0) \in \{0,1\}$. With a focus on detecting vulnerabilities and risks prior to crises, the ideal leading indicator is a binary variable $I_{i,t}(h) \in \{0,1\}$ with a specified forecast horizon h. Hence, it takes the value one in pre-crisis states and zero otherwise. To detect events using indicators or models, we need to estimate crisis probability forecasts $p_{i,t} \in [0,1]$. To mimic the ideal leading indicator, the probability $p_{i,t}$ is transformed into a binary point forecast $P_{i,t}$, which equals one if $p_{i,t}$ exceeds a specified threshold θ and zero otherwise. The quality of the prediction $P_{i,t}$ vis-à-vis the ideal leading indicator $I_{i,t}(h)$ can be summarized into a so-called contingency matrix.

In the univariate case, we use signal extraction to classify observations as being either in a tranquil or a vulnerable state. Signal extraction is a non-parametric approach pioneered by Kaminsky et al. (1998) to identify the threshold θ for an individual indicator using a minimization of a so-called noise-to-signal measure. This provides an optimal threshold value, above which the indicator signals. These signals might or might not be followed by a crisis. If a signal is followed by a crisis in a fixed time window, the signal correctly calls the crisis (A, see Table 3). If a signal is given but a crisis does not

Table 3: Signal analysis categorization and performance measures.

	Crisis	No crisis	Type I errors (%)	Type II errors (%)	Predicted crises (%)	Noise-to-signal
Signal	A	B	C/(A+C)	B/(B+D)	A/(A+C)	B/(B+D) / A/(A+C)
No signal	C	D				

follow, the signal is a false alarm (B). Likewise, we miss a crisis when a crisis occurs without a warning signal (C), and correctly do not call a crisis when no signal is given during tranquil times (D). The categorization of the cases is summarized in Table 3, which is also called a contingency matrix. In the optimal case, all signals are followed by a crisis after a certain time horizon and no alarm is false. In this study, we use several time windows in order to assess optimal horizons of indicators. It is also worth noting that we do not distinguish among the quarters, and are only concerned with whether or not signals are issued within the window. Hence, one could say that we treat each individual crisis as one observation (i.e., only count once for each crisis a correctly called A or missed crisis C). We argue that this way of calculating correctly called and missed crises is meaningful, as it provides information on the true number of called crises rather than the share of correct country-quarter observations. This implies that comparisons between the columns of the contingency matrix in Table 3 are not directly meaningful (due to large deviations in class size), but as can be seen in the table none of the measures compare performance over elements in different columns.

The noise-to-signal ratio is given by $[B/(B+D]/[A/(A+C)]$, where the upper case letters refer to the elements of the contingency matrix (or prediction-realization combinations). When this ratio is minimized, the share of correct signals is at the maximum relative to the share of false signals. Accordingly, the threshold, where the noise-to-signal value is minimized, is chosen. Yet, the noise-to-signal measure does not account for missed crises (C) in a proper way: in some cases C can be close or equal to zero due to a high threshold. In recent works, a pure noise-to-signal measure has seldom been used, as it has been shown to often lead to noise minimization if crises are rare, although the cost of missing a crisis is relatively larger (see Sarlin, 2013). Using the noise-to-signal measure, we follow Borio and Drehmann (2009) and CGFS (2012) by complementing it with a simple additional rule: it is minimized given that we call at least two-thirds (66.67%) of the crisis periods. For well-performing indicators, the noise-to-signal ratio is less than one, whereas, on average, the ratio takes the value of 1 for random signals (given balanced classes and preferences). Further, as we label $T_1 = C/(A+C)$ as the share of type I errors (share of missed crises) and $T_2 = B/(B+D)$ as the share of type II errors (share of false alarms), we can explicitly look at the performance of indicators depending on preferences between the errors. Based upon T_1 and T_2 weighted with policymakers preferences μ and $1-\mu$, we also report the Usefulness measure introduced by Sarlin (2013). Thus, we can not only gauge signaling performance for various preferences, but also the extent to which an indicator is better than the best guess of a policymaker given her aversion between the errors (μ) and the unconditional probability of crisis ($P_1 = (A+C)/(A+C+B+D)$) and tranquil periods ($P_2 = 1-P_1$). Based upon the loss function $L(\mu) = \mu T_1 P_1 + (1-\mu) T_2 P_2$, we can define the absolute Usefulness of an indicator:

$$U_a(\mu) = \min(\mu P_1, (1-\mu)\, P_2) - L(\mu).$$

Relating absolute Usefulness to the available Usefulness of an indicator, we can also define the so-called relative Usefulness of an indicator

$$U_r(\mu) = \frac{U_a(\mu)}{\min(\mu P_1, (1-\mu)\, P_2)},$$

which measures the share of available Usefulness that a model captures. The larger the preference parameter μ, the more concerned is the policymaker about missing a crisis.

While providing a ranking of indicators and tangible threshold values, this takes only a univariate perspective to risk and vulnerabilities preceding a crisis. For the multivariate approach, we make use of logit analysis. It is non-linear regression analysis that allows us to use efficiently the information in the panel data for estimating probabilities of an impending crisis. Logit models provide means for probabilistic classification tasks. Through a logistic function, they aim at explaining or predicting the probability of occurrence of a binary variable. In our case the dependent dummy variable $I_{i,t}$ gets the value of one whenever a crisis starts in that particular period, i.e.

$$I_{i,t} = \begin{cases} 1 & \text{if crisis starts in period } t \text{ in country } i \\ 0 & \text{otherwise} \end{cases} .$$

The estimated parameter vector defines the effect of the explanatory variables on the dependent dummy variable. Because we want to estimate vulnerable states, rather than the contemporaneous crisis occurrence, we lag the explanatory variables. If we explain the crisis dummy at period t by explanatory variables at period $t-k$, we have a k-period straight forecast to the crisis dummy. Parameters are estimated using the maximum-likelihood method. The fit of the model can be, loosely speaking, interpreted as the estimated probability that a crisis will start in period t in country i:

$$\hat{I}_{it} = P\left\{I_{i,t} = 1|\Omega_{t-k}\right\}$$

where $\hat{I}_{i,t}$ is the estimated fit for country i in period t, $P\left\{\cdot\,|\cdot\right\}$ is the conditional probability operator, and information set Ω_{t-k} contains all the information available at period $t-k$. Logit analysis uses the logistic probability density function to model the estimated probabilities describing the possible outcomes:

$$\hat{I}_{i,t} = \frac{e^{\hat{\beta}' x_{i,t-k}}}{1+e^{\hat{\beta}' x_{i,t-k}}}$$

where vector $\hat{\beta}$ contains the estimated coefficients and vector $x_{i,t-k}$ the explanatory variables for country i in period $t-k$. Beyond individual probabilities, we also account for probabilities over a range of quarters based upon the length of our forecast horizon k, in order to have a cumulative probability. Hence, we can by simple probability theory define the cumulative probability as follows:

$$P\left(I_{i,t}^{C}=1\right) = \left[1 - P\left(I_{i,t}^{C}=0\right)\right] = 1 - \prod_{j=1}^{k}\left(1 - P\left(I_{i,t}^{j}=1\right)\right),$$

where the probability of $I_{i,t}^{C}$ is a cumulative probability of the probabilities of $I_{i,t}^{j}$ for $j = 1, ..., k$. In our case, as we are concerned with the probabilities $\hat{I}_{i,t}$ since quarter $t-k$, the probability of a crisis $p_{i,t}$ is computed as follows:

$$p_{i,t} = 1 - \prod_{j=1}^{k}\left(1 - P\left(I_{i,t-j}=1\right)\right).$$

This is a more correct representation of the probability of a country experiencing a systemic banking crisis in one given quarter. It accounts for longer periods of elevated risks, despite not individually breaching a threshold, which acknowledges the additive nature of systemic risk.

As noted by Bussière and Fratzscher (2006), leading indicators might be affected by crisis and post-crisis periods, which would impact the relationship between the explanatory variables and the dependent variable. To control for this, we have omitted the observations I_{it} whenever the country i has suffered a financial crisis during period t and up to two years after the crisis has ended. By means of a simple example, Demirgüc-Kunt and Detragiache (1998) state that interest rates are likely to be affected by the loosening of monetary policy after crises. Moreover, as we aim to signal crises early on, we also drop so-called late pre-crisis periods (e.g., 1–3 quarters prior to a 4–15 quarter lead time). Because we are only interested in classifying between pre-crisis and tranquil periods, we have little down side in excluding observations that are uninformative regarding the transition from tranquil times to distress events.

3. Pre-crisis, crisis and post-crisis dynamics

This section provides descriptive statistics on pre-crisis, crisis and post-crisis dynamics.

3.1. Indicators around crises

In this subsection, we provide descriptive statistics of the behaviour of indicators around crises. Average behavior of the variables around crisis is used for a first visual inspection. Across countries, these plots depict how indicators behave on average before, during and after crises. In this line, the plots also enable comparisons of average patterns to behavior in individual economies or even individual crises. Figures 1–3 include average behaviour around crises, where data are available, and the behavior of indicators around the two Finnish crises of 1991 and 2008.

The left panel of Figure 1 above shows the annual growth rate for real house prices. On average, it takes values of almost 10% three years prior to a crisis. Thereafter, the growth rate declines, until reaching negative values slightly before a crisis. Although real house prices have developed in the same direction in Finland's 1991Q3 crisis, the growth rate reacted stronger and earlier. Real house prices grew over 30% before the crisis, turned negative almost two years before, and dropped by 20% at the start of the crisis. In the 2008Q3 crisis, Finland's development has followed more closely the average behavior of house prices, except for the steep post-crisis increase. The right panel of Figure 1 depicts the annual growth rate for the real mortgage stock. On average, mortgages increase 13% already three years prior to a crisis. Then, the growth rate decelerates and reaches negative values slightly after a crisis. Again, the real mortgage stock has developed in the same direction in Finland. Yet, the mortgage stock reacted stronger to both increases prior to crises and decreases towards and after crises in the crisis of 1991Q3. In Finland's 2008Q3 crisis, the development resembles average behavior except that the level is consistently somewhat higher.

Figure 2 presents household and private loans-to-GDP deviations from trend (or gaps) before, during and after a crisis. On average, household-loan gaps peak a year earlier than private-loan gaps. The average developments are otherwise rather similar, although prior to crises private-loan gaps widen more than they do for household loans. This is not surprising as the gap is calculated as the difference between the loans-to-GDP ratio and its trend, and the level of private loans must be higher as it includes both household and non-financial corporate loans. This motivates the use of gaps proportional to their trend, rather than absolute values. In Finland both types of gaps followed closely the average behaviour until two years prior to the 1991Q3 crisis, whereafter the trend deviations declined more rapidly. In the 2008Q3 crisis, the trend deviations have been clearly larger and Finland has not experienced such a rapid contraction as was the case in the 1991Q3 crisis.

The left panel of Figure 3 illustrates the annual growth rate of the loans-to-deposits ratio around crises. In terms of average growth rates, the figure shows a well-behaving cyclical pattern. Growth in the loans-to-deposits ratio peaks at 5% two years prior to a crisis, then decelerates to turn negative at the wake of the crisis and reach its trough after two years, whereafter a recovery commences. Patterns in both Finnish crises are in line with the average, except for stronger swings in the 1991Q3 crisis and a quicker recovery after the 2008Q3 crisis. The right panel of Figure 3 shows the annual growth rate of real GDP around crises. The average growth rate starts slowing down one year prior to a crisis, turns negative when a crisis occurs and reaches the trough one year after a crisis. Finland has roughly followed the average behaviour, although the contraction of real GDP has been clearly stronger in both crises.

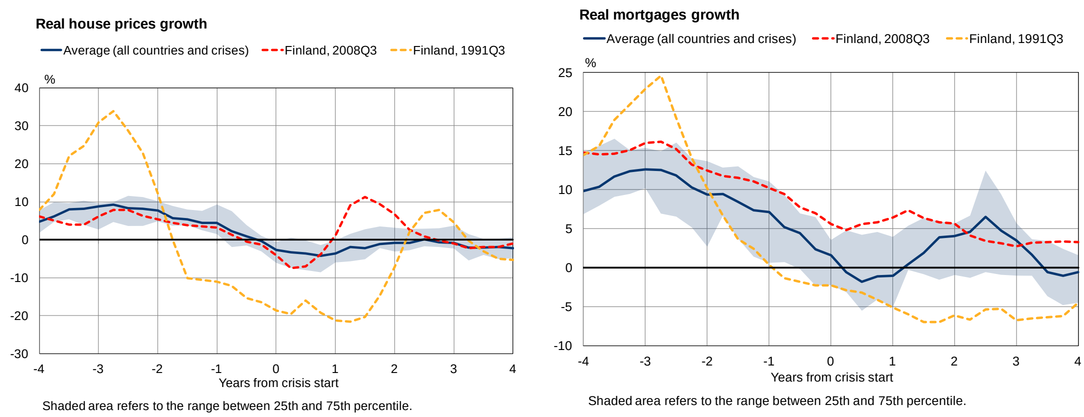

Figure 1: Real house price and mortgage growth around crises.

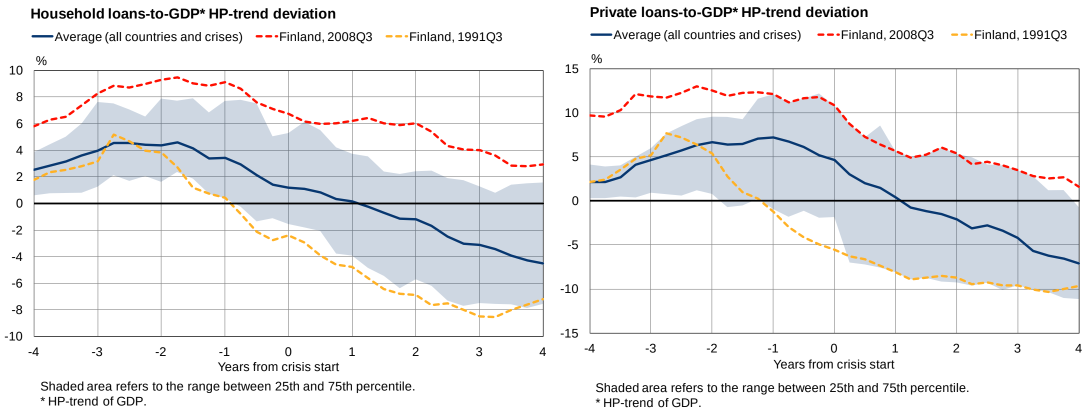

Figure 2: Household and private loan gaps around crises.

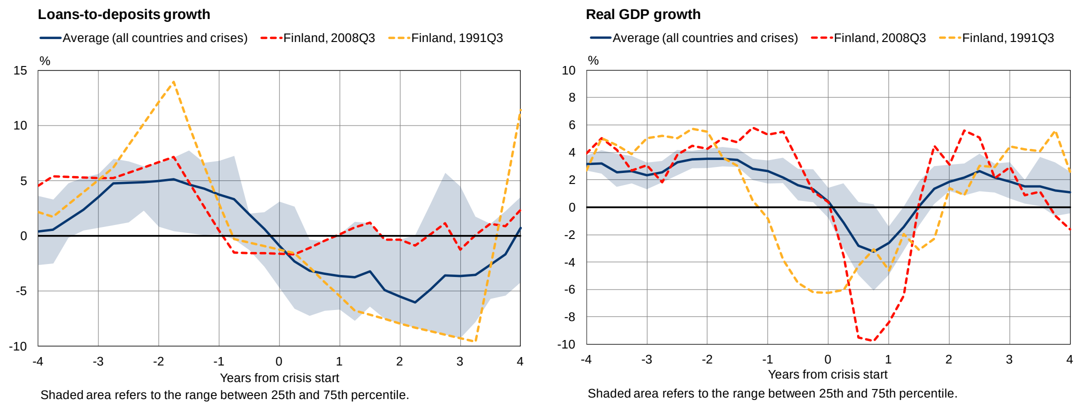

Figure 3: Loans-to-deposits and GDP growth around crises.

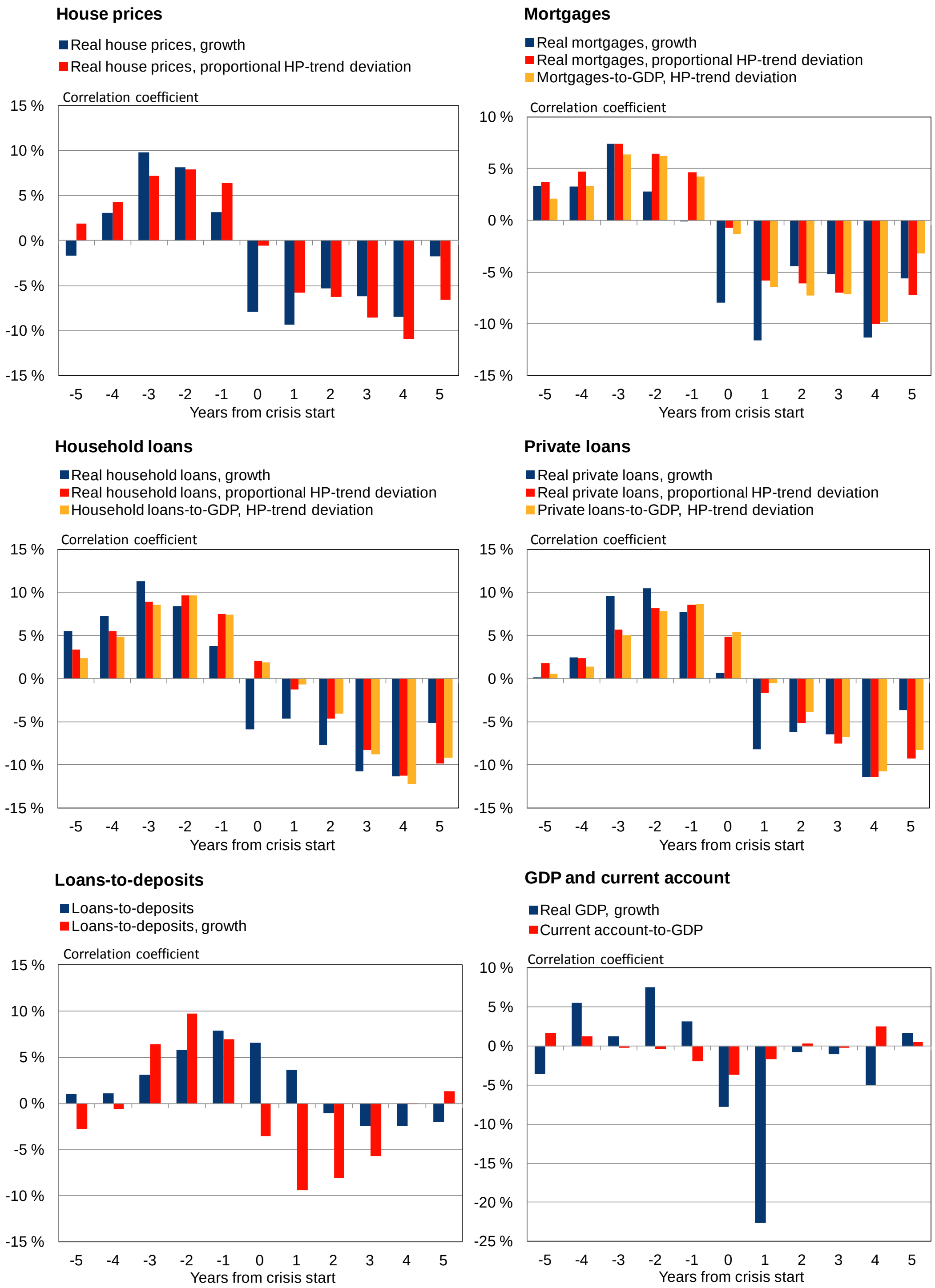

Figure 4: Cross correlations with the crisis dummy.

3.2. Cross correlations

Continuing with descriptive statistics, we investigate cross correlations between different lags of the indicators and the crisis dummy. Cross correlations is an elementary statistical method that allows studying the linear relationship between explanatory variables and a dependent crisis dummy variable. The plotted cross-correlation diagrams facilitate understanding the horizon with which an explanatory variable signals a crisis. We have calculated all correlations from four year lags to four year leads. The shown cross correlations in Figure 4 illustrate which lags might be most worthwhile to consider in further analysis. The cross correlations are computed on the full dataset, including the entire panel of countries.

Among house price indicators, the growth variable lagged by three years is most correlated with the crisis occurrences, whereas house price gaps relative (or proportional) to the trend lead by two years. While the growth rate shows stronger but more volatile correlations, the gap is more persistent, particularly with short horizons. The loan stock variables – mortgage, household and private – also show properties of leading indicators. Mortgage and household loan growth and gaps lead by three years, whereas growth in private loans leads by two years. Private and household loans are somewhat more correlated with the onset of a crisis than mortgages. Again, gaps for all loan stock variables are more persistent over different horizons.

The level of the loans-to-deposit ratio is rather correlated with the onset of a crisis, whereas the correlation of its growth rate peaks two years prior to the onset of a crisis. The largest correlations are found for a two-year lag of the growth variable, which generally exhibits a standard cyclical pattern by displaying negative correlation with the start of the crisis. Lagged macro variables – real GDP growth and current account to GDP – are not highly correlated with the onset of a crisis. Yet, GDP growth is a better leading indicator, with largest correlations two years prior to crises. The negative correlation of real GDP growth and the crisis dummy one year after a crisis illustrates the costs of a systemic banking crisis. While GDP growth is also negatively correlated during times of crisis, the impact on the real economy is at its highest one year after a crisis.

4. Assessing leading indicators of systemic banking crises

This section goes beyond visual inspection, by quantitatively assessing the performance of the above discussed leading indicators. First, we test the indicators using the univariate signal extraction approach, which provides means for both ranking indicators and assessing optimal horizons. Second, we turn to logit analysis in order to analyze leading indicators from a multivariate perspective.

4.1. Univariate signal extraction

We begin assessing leading indicators with the signal extraction approach, which univariately tests the noise-to-signal ratio for each indicator. The analysis in this section concerns various transformations of the following variables: house prices, mortgages, household and private loans, loans to deposits, GDP growth, inflation and current account deficits. Based upon these measures, we test a large number of transformations, including inflation adjustments, shares of GDP, growth rates, and absolute and relative trend deviations. Table 4 presents the signal extraction results for selected indicators for a lead horizon of 4 to 15 quarters prior to a crisis. The first column shows the category of the indicator and the second the name of the indicator. The third column reports the optimal threshold value of the particular indicator. In each case, the indicator issues a warning signal whenever this threshold is exceeded. The fourth and the fifth columns display the ratio of type I (missed crises) and type II (false alarms) errors, respectively. The sixth column reports the proportion of true signals to all signals, and the seventh column shows the proportion of crises that are predicted by the indicator. Finally, the last three columns show three aggregate measures: the noise-to-signal measure and the Usefulness with $\mu = 0.7$ and $\mu = 0.8$. As $\mu > 0.5$, we assume a policymaker to be more concerned about missing a crisis, and show results for two different parameter values.

By the noise-to-signal measure, the OECD loans-to-deposits growth indicator seems to be the strongest with a lead horizon of 4 to 15 quarters. Its value of 11% for the noise-to-signal measure is explained by its low type II error measure, and thus it does not issue many false alarms. 17% of all the times the indicator has reached the 7% threshold value, a crisis has followed within one to four

Table 4: Signal analysis results with a 4–15 quarter lead time.

Category	Indicator	Threshold (%)	Type I errors (%)	Type II errors (%)	Predicted crises (%)	Noise-to-signal (%)	$U_r(\mu$=0.7) (%)	$U_r(\mu$=0.8) (%)
House prices	**Real house prices, growth**	9	31	16	69	**23**	49	63
	Real house prices, proportional HP-trend deviation	14	33	26	67	38	35	59
Mortgages	Real mortgages, growth	13	29	24	71	34	42	60
	Real mortgages, proportional HP-trend deviation	10	31	36	69	52	25	56
	Mortgages-to-GDP*, HP-trend deviation	0	8	65	92	71	12	52
	Real interest rate of mortgages	3	30	81	70	116	-30	39
Other loans	**Real household loans, growth**	10	25	17	75	**23**	54	64
	Real household loans, proportional HP-trend deviation	9	31	21	69	31	43	61
	Households loans-to-GDP*, HP-trend deviation	2	13	27	88	31	55	64
	Real private loans, growth	9	29	14	71	**19**	54	64
	Real private loans, proportional HP-trend deviation	9	31	18	69	**26**	47	62
	Private loans-to-GDP*, HP-trend deviation	3	31	29	69	42	34	58
Loans-to-deposits	OECD loans-to-deposits	122	33	26	67	39	35	58
	OECD loans-to-deposits, growth	7	33	7	67	**11**	58	65
	ECB loans-to-deposits	128	30	40	70	57	21	54
	ECB loans-to-deposits, growth	3	30	32	70	46	31	57
Macro	**Real GDP, growth**	4	24	17	77	**22**	56	65
	Inflation	2	12	64	88	72	10	51
	Current account deficit-to-GDP	-2	25	55	75	74	7	50

Noise-to-signal values less than 30 % bolded.

* HP-trend of GDP.

years. While loans tend to grow in concert with deposits, increases in the indicator is predominantly an effect of excessive growth in loans (rather than a decrease in deposits). For an example, see the assessment of deposits and loans in Finland in Figure 7. Generally, we find successful indicators in most categories. If we want to use house prices as an early warning indicator, we should be looking at the real house price growth instead of the relative trend deviation, as the noise-to-signal measure is substantially lower for the growth variable. The same is true for loans as well. The difference is more significant for real household loan growth, for which also the trend deviation gives noise-to-signal measures below 30%. A potential argument for using growth rates in our setting, in which we have long lead times and disregard late pre-crisis periods, is that trend deviations tend to reach lower peaks and signal somewhat later, despite being slightly more persistent. This can be confirmed by the cross correlations in Figure 4.

In the macro-variable category, real GDP growth is the only variable that should be looked at with this time horizon. Its noise-to-signal measure is 22%, which is third lowest of all indicators. It is a strong leading indicator: it has succeeded in 77% of all crises. This compensates the large number of false alarms, as its type II error ratio is a bit higher than other well-performing indicators. Nevertheless, rapid GDP growth might be interpreted as a sign of accumulating financial imbalances. The mortgage category does not provide any excellent early-warning indicators for this lead horizon, although real mortgage growth receives a noise-to-signal measure slightly above 30%. Real interest rate of mortgages (i.e. loan stock) has a noise-to-signal ratio above one, which is poorer than a random guess. Overall, comparing the $U_r(\mu)$ performance for the two preference parameter values 0.7 and 0.8, we can observe that indicators generally perform better for a policymaker that is more concerned about missing crises than giving false alarms. This results from the fact that the noise-to-signal minimization given that we call at least two-thirds of the crises implies a large μ value (or large costs for missing a crisis). Moreover, except for the real intereste rate of mortgages, positive $U_r(\mu)$ values show that all other indicators signal better than the best guess of a policymaker.

Delaying the time window by one year to 8 to 19 quarters prior to a crisis declines the average noise-to-signal values slightly. The results are reported in Table A.1 in Appendix A. The average drops from 43% to 42%. Growth variables of real house prices, real household loans, real private loans and OECD loans to deposits are good indicators again. Yet, real GDP growth does not issue as good signals with this more distant window. It is also worth to note that now the mortgages-to-GDP gap seems to be among the best indicators. Good indicators for the closer time horizon seem to be good indicators for the more distant window too. The only exception is real GDP growth. Some of the signals get

Table 5: Crises signaled per indicator.

Indicator \ Crisis	Austria 2008Q3	Belgium 2008Q3	Germany 2008Q3	Spain 2008Q3	Finland 1991Q3	Finland 2008Q3	France 1994Q1	France 2008Q3	Italy 1990Q1	Italy 2008Q3	Nether-lands 2008Q3	Denmark 1987Q1	Denmark 2008Q3	Great Britain 1984Q1	Great Britain 1990Q3	Great Britain 2007Q3	Sweden 1991Q3	Sweden 2008Q3
Real house prices, growth		x		x	x	x		x	x			x	x		x	x	x	x
Real house prices, proportional HP-trend deviation		x		x	x	x		x	x			x	x		x	x		x
Real mortgages, growth	x	x		x	x	x		x	x	x								x
Real mortgages, proportional HP-trend deviation	x	x		x	x	x		x	x	x	x							
Mortgages-to-GDP*, HP-trend deviation	x	x		x	x	x	x	x	x	x	x		x			x		x
Real interest rate of mortgages		x	x		x	x	x	x		x	x							
Real household loans, growth	x			x	x	x			x	x	x	x	x	x	x	x	x	x
Real household loans, proportional HP-trend deviation		x		x	x	x		x	x	x			x		x	x		x
Households loans-to-GDP*, HP-trend deviation	x	x		x	x	x		x	x	x	x		x		x	x	x	x
Real private loans, growth	x			x	x	x		x	x	x		x	x	x	x		x	x
Real private loans, proportional HP-trend deviation				x	x	x		x	x	x		x	x		x	x	x	x
Private loans-to-GDP*, HP-trend deviation				x	x	x	x	x	x	x		x	x		x		x	x
OECD loans-to-deposits	x			x	x	x	x			x	x		x				x	x
OECD loans-to-deposits, growth		x		x	x	x			x		x	x	x				x	x
ECB loans-to-deposits				x		x		x		x	x					x		x
ECB loans-to-deposits, growth		x		x		x		x		x	x							x
Real GDP, growth	x		x	x	x	x			x		x	x	x		x	x	x	x
Inflation	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	
Current account deficit-to-GDP	x	x		x	x	x		x		x			x			x		

x = "Indicator has predicted the crisis from one up to four years time horizon"

noisier when moving to the more distant window (real house prices growth, real private loans growth, real private loans proportional trend deviation and OECD loans to deposits). Real household loans growth gives clearer signals with the more distant window. The household loans-to-GDP ratio is a good indicator for a delayed horizon. On average, the ratio of correctly called crises rises slightly for the delayed window. Type I errors decrease too with the delayed window: there are less missed crises. Nevertheless, the best indicators for the closer horizon are far better than the best for the delayed window. Loans-to-deposits growth works well for the 4 to 15 quarters time horizon, whereas its noise-to-signal ratio more than doubles when moving to 8 to 19 quarters horizon. Still, growth rates tend to be a prominent transformation in relation to trend deviations.

As is shown in Tables A.2 and A.3 in Appendix A, shortening the time horizon makes signals weaker. Using a time window of 4 to 11 quarters prior to a crisis, the noise-to-signal average is 52%. OECD loans-to-deposits growth is again a very good indicator with a noise-to-signal ratio of 14%. In addition, real household loans growth, real private loans growth and real private loans proportional trend deviation are again good indicators. Real GDP growth has also a good noise-to-signal ratio. Generally, the results point to prominence of credit-based indicators, as well as to growth rates performing well, despite previous observations of earlier signals vis-à-vis trend deviations. Further shortening reinforces the negative effect in signaling ability. If the window is only one year long – starting one year after the signal and ending two years after the signal – only loans-to-deposits growth has a noise-to-signal ratio below 30%. Again, we can observe prominence of credit-based indicators and growth rates as a transformation. Generally, when assessing the $U_r(\mu)$ measures for different lead times, indicators do not anymore consistently perform better with larger μ values. For instance, for a 4–7 quarter lead time, most loan stock variables exhibit a large share of type I errors, and hence perform better with $\mu = 0.7$.

An interesting aspect to assess is how often and which signals are given together. For most of the crises, many indicators have signaled underlying vulnerabilities and risks early on. Table 5 lists the indicators that have signaled in each given crisis using a three year time window (4–15 quarters prior to a crisis).[1] One can easily observe that signals of indicators are correlated for most of the crises, particularly growth in loan stocks combined with house price growth and growth in loans-to-deposits ratios.

4.2. Multivariate logit analysis

The second approach to assessing leading indicators makes use of multivariate logit analysis, and thus simultaneously accounts for several risk indicators. The estimation results for the panel regression models are presented in Table 6. The first column reports explanatory variables, which all are lagged by three years. The five next columns show the estimated coefficients for the explanatory variables included in the particular model. Asterisks illustrate the statistical significance of the coefficient, and estimated standard errors of the coefficients are shown in parenthesis below each corresponding coefficient. All models are estimated using the country-specific fixed effects method.

Real house price growth is significant in all models but the first. The coefficient is always positive, and thus a rise in real house prices increases the probability of a systemic banking crisis within three years. Models (2)–(4) include a single loan stock growth variable, in addition to real house price growth, real GDP growth and loans-to-deposits growth. Mortgage stock growth, private loan stock growth and household loan stock growth are all statistically significant and positive, whereas loans-to-deposits growth is insignificant when paired with private sector loan stock growth in model (4). In model (5), there is an interaction term, which takes the value 1 when both real house price growth and mortgage growth exceed their threshold values (9% and 13%, respectively) defined in signal extraction with 4 to 15 quarters time window, and otherwise 0. This coefficient is not statistically significant, while both individual variables are significant.

Models (6)–(10) study the impact of trend deviation of loan stock variables to the crisis probability. Like their growth counterparts, they are almost always statistically significant. The only exception is mortgages-to-GDP gap in model (10). It turns out to be statistically not different from zero when the current account-to-GDP ratio is included. Models (7)–(10) include inflation, which is not significant in any of the models, as is neither the current account-to-GDP ratio. The real interest rate of mortgages has a statistically significant negative estimate in model (10). That is, when money is cheap, the vulnerability to a crisis within three years increases.

Estimations are done also for three different time horizons: four years, two years and one year. These estimation results are reported in Tables B.1–3 in Appendix B. Generally, three-year horizon seems to yield the best results. With a four-year horizon, real house prices do not seem to have explanatory power. In contrast, loan stock variables perform well as indicators with a longer lead time, and there seems not to be a large difference between growth and trend deviations.

With a shorter horizon, trend deviations seem to be better explanatory variables. In models with two-year horizons, loan stock variables are statistically significant only if measured as trend deviations. House price variables are not statistically significant in these models. Neither is loans-to-deposits growth if the loan stock trend deviation variable is included in a model. Real GDP growth, on the other hand, improve model performance. Further shortening the horizon to one year yields similar results. Trend deviations of loan stock variables are statistically significant. Moreover, real house price growth is again significant, yet with a negative sign. Consequently, a house price decline is an indicator of an impending crisis.

To sum up the results in Table 6, they suggested that real house price growth is a good explanatory variable of the occurrence of a crises within three years. Including a loan stock variable and real GDP variable into the model further improves it, whereas the difference between growth and trend deviation variables is small. Moreover, as most of the cross correlations suggested, crises are best identified with a horizon of three years.

[1] It is worth to note that signaling a crisis requires only one breach of the threshold within the three year time window and that the level of thresholds vary among indicators (e.g., current account deficits have a negative threshold).

Table 6: Logit analysis results with a three-year lead time.

Explanatory variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Real house prices, growth	.037	.113**	.104*	.116**	.136**
	(.031)	(.055)	(.060)	(.046)	(.068)
Real mortgages, growth	.152***	.127**			.136**
	(.057)	(.059)			(.062)
Real household loans, growth			.401***		
			(.114)		
Real private loans, growth				.239***	
				(.082)	
OECD loans to deposits, growth		.276***	.210**	.070	.272**
		(.106)	(.095)	(.072)	(.107)
Real GDP, growth		-.464*	-.646**	-.420*	-.447*
		(.261)	(.268)	(.241)	(.261)
Interaction of real house prices and real mortgages					-.742
					(1.340)
N	593	528	524	618	528
Countries	11	10	10	10	10
Country Fixed Effects	YES	YES	YES	YES	YES
Prob > chi2	0.0045	.0006	0.0000	0.0000	0.0014
Explanatory variable	**Model (6)**	**Model (7)**	**Model (8)**	**Model (9)**	**Model (10)**
Real house prices, growth	.094*	.175**	.187**	.207**	.294**
	(.052)	(.085)	(.093)	(.088)	(.137)
Mortgages to GDP****, HP-trend deviation	.593***	.700***			.453
	(.171)	(.267)			(.399)
Households loans to GDP****, HP-trend deviation			1.190***		
			(.403)		
Private loans to GDP****, HP-trend deviation				.359***	
				(.116)	
OECD loans to deposits, growth		.609***	.546***	.482**	.532**
		(.220)	(.204)	(.186)	(.238)
Real GDP, growth		-1.084**	-.980*	-.983**	-.628
		(.519)	(.506)	(.490)	(.655)
Real interest rate of mortgages		-.363			-1.556*
		(.249)			(.829)
Current account to GDP			.139	.064	-.219
			(.285)	(.221)	(.438)
Inflation		.432	.774	-.026	-.143
		(.355)	(.644)	(.468)	(.669)
N	544	489	400	471	376
Countries	10	8	10	10	8
Country Fixed Effects	YES	YES	YES	YES	YES
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000

Dependent variable is the crisis dummy. Standard errors are reported in parenthesis below the estimated coefficient.
* Significant at 10 % level.
** Significant at 5 % level.
*** Significant at 1 % level.
**** HP trend of GDP.

Figure 5 displays estimated probabilities (in-sample) for three different model specifications – models (2)–(4) with three-year horizons – for two different countries: Spain and Finland. The time series represent the cumulative probability of crisis occurring within the next three years. The figure shows that the Spanish 2008 financial crisis would have been called several years beforehand, whereas cumulative probabilities stayed relatively low before 2005. After 2005, probabilities rose above or very close to 40%. The model would also have called the Finnish 1991 crisis three years before it started. Models (3) and (4) predicted it with an estimated probability of more than 60%. After the crisis probabilities fell close to zero and stayed there until 2009, which indicates that the 2008 crisis was missed by these models. This can be argued to be due to the stable financial conditions in Finland prior to the crisis, and the impact of global risks and triggers. For Finland, the indicators started signaling only after the crisis had already started. An interpretation of the estimated probabilities of the logit models indicates that neither the Spanish nor Finnish economies exhibit internal imbalances that expose them to a new crisis within the three following years.

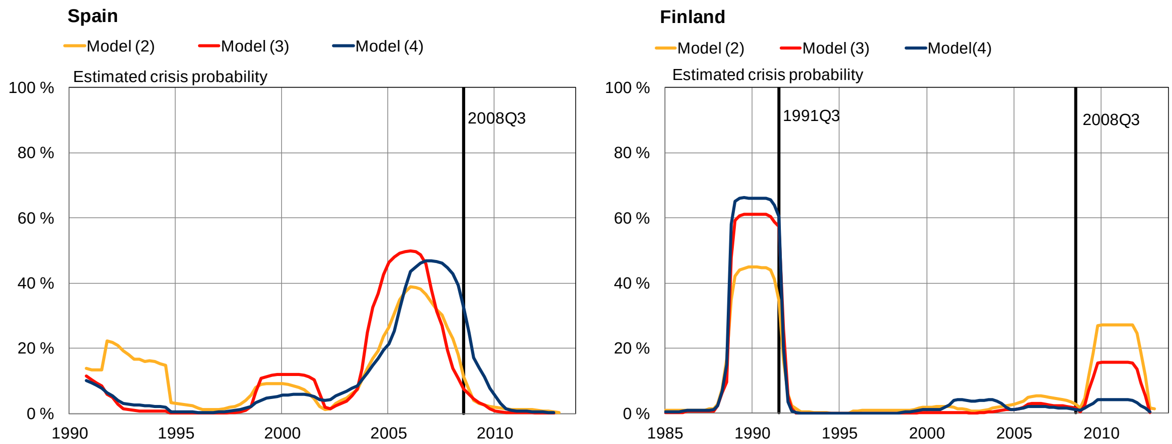

Figure 5: Probability plots for Spain and Finland.

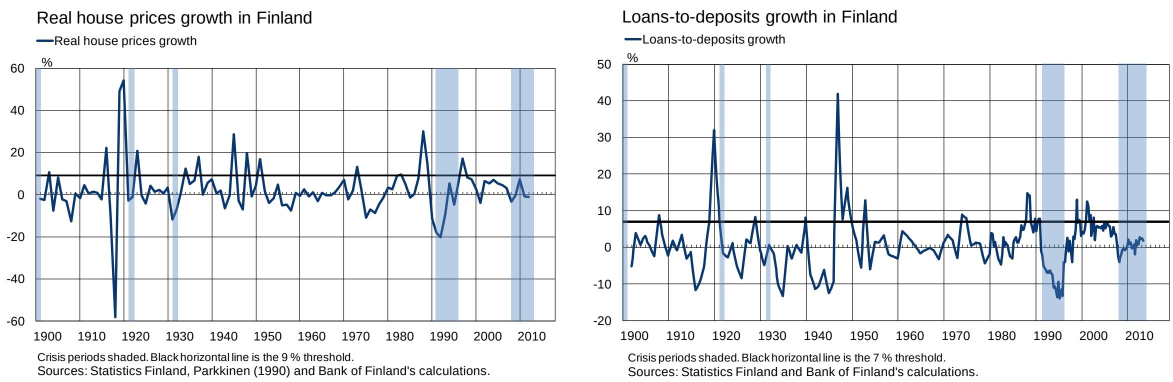

Figure 6: House prices and loans to deposits in Finland.

5. Historical explorations in Finland

This section taps into unique, long time series of the Finnish economy. We examine the behavior of a subset of the above discussed indicators for Finland from 1900 onwards. Most of the data are annual, which have been interpolated to quarterly, whereas the data from 1980 onwards is quarterly. The data are from Statistics Finland, Bank of Finland and Parkkinen (1990). Crisis periods are defined annually and have before 1980 been collected from Reinhart and Rogoff (2009) and Herrala (1999). The crisis periods of Finland since 1900 are: 1900, 1921, 1931, 1991–95 and 2008 onwards. Although Herrala (1999) defines also 1939 as a crisis period, it has been omitted from this study as the World War II can be seen as a key influence leading to the crisis and as it is neither defined as a crisis by Reinhart and Rogoff (2009). The threshold values are from the signal extraction exercise with a horizon of 4–15 quarters, as presented in Section 4.1. In Figures 6 and 7, we show time series plots of indicators, where shaded areas refer to occurred crises and the horizontal line to threshold values.

The left panel in Figure 6 presents the annual growth rate of real house prices in Finland. The threshold value is a growth rate of 9%. As can be seen from the figure, house prices have issued a signal at least one year and at most four years before the crises of 1921 and 1991, of which the former exhibits much larger variation, whereas the indicator missed the crises of 1931 and 2008. It issues a number of false alarms, particularly before and after World War II. The right panel in Figure 6 shows the growth rate of the loans-to-deposits ratio for Finland. The threshold value is an annual growth rate of 7%. For Finland, the loans-to-deposits ratio has performed significantly better than house prices,

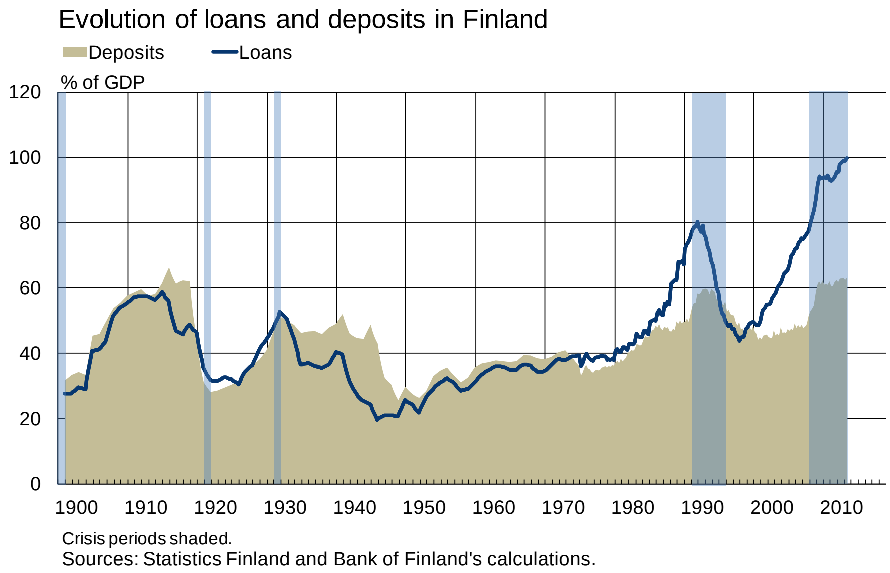

Figure 7: The evolution of loans and deposits in Finland.

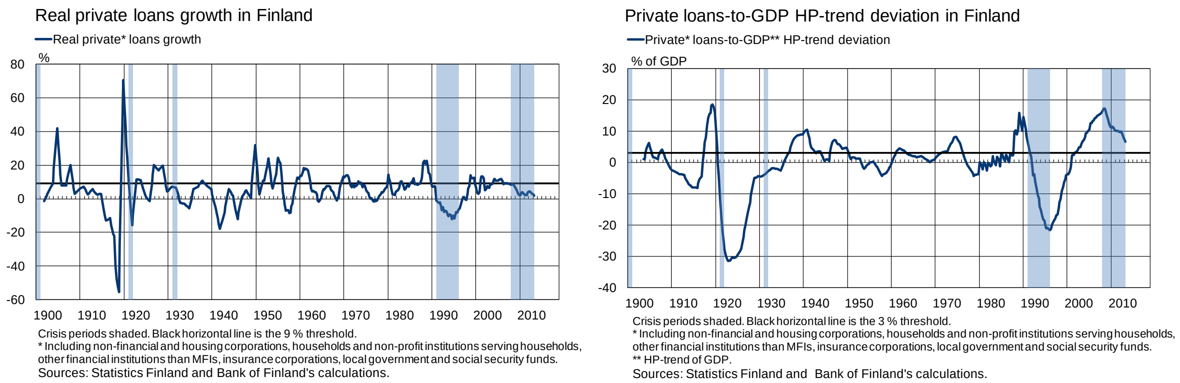

Figure 8: Private loans in Finland.

as it has breached the threshold at least one year and at most four years before every crisis. It also issues fewer false alarms. Altogether, loans-to-deposits growth seems to be the best leading indicator for Finland, as it was also for the entire panel of EU countries. To illustrate whether increases in the indicator descend from the nominator or the denominator, we show the evolution of loans and deposits in Finland in Figure 7. The figure shows, as we also find for the entire panel, that they co-move and that signals predominantly descend from increases in loans rather than decreases in deposits.

The left panel in Figure 8 depicts the annual growth rate of real private loans in Finland.[2] The threshold value is a growth rate of 9%. Also this indicator issues a correct signal before every crisis. Nevertheless, it issues more false alarms than loans-to-deposits growth. As real house prices, real private loans display some extraordinary behavior before the 1921 crisis. First they halve and then

[2]Due to data availability, the definition of private sector slightly differs from previous sections as it also includes other financial institutions than MFIs, insurance corporations, local government and social security funds. These entities, however, carry very little debt in relation to households and non-financial corporations. Thus, it only marginally affects the level of private loans.

they double. This behavior is most likely explained by variation in price levels. In 1918 inflation accelerates to 242% in conjunction with the Finnish Civil War. The exceptionally high inflation rate pushes the real value of houses and private loans down, although nominal values continue to grow. In 1919, however, prices deflate by 11%, which combined with fast nominal growth pushes their real values up again.

Finally, the right panel in Figure 8 presents the HP trend deviation of private loans-to-GDP ratio for Finland. The threshold value is 3% of GDP deviation from its HP trend. The indicator has performed fairly well as it has issued a correct signal before every crisis, except for the crisis of 1931. In addition, it has clearly breached the threshold value as the trend deviation has been above 10% of GDP before all correctly signaled crises. Yet, the HP trend deviation of private loans-to-GDP ratio also issues false alarms, yet only few.

6. Conclusion

In this paper, we have investigated leading indicators of systemic banking crises for a panel of 11 EU countries. We make use of univariate signal extraction and multivariate logit analysis to assess the usefulness of a large set of macro-financial indicators, their various transformations and optimal lead horizons. We have shown that the most successful indicators are the growth rates of loans-to-deposits and house prices. The findings on the usefulness of loans-to-deposits ratios are new compared to previous literature. In addition, the growth rate and trend deviation of mortgages, household loans and private loans are also useful leading indicators. All these indicators show best performance with a lead time of a three-year horizon, but generally perform well with up to a four year lead horizon. Besides real growth of GDP, we did not find much evidence macroeconomic variables being good leading indicators. Inflation and current account deficits do not perform well as leading indicators of crises. Likewise, we find little evidence of real interest rates as good leading indicators. Overall, we find that differences between absolute and relative trend deviations are only minor and that growth rates tend to be the most prominent transformation. If trend deviations of ratios are used, we propose to detrend GDP as a denominator to support persistence with respect to short-term variation in the real economy. This provides useful input to policymakers in control of macroprudential tools, such as countercyclical capital buffers, loan-to-value caps and risk weights. Despite long activation times, indicators with a three-year lead time can be seen early enough to support macroprudential tools.

In the paper, we have also investigated differences in leading indicators depending on lead times and transformations. The signal extraction method shows that indicators perform slightly better with a lead-time horizon of 4 to 15 quarters, than with the horizon of the same length starting one year later. Shortening the horizon impairs the quality of the signals. Moreover, we find little difference in signaling quality for trend deviation and growth rate transformations of the variables.

The results with multivariate logit analysis support the findings in the signal extraction analysis. With a three year lead time, statistical significance does not depend on whether we use trend deviations or growth rates. For the shorter lead time window, trend deviations of the loan stock variables are better explanatory variables than growth rates. Interestingly, the sign of house price growth reverts to negative when the time horizon is shortened, which indicates that rising house prices imply an impending crisis within three years, whereas one year prior to a crisis house prices have already started to depreciate. Loan stock variables and house price growth have been found as useful indicators also in the previous literature. The finding that real GDP growth is also a good indicator is in line with the literature. Yet, we show that it is not as good as the above mentioned variables, particularly in logit analysis. In contrast to some of the previous studies, we did not find any evidence on the usefulness of the current account deficit as a leading indicator. Likewise, we contrast previous studies by finding the growth rate of the loans-to-deposits ratio to be a useful leading indicator.

When turning to the Finnish case, the indicators that have worked for the whole sample also seem to work for the Finnish economy, at least when judged qualitatively. While the growth of the loans-to-deposits ratio was the best-in-class indicator by signaling within three years prior to each Finnish crisis, the growth rates of real house prices and real private loans and the private loans-to-GDP gap also signaled most of the crises since the beginning of the 20th century.

While this paper has studied leading indicators from an explanatory viewpoint, it does not attempt to provide evidence on the predictability of systemic banking crises overall and the ongoing crisis in particular. To answer this question, one should test for robustness related to estimating and evaluating early-warning models for real-time use, which inter alia includes objective in-sample variable selection and out-of-sample evaluation, and accounting for publication lags and data revisions. Future research should also go beyond banking crises by looking into indicators of different crisis types and spillovers among them, such as using the event database by Babecky et al. (2013) on banking, debt and currency crises.

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Appendix A. Signal extraction and alternative lead time

Table A.1: Signal analysis results with a 8–19 quarter lead time.

Category	Indicator	Threshold (%)	Type I errors (%)	Type II errors (%)	Predicted crises (%)	Noise-to-signal (%)	$U_r(\mu=0.7)$ (%)	$U_r(\mu=0.8)$ (%)
House prices	**Real house prices, growth**	8	29	20	8	**28**	47	62
	Real house prices, proportional HP-trend deviation	7	15	46	4	54	28	56
Mortgages	Real mortgages, growth	13	23	23	6	30	48	62
	Real mortgages, proportional HP-trend deviation	16	33	22	6	32	40	60
	Mortgages-to-GDP*, HP-trend deviation	3	33	14	9	**21**	49	63
	Real interest rate of mortgages	1	0	98	2	98	-21	42
Other loans	**Real household loans, growth**	10	25	15	12	**19**	57	65
	Real household loans, proportional HP-trend deviation	8	31	22	8	32	42	60
	Households loans-to-GDP*, HP-trend deviation	2	19	24	9	30	52	63
	Real private loans, growth	7	12	24	8	**27**	59	66
	Real private loans, proportional HP-trend deviation	8	31	20	8	**29**	45	61
	Private loans-to-GDP*, HP-trend deviation	2	19	34	6	42	40	60
Loans-to-deposits	OECD loans-to-deposits	118	33	31	5	46	29	57
	OECD loans-to-deposits, growth	4	23	17	8	**22**	56	65
	ECB loans-to-deposits	123	10	51	7	57	27	56
	ECB loans-to-deposits, growth	4	30	24	12	35	40	60
Macro	Real GDP, growth	3	6	39	5	41	47	62
	Inflation	2	18	64	3	78	4	49
	Current account deficit-to-GDP	-2	25	55	3	73	7	50

Noise-to-signal values less than 30 % bolded.

* HP-trend of GDP.

Table A.2: Signal analysis results with a 4–11 quarter lead time.

Category	Indicator	Threshold (%)	Type I errors (%)	Type II errors (%)	Predicted crises (%)	Noise-to-signal (%)	$U_r(\mu=0.7)$ (%)	$U_r(\mu=0.8)$ (%)
House prices	Real house prices, growth	7	29	30	71	43	33	58
	Real house prices, proportional HP-trend deviation	7	29	51	71	72	8	50
Mortgages	Real mortgages, growth	12	29	29	71	41	35	59
	Real mortgages, proportional HP-trend deviation	4	29	50	71	70	10	51
	Mortgages-to-GDP*, HP-trend deviation	0	21	67	79	85	-4	47
	Real interest rate of mortgages	3	30	78	70	111	-26	40
Other loans	**Real household loans, growth**	10	24	20	76	**26**	52	63
	Real household loans, proportional HP-trend deviation	9	31	23	69	**34**	40	60
	Households loans-to-GDP*, HP-trend deviation	2	13	30	88	**34**	51	63
	Real private loans, growth	9	29	15	71	**22**	52	63
	Real private loans, proportional HP-trend deviation	9	29	19	71	**26**	48	62
	Private loans-to-GDP*, HP-trend deviation	2	29	38	71	53	24	55
Loans-to-deposits	OECD loans-to-deposits	122	33	27	67	40	34	58
	OECD loans-to-deposits, growth	6	27	10	73	**14**	61	66
	ECB loans-to-deposits	128	30	42	70	60	18	53
	ECB loans-to-deposits, growth	2	30	38	70	55	23	55
Macro	**Real GDP, growth**	4	33	17	67	**26**	46	62
	Inflation	2	22	63	78	81	0	48
	Current account deficit-to-GDP	-3	25	66	75	88	-6	46

Noise-to-signal values less than 40 % bolded.

* HP-trend of GDP.

Table A.3: Signal analysis results with a 4–7 quarter lead time.

Category	Indicator	Threshold (%)	Type I errors (%)	Type II errors (%)	Predicted crises (%)	Noise-to-signal (%)	U_r (μ=0.7) (%)	U_r (μ=0.8) (%)
House prices	Real house prices, growth	4	24	53	76	69	12	14
	Real house prices, proportional HP-trend deviation	6	29	55	71	78	3	4
Mortgages	Real mortgages, growth	6	21	61	79	78	3	9
	Real mortgages, proportional HP-trend deviation	4	29	51	71	71	9	9
	Mortgages-to-GDP*, HP-trend deviation	0	21	68	79	86	-5	2
	Real interest rate of mortgages	3	30	75	70	107	-22	-17
Other loans	Real household loans, growth	7	29	45	71	63	16	14
	Real household loans, proportional HP-trend deviation	9	31	26	69	**37**	37	31
	Households loans-to-GDP*, HP-trend deviation	2	19	33	81	**41**	40	41
	Real private loans, growth	7	33	29	67	**44**	31	24
	Real private loans, proportional HP-trend deviation	7	29	30	71	**43**	33	29
	Private loans-to-GDP*, HP-trend deviation	2	29	39	71	56	22	20
Loans-to-deposits	**OECD loans-to-deposits**	122	33	28	67	**42**	32	25
	OECD loans-to-deposits, growth	5	33	15	67	**22**	48	39
	ECB loans-to-deposits	122	20	62	80	77	4	11
	ECB loans-to-deposits, growth	-1	20	74	80	93	-11	-2
Macro	Real GDP, growth	3	22	41	78	53	27	28
	Inflation	1	0	90	100	90	-10	10
	Current account deficit-to-GDP	-3	25	65	75	87	-5	0

Noise-to-signal values less than 50 % bolded.

* HP-trend of GDP.

Appendix B. Logit analysis with alternative lead time

Table B.1: Logit analysis results with a four-year lead time.

Explanatory variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Real house prices, growth	.037	.113**	.104*	.116**	.136**
	(.031)	(.055)	(.060)	(.046)	(.068)
Real mortgages, growth	.152***	.127**			.136**
	(.057)	(.059)			(.062)
Real household loans, growth			.401***		
			(.114)		
Real private loans, growth				.239***	
				(.082)	
OECD loans to deposits, growth		.276***	.210**	.070	.272**
		(.106)	(.095)	(.072)	(.107)
Real GDP, growth		-.464*	-.646**	-.420*	-.447*
		(.261)	(.268)	(.241)	(.261)
Interaction of real house prices and real mortgages					-.742
					(1.340)
N	593	528	524	618	528
Countries	11	10	10	10	10
Country Fixed Effects	YES	YES	YES	YES	YES
Prob > chi2	0.0045	.0006	0.0000	0.0000	0.0014
Explanatory variable	**Model (6)**	**Model (7)**	**Model (8)**	**Model (9)**	**Model (10)**
Real house prices, growth	.094*	.175**	.187**	.207**	.294**
	(.052)	(.085)	(.093)	(.088)	(.137)
Mortgages to GDP****, HP-trend deviation	.593***	.700***			.453
	(.171)	(.267)			(.399)
Households loans to GDP****, HP-trend deviation			1.190***		
			(.403)		
Private loans to GDP****, HP-trend deviation				.359***	
				(.116)	
OECD loans to deposits, growth		.609***	.546***	.482**	.532**
		(.220)	(.204)	(.186)	(.238)
Real GDP, growth		-1.084**	-.980*	-.983**	-.628
		(.519)	(.506)	(.490)	(.655)
Real interest rate of mortgages		-.363			-1.556*
		(.249)			(.829)
Current account to GDP			.139	.064	-.219
			(.285)	(.221)	(.438)
Inflation		.432	.774	-.026	-.143
		(.355)	(.644)	(.468)	(.669)
N	544	489	400	471	376
Countries	10	8	10	10	8
Country Fixed Effects	YES	YES	YES	YES	YES
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000

Dependent variable is the crisis dummy. Standard errors are reported in parenthesis below the estimated coefficient.

* Significant at 10 % level.

** Significant at 5 % level.

*** Significant at 1 % level.

**** HP trend of GDP.

Table B.2: Logit analysis results with a two-year lead time.

Explanatory variable	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**
Real house prices, growth	.034	.009	.008	-.007	.037
	(.033)	(.054)	(.059)	(.048)	(.062)
Real mortgages, growth	.005	.011			.025
	(.055)	(.058)			(.059)
Real household loans, growth			.098		
			(.090)		
Real private loans, growth				.109	
				(.077)	
OECD loans to deposits, growth		.138*	.137**	.098	.140*
		(.079)	(.068)	(.065)	(.080)
Real GDP, growth		.559**	.533**	.471*	.561**
		(.280)	(.268)	(.244)	(.280)
Interaction of real house prices and real mortgages					-1.153
					(1.331)
N	637	568	564	658	568
Countries	11	10	10	10	10
Country Fixed Effects	YES	YES	YES	YES	YES
Prob > chi2	0.5843	0.0129	0.003	0.0028	0.0188
Explanatory variable	**Model (6)**	**Model (7)**	**Model (8)**	**Model (9)**	**Model (10)**
Real house prices, growth	.021	-.068	-.115	-.026	-.082
	(.056)	(.078)	(.105)	(.077)	(.103)
Mortgages to GDP****, HP-trend deviation	.367***	.493**			.429*
	(.126)	(.199)			(.256)
Households loans to GDP****, HP-trend deviation			.882***		
			(.289)		
Private loans to GDP****, HP-trend deviation				.319***	
				(.110)	
OECD loans to deposits, growth		.122	.190	.178	.136
		(.123)	(.147)	(.144)	(.137)
Real GDP, growth		.663*	.696	.431	.814*
		(.390)	(.446)	(.400)	(.461)
Real interest rate of mortgages		.111			-.192
		(.259)			(.482)
Current account to GDP			-.058	.025	-.175
			(.224)	(.203)	(.231)
Inflation		.190	.548	.208	.001
		(.289)	(.524)	(.401)	(.458)
N	588	517	428	495	400
Countries	11	8	10	10	8
Country Fixed Effects	YES	YES	YES	YES	YES
Prob > chi2	0.0044	0.003	0.0000	0.0000	0.0029

Dependent variable is the crisis dummy. Standard errors are reported in parenthesis below the estimated coefficient.

* Significant at 10 % level.

** Significant at 5 % level.

*** Significant at 1 % level.

**** HP trend of GDP.

Table B.3: Logit analysis results with a one-year lead time.

Explanatory variable	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**
Real house prices, growth	-.026	-.043	-.078	-.074	-.056
	(.046)	(.057)	(.071)	(.053)	(.058)
Real mortgages, growth	-.083	-.090			-.102
	(.063)	(.067)			(.070)
Real household loans, growth			-.037		
			(.091)		
Real private loans, growth				.092	
				(.063)	
OECD loans to deposits, growth		.107*	.094	.073	.111*
		(.065)	(.065)	(.063)	(.065)
Real GDP, growth		-.072	-.096	-.067	-.070
		(.219)	(.209)	(.200)	(.219)
Interaction of real house prices and real mortgages					1.273
					(1.259)
N	681	608	604	698	608
Countries	11	10	10	10	10
Country Fixed Effects	YES	YES	YES	YES	YES
Prob > chi2	0.2638	0.1949	0.2900	0.2568	0.2271
Explanatory variable	**Model (6)**	**Model (7)**	**Model (8)**	**Model (9)**	**Model (10)**
Real house prices, growth	-.100	-.238**	-.287**	-.200*	-.227*
	(.062)	(.118)	(.121)	(.103)	(.127)
Mortgages to GDP****, HP-trend deviation	.237**	.452***			.378*
	(.109)	(.172)			(.210)
Households loans to GDP****, HP-trend deviation			.510***		
			(.189)		
Private loans to GDP****, HP-trend deviation				.263***	
				(.090)	
OECD loans to deposits, growth		-.034	.085	.026	-.063
		(.106)	(.100)	(.093)	(.106)
Real GDP, growth		.138	-.004	.054	.362
		(.264)	(.316)	(.299)	(.319)
Real interest rate of mortgages		.377			.275
		(.245)			(.367)
Current account to GDP			-.106	-.130	-.186
			(.190)	(.166)	(.197)
Inflation		-.329	-.125	-.072	-.319
		(.324)	(.419)	(.357)	(.397)
N	632	545	456	519	424
Countries	11	8	10	10	8
Country Fixed Effects	YES	YES	YES	YES	YES
Prob > chi2	0.0469	0.0632	0.001	0.0008	0.1156

Dependent variable is the crisis dummy. Standard errors are reported in parenthesis below the estimated coefficient.

* Significant at 10 % level.

** Significant at 5 % level.

*** Significant at 1 % level.

**** HP trend of GDP.