FI analysis

Finansinspektionen's vulnerability indicators

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Summary

The financial system has a number of inherent vulnerabilities. These vulnerabilities in themselves need not entail a threat to financial stability, but together with a trigger they could lead to financial or macroeconomic instability. Triggers are difficult to predict, as they often occur suddenly and can be initiated by a large number of conceivable events. Moreover, Finansinspektionen (FI) seldom has the opportunity to prevent or alleviate either the trigger itself or its scope. On the other hand, it is possible to follow the build-up of vulnerabilities, which usually takes place over a longer period of time. Unlike triggers, it is often also easier for FI and other authorities to take measures to deal with vulnerabilities. FI therefore aims mainly to identify and reduce the vulnerabilities in the financial system.

FI regularly monitors the vulnerabilities in the financial system. Now FI is taking this a step further by creating a categorization for grouping and studying indicators of vulnerability. A systematic review of indicators helps to identify and follow vulnerabilities, which makes it easier to understand the risks of financial and macroeconomic instability. This information is summarised into a "heat map". The indicator analysis presented here is intended as a complement to traditional expert judgements – the indicators are primarily used as an input to the assessment work.

The vulnerability indicators are grouped according to sector and vulnerability category. This grouping gives an overall picture from the indicators in each sector and category. In the article we focus on the banking and household sectors. The vulnerability categories used are liquidity, solvency and exposures. For each indicator thresholds are estimated that when exceeded signal elevated or high vulnerability.

Currently, most indicators show low vulnerability. The exceptions for the household sector are the credit gap and housing prices, which show elevated or high vulnerability. The exceptions for the banking sector are the credit gap, some liquidity indicators and concentration measures, which also show elevated or high vulnerability.

Finansinspektionen
08-787 80 00
finansinspektionen@fi.se

www.fi.se

Ref.: 15-15980

Introduction

The financial system has a number of inherent vulnerabilities. These vulnerabilities need not in themselves entail a threat to financial stability. Additionally, a trigger is required to initiate an instability scenario. External triggers arise suddenly and are thus difficult to predict. Moreover, Finansinspektionen (FI) seldom has the tools necessary to prevent or alleviate either the trigger itself or its scope. On the other hand, the build-up of vulnerabilities is easier to monitor and easier for both FI and other authorities to address through the implementation of measures. FI's work on financial stability is therefore mainly aimed at identifying and reducing vulnerabilities in the system.

FI regularly monitors the vulnerabilities in the financial system. FI is now taking this a step further by creating a categorization for grouping and studying indicators of vulnerability. A systematic review of indicators helps to identify and follow vulnerabilities, which makes it easier to understand the risks of financial or macroeconomic instability. The indicator analysis presented here is intended as a complement to traditional expert judgements – the indicators are primarily used as a complement to further analysis.[1]

This FI Analysis describes FI's analysis of indicators, where indicators are used to study the degree of vulnerability in the different parts of the financial system. The report is intended as a first analysis and further reports will be made as new sectors are added. FI's categorization is similar in many ways to those used by other organisations – such as the European Systemic Risk Board (ESRB), the European Central Bank (ECB) and the Bank of Canada (BoC).[2] FI follows to a large degree ESRB's method for grouping the indicators according to financial sectors and vulnerability categories.

The indicators used are selected because they already comprise an important part of FI's monitoring of the financial system or because studies have found that the indicators are informative. Next, we determine thresholds for each indicator, which generate a colour signal when passed. The signals are summarised by means of a heat map.[3]

FI has previously not used heat maps extensively and the heat map is likely to evolve over time, both with regard to the degree of sophistication and the indicators included.

This study begins with a discussion of why FI monitors financial vulnerabilities and how the indicators can support such work. The indicators are first grouped into two dimensions: sector (e.g. banks) and vulnerability category (e.g. solvency). The article then discusses the indicators we use and how we determine the threshold used to generate signals. Finally, we provide a summary of the current state of the vulnerabilities in a heat map. Technical details and a list of indicators included have been added in appendices.

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1 See FI's reports "Stability in the financial system" and FI (2014a) which describe how FI conducts its overall stability work.

2 See ESRB (2015a), ESRB (2015b), BoC (2014) and ECB (2014).

3 A heat map is a graphical illustration of information where the individual values are represented by colours. Each colour has a signal value, where for instance green signals that the selected quantitative indicators assess that the situation is under control, while red signals the opposite.

Vulnerability indicators give the analysis structure

FI already uses quantitative indicators to analyse financial stability. The purpose of a formalised indicator analysis is to supplement this work to identify any gaps and further clarify the information on the vulnerabilities.

FINANSINSPEKTIONEN AND FINANCIAL STABILITY

FI's objective is to promote a stable financial system.[4,5] By financial stability, FI means that the system is able to maintain its basic functions – mediating payments, converting savings into financing and managing risks – even under changing economic conditions. Maintaining the basic functions and working to ensure that the system is resilient to the effect of triggers can be regarded as the authority's traditional objectives. FI has also recently received an additional assignment that involves stabilising the credit market.[6] One example of such an imbalance is the high household indebtedness, which can increase the risk of deep economic recessions.

TRIGGERS AND VULNERABILITIES CONSPIRE TO CREATE FINANCIAL INSTABILITY

The sequences of events that create financial instability are often complex and difficult to identify in advance. To structure this work, we use the concepts *vulnerability* and *trigger* to describe such sequences. This distinction has been inspired by the ESRB's work on risk classification.[7]

The indicator analysis presented here defines vulnerabilities as a lack of sufficient resilience to financial stress. Such vulnerabilities always exist to a varying degree in the financial system. One example of a vulnerability is the Swedish banks' dependence on short-term financing. If the banks do not have access to financing, they must limit their lending or sell assets. Ultimately, this may threaten financial stability.

The build-up of vulnerabilities does not in itself lead to financial instability. This requires something that provokes a crisis. We call these factors triggers. An important difference between triggers and vulnerabilities is that triggers arise suddenly, while vulnerabilities are built

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4 For further details on FI's objectives, see FI (2014a).

5 According to Section 2 of Finansinspektionen's Instructions Ordinance, FI shall work "...to promote a stable financial system that is characterised by a high level of confidence and has well-functioning markets that meet the needs of households and corporations for financial services, and provide comprehensive protection for consumers."

6 More specifically, FI has the responsibility "to take measures to counteract financial imbalances with a view to stabilising the credit market, but taking into consideration the effect of the measures on economic development", see Section 1, Point 3 of Finansinspektionen's Instructions Ordinance (2009:93).

7 The ESRB's terminology uses trigger and vulnerability. To evaluate the damage to the financial system, which the ESRB terms risk, they weigh together the probability of a trigger and the effect of a vulnerability. See ESRB (2015b). The Bank of Canada also uses a more or less identical classification in three main components: "vulnerability", "trigger" and "risk"; where risk is classified according to the probability of the event and its effects, see BoC (2014). Further, the ECB also used an identical allocation, for instance, in its risk reports.

up over time. Triggers can stem from the financial system, but they can also be created outside of the system. One example of a trigger is the stress on the interbank markets that was provoked in 2008 by the US allowing Lehman Brothers investment bank to go bankrupt.

Apart from the triggers arising suddenly and thus being difficult to predict, another important difference in relation to vulnerabilities, is that FI can rarely limit a trigger. On the other hand, FI can monitor and often influence vulnerabilities. For instance, in the example with the banks' dependence on short-term financing, FI can reduce this vulnerability by requiring the banks to hold higher liquidity buffers.

Moreover, the vulnerability needs to be exposed to the trigger that arises to cause financial instability. A crisis in a smaller foreign economy will probably not destabilize the Swedish financial system. On the other hand, it is likely that the Swedish financial system will be affected if a systemically-important Swedish bank has large lending in the crisis-stricken country. In other words, whether or not a bank is exposed to the crisis-stricken country is a decisive factor.

When financial instability reached such severity that it threatens to spill over and seriously affect the entire economy, the risk is known as a systemic risk.[8] It is primarily this sort of risk that justifies intervention and regulation with the aim of strengthening financial stability. One example of a potential systemic risk is a scenario in which Swedish banks substantially limit their lending. This could comprise a threat to financial stability, as the reduced lending makes it impossible for the financial markets to convert savings into financing (one of their basic functions). The severe credit crunch in turn leads to a decline in activity in the economy.

FI's extended assignment, with regard to the build-up of imbalances on the credit market, also requires the monitoring of vulnerabilities that build up in the real economy as a result of financial imbalances. Households' debt burden is one example of a real economic vulnerability, which, combined with a trigger (such as a fall in house prices) could lead to a severe economic downturn, see for instance FI (2014b).

There are thus several reasons why it is natural to monitor vulnerabilities. The rest of the report therefore focuses on vulnerabilities.

VULNERABILITIES ARE GROUPED INTO TWO DIMENSIONS

FI follows the development of vulnerabilities, for instance, with the aid of indicators. As there are a large number of vulnerabilities, we have chosen to group vulnerability indicators into two dimensions. This grouping improves clarity. It also makes the visualisation of the vulnerabilities easier and thus the discussion on the possible need for measures. The first dimension refers to the sector in the financial system where the vulnerability is located and the second describes what type of vulnerability is referred to. The allocation is roughly in line with the ESRB (2015a).

We only include the sectors that could comprise a threat to financial stability and therefore put the main emphasis on the banking sector. The household sector is also included as it comprises an important part of FI's macroprudential policy task. Insurance companies and

8 The ESRB's definition of a systemic risk is: "*a risk of disruption in the [EU] financial system with the potential to have serious negative consequences for the internal market and the real economy*" (ESRB, 2015b, p. 12).

Figure 1: Vulnerability matrix

		Category		
		Solvency	Liquidity	Exposures
Sector	Bank			
	Household			
	Insurance			
	Financial Markets			
	Real Estate			

financial markets are important in this context, but they will not be included in this first report. Non-financial companies do not normally pose a threat to financial stability. The exception is property companies, which will be included in the future.[9]

The other dimension consists of three so-called vulnerability categories (see also FI, 2014a).

- *Solvency* describes a sector's resilience to changes in prices and unexpected losses. This refers primarily to the capacity to meet long-term obligations.
- *Liquidity* describes how good access to liquidity a sector has to be able to meet its obligations. This refers primarily to resilience to triggers of a more transitory nature.
- *Exposures* capture the fact that a vulnerability must be linked to a trigger for financial stability to be affected. Exposures can be direct – for instance, a sector's holdings of shares and bonds from another sector – or indirect, for instance because they are affected by pricing on a common market. Both indirect and direct exposures contribute to problems between institutions and sectors spreading through the system.

Several factors contribute to a trigger spreading through the financial system. The degree of inter-linkage is one such factor; the more interlinked the system is, the easier it is for the trigger to spread. Risk concentration is another such factor – that many institutions are exposed to one and the same risk makes the system more sensitive. An individual institution's dominant position can also elevate the level of risk, as the failure of a systemically-important institution can have considerable contagion effects. Finally, some exposures are more risky than others. For instance, risks linked to loans to households have historically been lower than those linked to corporate loans.[10]

The final categorisation of vulnerabilities is shown in Figure 1. Each cell in the figure can contain information from several vulnerability indicators. Weighing together the indicators in the respective fields provides an overall degree of vulnerability for that sector and category. This grading is shown in the form of a colour signal, which is described in the next section.

9 Both the Bank of England and the Bank of Canada also allocate according to sector. The Bank of England divides the indicators into the sectors banks, non-banks and markets, see BoE (2014); while the Bank of Canada uses the sectors financial institutions, asset markets, non-financial institutions and financial infrastructure, see BoC (2014).

10 Unlike FI, the ESRB has chosen to categorise its vulnerabilities according to so-called intermediary objectives. These are: ”excessive credit growth & leverage”, ”balance sheet mismatches & market illiquidity”, ”exposure concentration”, ”misaligned incentives”, ”financial structure resilience” (see ESRB, 2013, and ESRB, 2014a). The ESRB's five objectives have also recently been supplemented by two additional objectives: ”resilience” and ”financial cycle”. In relation to the ESRB's intermediary objectives, we have chosen to exclude ”misaligned incentives” as this is difficult to survey with the aid of indicators. Moreover, like for instance the BoC (2014), we think that the financial structure falls more naturally under the sector rather than the category dimension that ESRB used (”financial structure resilience”)“. Finally, we have chosen to exclude the ESRB's additional objectives, as we find that they do not provide sufficiently useful information over and above the already-existing categories.

Figure 1 gives a structure to the vulnerability analysis. This structure works well for both judgement based and quantitative analysis. In the remaining report the starting point of the analysis is the presented categorization of vulnerabilities into a sector and category dimension.

Selection of indicators and colour signalling

This section describes how the indicator selection is made and how we set the thresholds that determine the signals from the respective indicators.

As it takes time for the measures taken to have an effect, it is important that the vulnerability build-ups are identified in good time. The earlier measures can be taken to dampen vulnerabilities, the less dramatic these measures need to be. This in turn reduces the risk that overly strong measures will in themselves generate financial instability. In our selection procedure we therefore wish to take into account in particular the leading properties of the indicators (which are described in the next section).

THE INDICATORS ARE SELECTED USING STATISTICAL METHODS AND JUDGEMENTS

There are of course a large number of potential vulnerabilities. It is neither possible nor desirable to follow all of them, which is why we make a selection. To limit the number of vulnerabilities to a manageable amount, in the first stage of the analysis we start out by including indicators put forward in academic studies and those monitored regularly by FI.

The selected indicators relate to the Swedish economy and entities in Sweden and span different time periods. There are observations for some indicators, such as household indebtedness, going back to before the 1990s crisis, while we only have a couple observations of others, such as the NSFR. The length of the series determines how we can handle the indicators. In the second stage, therefore, we make statistical tests of the indicators that cover at least one crisis period. The purpose of the test is partly to assess whether the indicator co-varies with crisis periods and partly to estimate the signalling threshold. With regard to those indicators that do not pass the statistical tests, we make a new judgement based assessment, which results in the indicator being either excluded or included.

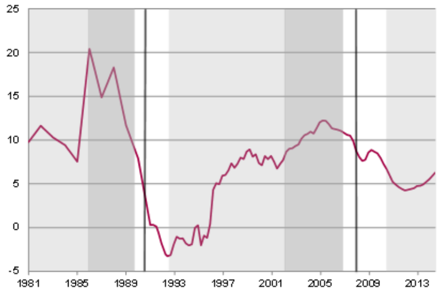
In the third stage the thresholds are determined. For the indicators that can be evaluated in a statistical manner the tests also provide thresholds. For indicators that cannot be evaluated in this way, the threshold is set by expert judgement. Expert judgement is also used for some variables when tests can be applied, namely because there are legal requirements (for instance, the LCR), when the tests generate misleading results (ROE profitability) and where the indicators do not pass the tests but are nevertheless judged to be important (LTV). In general, we prefer to rely on expert judgement rather than statistical analysis because of a number of weaknesses explained more in detail in the next section.

STATISTICAL TESTS

To evaluate the statistical properties of an indicator, we need to define Swedish crisis periods. We chose to follow ESRB (2014b) and ESRB

Chart 1: Division of the indicator bank loans to households into three samples

(Annual percentage change)



Source: Statistics Sweden.

Note. The vertical lines mark the first quarter in a crisis period. The dark grey fields contain observations between twelve and five quarters prior to a crisis breaking out that defines our crisis signalling data. The light grey fields show calm periods and the observations not in any of the grey fields are disregarded in the statistical analysis.

(2015c), which have identified crisis periods for a number of European countries.[11] According to their definition of a banking crisis, the periods 1990 Q3 – 1993 Q4 and 2008 Q3 – 2010 Q4 were crisis periods in Sweden.[12,13]

In the statistical evaluation we follow Laina et al. (2015) and Ferrari and Pirovano (2015) and divide the respective indicators' outcomes into three samples. Chart 1 shows these samples for the indicator bank loans to households. The first sample consists of observations one year before to two years after the beginning of a crisis period. These observations concern an ongoing crisis. We therefore disregard them, as a signal during a crisis is not especially informative; one knows when one is in the middle of a crisis. The fact that ongoing crisis also includes observations one year prior to the crisis has broken out is because the indicators' forward-looking properties should guide the exercise.

The second sample consists of observations five to twelve quarters prior to a crisis breaking out, the so-called crisis signalling data. The remainder of the observations come under the third sample, which consists of calm periods. We use the crisis signalling data and the calm periods to sort the individual observations as shown in Table 1.

Table 1: Evaluation matrix

	Crisis signalling data	Calm period
Signal	A_{Tr}	B_{Tr}
No signal	C_{Tr}	D_{Tr}

Note. Crisis signalling data here refers to the indicator observations that are found five to twelve quarters prior to a crisis breaking out, while calm periods refer to all other observations that fall outside a crisis period (defined as one year prior to two years post the start of a crisis). An indicator observation generates a signal if its threshold Tr is exceeded. The number of observations of the type A_{Tr}, B_{Tr}, C_{Tr} and D_{Tr} therefore depends on which threshold they are evaluated against.

It is desirable that an indicator signals a coming crisis when a crisis actually occurs (A_{Tr}) and that it does not signal when there is no crisis (D_{Tr}). A good indicator also shows a low frequency of incorrect signals (C_{Tr} and B_{Tr}). By setting the rate of correctly-signalled crises against incorrect signals, we can calculate the so-called AUROC sta-

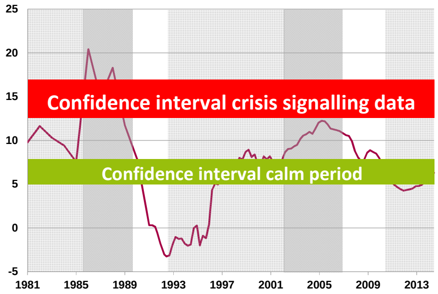
11 The ESRB has in its turn based its crisis periods on the ESCB Heads of Research (HoR) Group database on crisis periods (see Babecký et al (2011) for further information), which have been adjusted on the basis of expert judgements.

12 More specifically it requires that some of the following criteria are met: 1) non-performing loans exceeding 20% or bank assets corresponding to at least 20% being sold, or 2) fiscal reconstruction of banks corresponding to at least 5% of GDP. These quantitative criteria are supplemented with qualitative information to determine whether a period should be classified as a crisis.

13 Several other studies have also produced crisis periods for Sweden (Alessi and Detken (2009); Schularick and Taylor (2012); Duprey, et al. (2014)), but the differences between the crisis periods identified are usually small. The exceptions are Alessi and Detken (2009) and Duprey, et al. (2014) who also identify the dotcom-bubble around the millennium as a crisis. This is probably because these studies are based on financial market data, while the other two studies are not.

Chart 2: Confidence interval for bank loans to households

(Annual percentage change)



Source: Statistics Sweden and FI

Note. The chart illustrates Ferrari and Pirovano's (2015) test. The red region shows the confidence interval based on the crisis-signalling data and the green corresponds to the interval for calm periods. The probability content in the interval is 95 per cent in both cases. The illustrated intervals are based on the full sample. In practice the intervals change as new observations are published. As the crisis-signalling interval is higher than the interval for calm periods, the indicator passes the test.

tistics.[14] If AUROC exceeds 0.5 the indicator is informative, see Appendix 2 for further information on AUROC. This is our first statistical test.

The second test is based on Ferrari and Pirovano (2015). In this test, one confidence interval is calculated for the crisis-signalling data and another for observations during calm periods (see Appendix 2 for details). These intervals are shown in Chart 2.

If high values on the indicator are a sign of increased vulnerability, the confidence interval for the crisis-signalling data shall exceed the confidence interval for the calm observations. On the other hand, if one interval encloses the other or if the interval for calm periods is above the interval for the crisis-signalling data, the indicator is not considered useful from a statistical point of view. This is our second test.

VULNERABILITY MONITORING DIFFERS FROM A CRISIS-SIGNALLING SYSTEM

The purpose of a crisis-signalling system is, as the name suggests, to signal that a crisis is imminent. The challenge with such a system is to correctly predict a crisis in advance – to signal during a crisis gives no added value. To succeed in this one must identify an elevated vulnerability and correctly predict that a relevant trigger will occur to activate the vulnerability. This is very difficult in practice, if not impossible.

Instead of a system for crisis-signalling, FI has chosen to identify vulnerabilities that are building up. In other words, we do not try to predict whether triggers will occur to provoke a crisis situation. It is therefore quite possible that an indicator will signal elevated vulnerability without a crisis occurring or that a signal will not coincide with a crisis. This applies, for instance, prior to the 2008-10 financial crisis when several Swedish indicators gave signals, despite the trigger beginning outside Sweden.

From a statistical perspective, a crisis-signalling system is based only on indicators that pass the statistical tests. This means that indicators with short time series are not included, as the tests require that at least one crisis period is covered for an indicator to be assessed. Finally, the statistical evaluation is based on (a maximum of) two Swedish crises. The next crisis need not be like any of these. Using only statistical tests can paradoxically increase the risk of missing vulnerabilities that are building up.

Monitoring vulnerabilities, on the other hand, is not solely based on indicators that pass the statistical tests, but also involves expert opinions becoming an important part of the evaluation. This makes it possible to include both indicators with short time series and indicators that have not proved relevant during earlier crises, but can be considered to be relevant in future.

THRESHOLDS AND COLOUR SIGNALLING

Thresholds for signalling

The thresholds are determined either statistically or through expert judgements. This section describes statistical determination of the thresholds. In general, we prioritise expert judgements as we have

14 AUROC is short for the Area Under the Receiver Operating Characteristics (ROC) curve. The ROC curve shows the link between the percentage of incorrectly signalled crises B/(B+D), against the percentage of correct signals, A/(A+C).

access to a limited amount of data, which reduces the precision of the statistical calculations.

At each point in time we want to represent the indicator with a colour showing how extreme the indicator is. If it is possible, the colour signal for the indicator is determined by two estimated thresholds:

- If the observed value for the indicator is less than threshold Tr_1 the indicator signal is green.
- If the observed value for the indicator is greater than threshold Tr_2 the indicator signal is red.
- If the value is between Tr_1 and Tr_2 the colour is yellow.

In the next step, the different indicators are weighed together to complete the vulnerability matrix (Figure 1).

We use two statistical approaches to estimate thresholds. These two approaches are those used by ESRB in its heat map (see ESRB, 2015a).

The unconditional approach for determining thresholds
The unconditional approach is simple. The observations that are lower than an historical average are shown with the colour green and the observations that are among the 30 per cent highest historical indicator values are allocated the colour red. The observations that come between these two are represented by the colour yellow.[15] These are similar thresholds to those used by the ESRB (see ESRB, 2015a).

The conditional approach for determining thresholds
Ferrari and Pirovano (2015) can be used not just as a test (see the section statistical tests) but also to estimate thresholds. We call this threshold procedure the conditional approach. It is based on the allocation described in the section on statistical tests and is described in greater detail in Appendix 2.

We calculate the confidence interval for the mean value of the crisis-signalling data and calm periods respectively in the same way as in the test. The indicator outcomes in the confidence interval for calm periods or lower are given the colour green. Furthermore, we set the colour red for the observations within or above the confidence interval for the crisis-signalling data. If the estimated confidence intervals overlap one another, the colour yellow is given for the observations included in both intervals. When the intervals do not overlap, we give the colour yellow to the observations falling between the two confidence intervals.

The conditional approach may appear more reasonable, but the unconditional method is justified by the fact that the next crisis may be unlike the earlier ones.

Colour signalling
Chart 3 shows the colour signalling from both approaches. In the unconditional approach the colours are determined by the percentiles in

15 This threshold set-up applies to vulnerability indicators where high levels are a sign of high vulnerability. If instead low levels are used to indicate high vulnerability, then the green colour applies if the value is above the average, red if the value is among the 30 per cent lowest and yellow in between these.

Chart 3: Colour signalling of the indicator bank loans to households according to two approaches

(Annual percentage change)

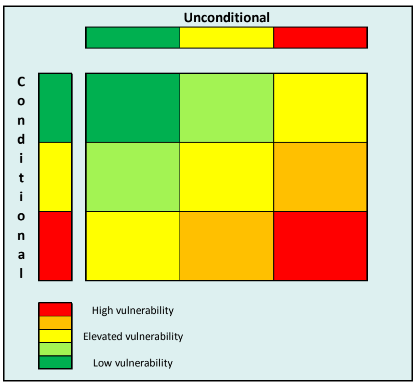
Unconditional approach

Conditional approach

Sources: Statistics Sweden and FI

Note. The light grey region corresponds to a green interval, the dark grey interval corresponds to red observations and in the region between these are the observations in the yellow interval.

Figure 2: Combined colour scheme



the data and in the conditional approach they are determined by the estimated confidence intervals.

Like the ESRB, we use a combination of the data-based approaches to set the final colours for the respective indicator observations. The combination of the two approaches gives a five-grade colour scheme (Figure 2).

If an indicator series is too short to include any crises or if the indicator has too few crisis observations (applies to indicators on an annual basis) the unconditional approach may sometimes be used – which gives three colours: green, yellow and red. We also use three colours when the threshold is set by means of expert judgements.

DIVISION INTO SUB-GROUPS GIVES A BETTER BALANCE WHEN AGGREGATING DATA

The statistical tests and assessments give a set of indicators with individual thresholds, which in turn generate colour signals. Then these signals are aggregated into a classification as in Figure 1. However, a direct aggregation of all indicators into a sector/category can lead to some vulnerabilities being allocated too high a weight. This is illustrated best by means of an example. Let us assume that we have four solvency indicators that refer to capital adequacy and one that refers to profitability. If we give all of the indicators the same weight, capital adequacy will account for 80 per cent of the aggregate and profitability for 20 per cent. However, in the compilation we want capital adequacy and profitability to be equally important, and we therefore divide the indicators into sub-groups. In the example, the capital adequacy indicators form one sub-group and profitability forms another sub-group, despite the latter being a sole indicator. Finally, we aggregate the sub-groups, with equal weights, to what is reported in a cell in Figure 1. If no sub-groups have been defined, the indicators are instead given equal weight.

The aggregation in Figure 1 can be done in several ways – the most common colour, the median colour, the average colour or the importance-weighted average colour – are some examples.[16] We have chosen to use the average colour.

Signals from the vulnerability indicators, second quarter of 2015

The final data set is described in Appendix 1. The sample shall be regarded as the current sample – new indicators will be added, while other indicators may disappear. Tables 2 and 3 show how the indicators have been divided into categories (main category and subcategory if such exist), what transformation has been made (level or annual growth) and the estimated AUROC statistics. The tables also show which method has been used to determine the threshold (unconditional, conditional or judgement), and how many colours are included in the final colour scale for the respective indicators.

The household indicators usually extend far back in time and there we can estimate thresholds with the aid of both the unconditional and the conditional approach. We have determined the thresholds for the savings ratio through the unconditional approach only, as we only have

16 An importance-weighted average colour means that one use judgement to give different indicators different levels of weight.

data on an annual basis, which gives too few observations for the conditional approach to be used. All of the indicators for the household sector show an AUROC above 0.5, which is the main criterion, except loan-to-value ratio (LTV). LTV is included nevertheless, as it is an indicator judged to be of central significance.

The bank indicators are usually short and they cannot be evaluated on a statistical basis, so the thresholds are typically determined by judgement. The exception is the two credit indicators (CreditgapNon-fin, BankloanNon-fin) where we have data from the early 1980s and can use both the conditional and the unconditional approaches. We also have a sufficiently long time series for the core leverage ratio to be able to set thresholds with the unconditional method.

With a few exceptions for the exposure sub-groups concentration and credit, we put the focus on the four major banks (see Appendix 1). As all of the major banks are systemically important, it is enough if only one of these banks suffers problems for the entire system to be threatened. This could justify using the indicator for the weakest of the four banks. However, we generally choose to calculate an average of the four banks, as this better captures the representative major bank. The exceptions are SurplusB and LCR which are linked to legislative requirements, where we have chosen to be more restrictive and use the weakest major bank. It is reasonable to assume that a bank will make a considerable effort to avoid breaking a legal requirement, and that such a violation therefore is an indication of a potentially more serious problem than the breaking of any other non-legally binding threshold. Appendix 3 shows the differences between using the average value and the weakest bank.

Table 2: Indicators for the banking sector

Indicators	Cat.	S-C	Trans.	AUROC	Thresholds			Colours
					Un-cond.	Cond.	Judge	
SurplusB	S	Capital	Level	–			X	3
Core.lev.ratio	S	Capital	Level	–	X			3
ROE prof.	S	Profitability	Level	–			X	3
NSFR tot.	L	NSFR	Level	–			X	3
LCR USD	L	LCR	Level	–			X	3
LCR EUR	L	LCR	Level	–			X	3
LCR tot.	L	LCR	Level	–			X	3
Conc Asset	E	Conc.	Level	–			X	3
Conc VP	E	Conc.	Level	–			X	3
Credit-gap_NF	E	Credit	Level	0.78	X	X		5
Bank loan_C	E	Credit	Y/Y	0.87	X	X		5
LoanComC	E	Credit	Y/Y	–			X	3
CDS	E	Unspeci-fied risk	Level	–			X	3
CDS spread	E	Unspeci-fied risk	Level	–			X	3
ROE risk	E	Unspeci-fied risk	Level	1			X	5

Note. The indicators can belong to the vulnerability categories solvency (S), liquidity (L) or exposure (E). They can also belong to a number of sub-categories (S-C). The indicators are used either on a level or as an annual growth rate (Y/Y). Thresholds can be determined by the unconditional approach, the conditional approach or by judgement. The number of colours used is a function of which approach(es) is used (see the section colour signalling). A detailed review of the indicators is provided in Appendix 1.

Table 3: Indicators for the household sector

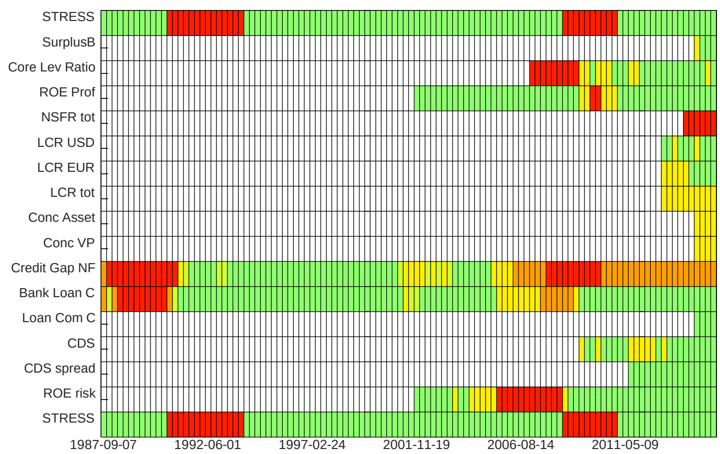
Indicators	Cat.	S-C	Trans.	AUROC	Thresholds Uncond.	Cond.	Judge	Colours
LTV	S	–	Level	0.35	X			3
Debt/Asset	S	–	Level	0.60	X	X		5
LTI	L	–	Y/Y	0.76	X	X		5
Savings ratio	L	–	Level	–	X			3
Debt service ratio	L	–	Level	0.51	X			3
Creditgap_HH	E	Credit	Level	0.86	X	X		5
Bank loan_HH	E	Credit	Y/Y	0.93	X	X		5
Ten.owned prices	E	Housing price	Y/Y	0.91	X	X		5
House prices	E	Housing price	Y/Y	0.95	X	X		5

Note. See appendix 1 for further information on the indicators.

Figures 3 and 4 show estimated heat maps for the bank indicators and the household indicators respectively. We do not make a complete vulnerability assessment here, as it is outside the range of this article.

With regard to the banking sector in Figure 3, there are only two indicators that go back before the 1990s crisis, namely the two referring to loans to non-financial companies (CreditgapNon-fin, BankloanNon-fin). Both of these show high vulnerability in the years prior to the 1990s and also signal elevated vulnerability prior to the financial crisis. We also have data for core leverage ratio and return on equity (ROE) prior to the financial crisis. The core leverage ratio shows high vulnerability while ROE does not.

Figure 3: Heat map for the banking sector indicators 1987-2015

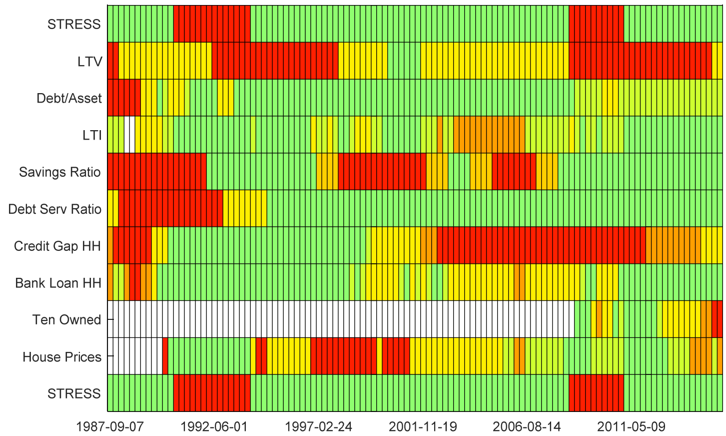


Source: FI.

Note. The top and bottom rows in the heat map show the crisis period according to the ESRB classification (2014b).

In Figure 4, many indicators signal yellow or red before the crisis periods, which is in line with our aim to try to find indicators with leading properties. The indicators show that the build-up of vulnerabilities in the household sector was more serious prior to the 1990s crisis than prior to the financial crisis. This result is reasonable as the most recent crisis was not largely of a domestic nature, while the previous one was. At present, most indicators signal that resilience is good.

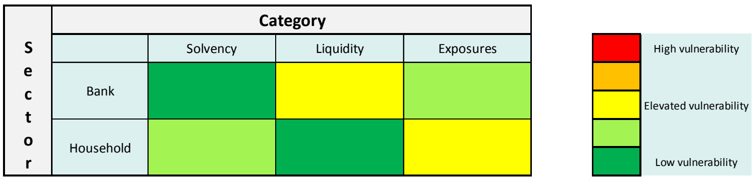
Figure 4: Heat map for the household sector's indicators 1987-2015



Source: FI.
Note. See the note to Figure 3.

Figure 5 aggregates the signals from the indicators in Figures 3 and 4 on the basis of the main categories: solvency, liquidity and exposures. The solvency in the Swedish banking system is judged to be resilient – the signal is green. The reason for this is the high capital buffers, both in relation to FI's requirements (SurplusB) and in absolute figures (CoreLevRatio), but also due to high profitability (ROE prof). On the other hand, the banks' vulnerability with regard to liquidity is elevated. The liquidity coverage ratio (LCR) shall be greater than 1 according to legislative requirements and these indicators show as (sub)group low vulnerability. On the other hand, the signals from the banks' access to stable funding (NSFR) suggest that the vulnerability is high. The exposures category has three sub-groups that are weighed together with equal weights: concentration, credit and the unspecified risk group. The Swedish banking system is concentrated to a few major banks, which means that the concentration sub-group signals elevated vulnerability. This is partly counteracted by a moderate growth in credit to the non-financial sector and to the property sector, despite the credit gap for non-financial companies showing an elevated vulnerability. The third sub-group contains unspecified risks. Low CDS spreads in absolute terms, but also in relation to the European sector average, signal a low build-up of risk. Finally, we have also included ROE here, but in this case for the purpose of measuring the build-up of risk. Studies have shown that a high ROE entails higher risk taking, which increases the probability of a banking crisis (Behn et al., 2013). This indicator does not show any increased build-up of risk either, and the overall result for the exposure is somewhat elevated risk (yellow-green).

Figure 5: Summary heat map for 2015 Q2



Source: FI.

The vulnerabilities in the household sector on the whole give the same message as those for the banking sector, but the allocation into the different categories is different. The highest estimated vulnerability is found in the exposures category (yellow). Property ownership comprises an important part of household wealth, which makes households sensitive to changes in property prices. When property prices increase substantially, it may be a sign that prices are deviating from their fundamental values, which can ultimately lead to large price falls. It is these property price falls that can lead to strains for households and in the worst case to a macroeconomic recession. Property prices are currently growing at a rapid rate and these indicators therefore show red. The estimated credit gap for households shows elevated vulnerability, while the growth rate in bank loans does not – at least in relation to the growth rates observed prior to earlier crises.

Household solvency shows a somewhat elevated vulnerability (yellow-green), which should be interpreted as good resilience. Seen across all households, the loan-to-value ratio (LTV) is relatively low.[17] Moreover, total debt divided by total assets (Debt/Asset) also shows similar good resilience (yellow-green).

When it comes to household liquidity, the aggregated indicator value is green – low vulnerability. The high savings (Savings ratio) and the low interest expenditure in relation to disposable income (Debt service ratio) contribute to households' good liquidity situation. The third liquidity indicator, loans in relation to disposable income (LTI), shows a low vulnerability – green. We use LTI as an annual percentage change, and growth in LTI is not high in an historical perspective.[18]

17 It is not only the average loan-to-value ratio that may comprise a vulnerability, the distribution is also important. However, this is not something we study in this initial stage.

18 FI (2013) describes a number of factors that to a large extent can explain the current LTI level. These factors are related to, for instance, the conversion of rented apartments to tenant-owned apartments and tax legislative changes. These factors in themselves do not constitute any threat to financial stability, which illustrates the problems of using the level of the LTI as a base.

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Appendix 1: Selected indicators

BANK

Indicators	Category	Subcategory	Description	Justification
SurplusB	Solvency	Capital	CET 1 capital, above the CET 1 capital requirement, in relation to the capital base.	The indicator is adjusted for the inherent risk in the bank's operations as the capital is related to the capital requirement.
Core.lev-ratio	Solvency	Capital	CET 1 capital in relation to adjusted total assets. Total assets include, for instance, off-balance sheet items.	Barrell et al. (2010); Behn et al. (2013); Sarlin and Peltonen (2013).
ROE prof.	Solvency	Profitability		Return on equity is a central measure to describe the profitability of a bank.
LCR	Liquidity	LCR	Adequate liquidity reserve to manage stressed conditions. USD, EUR and total foreign currency exposure included.	ESRB (2014c).
NSFR	Liquidity	NSFR	Stable borrowing in relation to illiquid assets. Only total currency exposures included.	
Credit gap Non-fin.	Exposure	Credit	Credit to non-financial companies in relation to GDP, measured as a deviation from the HP trend.	Borio and Lowe (2002); Borio and Drehmann (2009); Drehmann et al. (2010); Alessi and Detken (2011); Juks and Melander (2012); ESRB (2014b).
Bank loan Non-fin.	Exposures	Credit	Growth rate in credit granting to non-fin. companies.	
Loan-ComP	Exposures	Credit	Loans to commercial property companies (annual growth) in relation to total lending.	Property credits have entailed high losses and have contributed to crises. This type of exposure therefore entail an elevated risk.
CDS	Exposures	Unspecified risk	5 year CDS, senior, EUR.	
CDS spread	Exposures	Unspecified risk	CDS minus iTraxx european, financials, senior, 5 year, EUR.	
ROE risk	Exposures	Unspecified risk		High ROE indicates increased risk taking. See Behn et al. (2013).

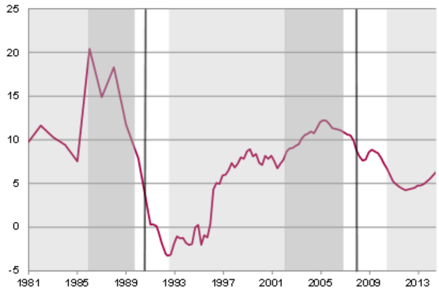
Indicators	Category	Sub-category	Description	Justification
Conc-Assets	Exposures	Concentration	Measures how concentrated the banking system is, based on the 20-30 largest banks. Herfindahl index calculated on the banks' share of total assets.	
Conc. Securities	Exposures	Concentration	Measures how concentrated the banking system is, based on the 20-30 largest banks. Herfindahl index calculated on the banks' share of the total value of the outstanding debt instruments.	This is one of the indicators included in the sub-group interlinkage according to EBA/GL/2014/10 which is used when calculating systemic importance.

HOUSEHOLDS

Indicators	Cat.	Sub-cat.	Description	Justification
LTV	Solvency	Capital	Loans in relation to value home value - all households.	Kiyotaki and Moore (1997), ESRB (2014c).
Debt/Asset	Solvency	Capital	Households' aggregate debts in relation to aggregate assets (financial and real).	
LTI	Liquidity	–	Loans in relation to disposable income - all households.	
Savings ratio	Liquidity	–	Savings (excl. occupational and premium pensions) in relation to disposable income.	
Debt service ratio	Liquidity	–	Interest expenditure in relation to disposable income.	Drehmann and Juselius (2012); IMF (2014).
Credit-gap_HH	Exposures	Credit	Household credit in relation to GDP, measured as a deviation from the HP trend.	Literature supporting the credit gap in general: Borio and Lowe (2002); Borio and Drehmann (2009); Drehmann et al. (2010); Alessi and Detken (2011); Juks and Melander (2012); ESRB (2014b) Literature that supports the debt burden for households being relevant: Mian and Sufi (2009, 2011); Büyükkarabacak et al. (2010); Beck et al. (2012).
Bank loans_HH	Exposures	Credit	Growth rate in banks' credit, extended to households.	Berkmen et al. (2009); Frankel and Saravelos (2010); Beck et al. (2012); EU-com (2012); ESRB (2014c) Growth in household credits: Repullo and Saurina (2011); Schularick and Taylor (2012).
Ten.owned prices	Exposures	House prices	The real annual growth rate in HOX's sub-index tenant-owned apartments in Stockholm.	Borio and Drehmann (2009); ESRB (2015a); Laina et al. (2015).
House prices	Exposures	House prices	The real annual growth rate in the FPI index.	Borio and Drehmann (2009); ESRB (2015a); Laina et al. (2015).

Chart 2.1: Division of the indicator bank loans to households into three samples

(Annual percentage change)



Source: Statistics Sweden.

Note. The vertical lines mark the first quarter in a crisis period. The dark grey fields contain observations between twelve and five quarters prior to a crisis breaking out. The light grey fields show calm periods and the observations not in any of the grey fields are disregarded in the statistical analysis.

Appendix 2: Statistical tests and thresholds

The process behind the selection of the indicators is described in the main text. We have taken a sample of indicators from a very large set of possible vulnerabilities. Some of the indicators consist solely of a few observations and there we assess the thresholds on a non-statistical basis used to signal elevated vulnerability (yellow) and high vulnerability (red). If the indicators extend further back in time – at least back to 2005 – we can test whether they contain information on future crises. If the indicators pass the tests, they are also given thresholds.

A common theme to the statistical tests is their ability to identify the relationship between an indicator and crises. However, it is not self-evident that the tests correctly identify the relationship with regard to a vulnerability indicator. There can be relationships that the tests do not detect, potentially due to the lack of any relevant trigger during the sample period. It may also be the case that a relationship is found, despite there not really being a link. This happened prior to the financial crisis. Several indicators signalled high level of vulnerability, despite the crisis beginning outside Sweden. Some of these signals may have come from vulnerabilities that were unrelated to the triggering of the actual crisis. This means that the tests do not automatically discriminate between which indicators should be included in the analysis. The tests sometimes need to be supplemented with judgements.

A DIVISION OF INDICATOR OBSERVATIONS INTO THREE SAMPLES

The statistical tests are based on the notion that indicators are expected to behave differently prior to a crisis than during calm periods. To test this, we first need to define crisis periods. We follow the ESRB (2014b) and ESRB (2015c) that have defined the periods 1990 Q3 – 1993 Q4 and 2008 Q3 – 2010 Q4 as crisis periods in Sweden.

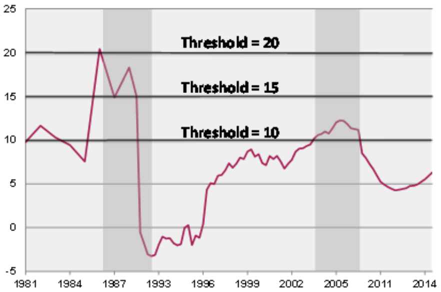
Each indicator is divided into three samples, see Chart 2.1 where the indicator for the banks' lending to households is used as an example. The *first* sample consists of observations one year before to two years after the beginning of a crisis period. These observations are disregarded in tests and when determining thresholds. Observations during and immediately after a crisis are not especially informative; one knows when one is in a crisis. We also disregard observations one year prior to the crisis, because the indicators' forward-looking properties should provide guidance for the thresholds.

The *second* sample contains observations five to twelve quarters prior to a crisis breaking out, the so-called crisis signalling data. The remainder of the observations fall under the *third* sample, which is defined by calm periods.

We use the crisis signalling data and the "calm" observations as a starting point and then sort the observations into those providing a signal and those that don't (Table 2.1).

Chart 2.2: Various thresholds for the indicator banks' lending to households

(Annual percentage change)

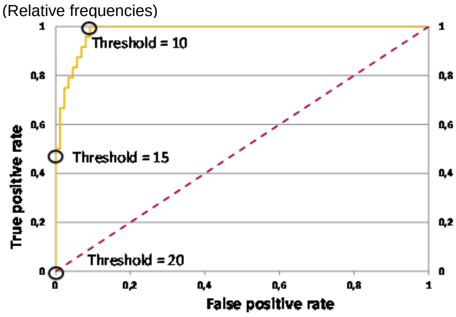


Source: Statistics Sweden.

Note. In this chart we have set the threshold at: 10, 15 and 20. Note that the observations immediately prior to and during the crises are excluded in this chart, in relation to Chart 2.1.

Chart 2.3: ROC curve based on various thresholds of the indicator banks' lending to households

(Relative frequencies)



Source: Statistics Sweden.

Note. In the chart we have marked the three thresholds in Chart 2.2 with circles. The broken line shows points where false positive percentage and true positive percentage are equal.

Table 2.1: Evaluation matrix

	Crisis signalling data	Calm period
Signal	A_{Tr}	B_{Tr}
No signal	C_{Tr}	D_{Tr}

Note. Crisis signalling data here refers to the indicator observations that are found five to twelve quarters prior to a crisis breaking out, while calm periods refer to all other observations that fall outside a crisis period (defined as one year prior to two years post the start of a crisis). An indicator observation generates a signal if the threshold Tr is exceeded. The number of observations of the type A_{Tr}, B_{Tr}, C_{Tr} and D_{Tr} therefore depends on the threshold value.

TEST STATISTICS BASED ON PROPERTIES PRIOR TO A CRISIS

Based on the data in table 2.1 a test measuring the information content of the respective indicator can be created. A_{Tr}, B_{Tr}, C_{Tr} and D_{Tr} are observed frequencies given threshold Tr. A_{Tr} and C_{Tr} constitute the crisis-signalling data as we have defined above and B_{Tr} and D_{Tr} are observations in calm periods. Chart 2.2 shows three hypothetical thresholds for the growth rate in the banks' lending to households. If, for example, we set the threshold at 15, we get the following observed frequencies A_{15}=11, B_{15}=0, C_{15}=13 and D_{15}=87. Threshold value 15 is a mere example and not the threshold used in the study.

It is desirable that the frequency A_{Tr} is high in relation to C_{Tr}, and D_{Tr} is high in relation to B_{Tr}. The transformations $A_{Tr}/(A_{Tr}+C_{Tr})$ and $B_{Tr}/(B_{Tr}+D_{Tr})$ show how the observations in the crisis-signalling data are allocated and are called true positive rate (TPR) and false positive rate (FPR), respectively. Different thresholds also give different frequencies and thus different TPRs and FPRs. The "Receiver operating characteristics" (ROC) curve shows TPR (Y axis) and FPR (X axis) for different thresholds, see Chart 2.3. With a threshold of 15, the TPR will be 0.45 and the FPR 0 which corresponds to a point on the ROC curve. If the threshold is set lower (for instance, at 10) both TPR and FPR increase.

If the area below the ROC curve, AUROC, exceeds 0.5 this means that the indicator gives a higher rate of correct signals than incorrect ones (TPR > FPR over different thresholds), that is, the indicator contains information regarding future crises. Even if we are not looking for crisis signals, we use this information to test whether the indicator can be used to demonstrate a build-up of vulnerability. This is our first test.

CONFIDENCE-INTERVAL-BASED TEST

The allocation of the observations into crisis-signalling data and calm periods can also be used in a more direct manner, namely to calculate confidence intervals for the respective periods. The confidence intervals are estimated through a regression:

$$x_t = \phi_0 \check{F}_t + \phi_1 \hat{F}_t + \varepsilon_t,$$

where x_t is a vulnerability indicator at the point in time *t* and $\hat{F}_t$=1 if the observation belongs to the crisis-signalling data and 0 wise. $\check{F}_t = 1 - \hat{F}_t$ is an indicator series that is 1 for observations in calm periods and otherwise 0. The random term ε_t contains the variation in x_t that is common to crisis and calm observations.

The regression equation is justified because it can separate information in the indicator that is due to crises from one that is not due to crises.[19] Moreover, the regression allows the uncertainty in the parameter estimates to be calculated by means of a bootstrap procedure.[20] We estimate a confidence interval for the crisis-signalling data through the confidence interval for ϕ_1. The corresponding confidence interval for calm periods is given by an interval for ϕ_0. Ferrari and Pirovano (2015) describe this approach in detail.

The confidence intervals make it possible for us to draw conclusions about the indicator. We consider the indicator to be informative if no confidence interval encloses another and the confidence interval for the crisis-signalling data does *not* lie below the confidence interval for the calm period.[21] This is our second test.

CONDITIONAL APPROACHES FOR SETTING THRESHOLDS

The frequencies in Table 2.1 can be used to calculate a loss function $L(Tr)$. This loss function weighs together the two error signals the indicator can give – signalling crises that do not occur (B_{Tr}) and not signalling crises (C_{Tr}) that do occur:

$$L(Tr) = \theta \frac{C_{Tr}}{A_{Tr} + C_{Tr}} P_1 + (1 - \theta) \frac{B_{Tr}}{B_{Tr} + D_{Tr}} P_0,$$

where P_1 and P_2 are defined as:

$$P_1 = \frac{A_{Tr} + C_{Tr}}{A_{Tr} + B_{Tr} + C_{Tr} + D_{Tr}}, P_0 = 1 - P_1.$$

The loss function consists of a weighting parameter θ, observed rates of type I error, C_{Tr} /(A_{Tr}+C_{Tr}), and type II error, B_{Tr}/(B_{Tr}+D_{Tr}), and the unconditional probability of a crisis P_1. The weight θ is contained within the [0, 1] interval and provides the relative weight of the two errors in the loss function. If type I errors are considered as more serious than type II errors, θ is set greater than 0.5. The unconditional probability of a crisis is given by the relative share of observations in the crisis-signalling data. The estimated threshold is the one that minimises the loss function, see Laina et al. (2015).

Ferrari and Pirovano's procedure also determines thresholds. The upper limit in the confidence interval for the calm period is taken to be the first threshold – indicator outcomes within the interval or lower are given the colour green. Moreover, the lower limit for the confidence interval for the crisis-signalling data is set equal to the second threshold and observations within this interval or higher are given the colour red. If the estimated confidence intervals overlap one another, the colour yellow is given for the observations included in both intervals. When the intervals do not overlap, we give the colour yellow to the observations between the two confidence intervals.

19 In the equation the residuals are "common". The equation can be extended to include explanatory variables that are common to all observations.

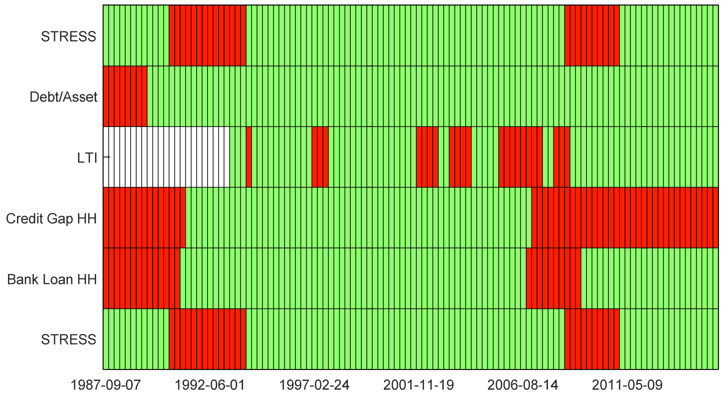
20 Bootstrap procedures are used in small random samples when the asymptotic distribution is unknown or not applicable.

21 The reasoning is based on the assumption that a high indicator value is a sign of high vulnerability.

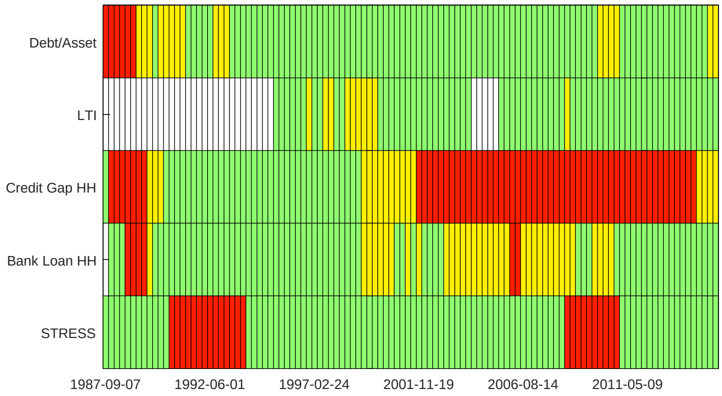
Chart 2.1 shows heat maps based on the loss function and confidence interval approach. The approaches give similar historical signals. We have chosen to use the confidence interval approach because it is more intuitive. The loss function approach is based on an optimisation of the threshold and requires that relative significance between type I and type II errors is specified. Moreover, we prefer that the confidence interval approach gives three signals compared with the two signals from the loss function approach.

Figure 2.1: Heat maps for conditional approaches

The loss function approach



The confidence interval approach



Note. Both of the heat maps are estimated in real time, that is, no information beyond the respective point in time has been used in estimating and signalling. Where there are no colours in the charts, AUROC or the confidence interval test has rejected the indicator as not usable.

AN UNCONDITIONAL APPROACH FOR THE DETERMINATION OF THRESHOLDS

We also use an approach that does not depend on earlier crises – the unconditional approach. The motivation for using the unconditional approach is that the next crisis need not bear any resemblance to any of the earlier crises.

In the unconditional approach, the colour green is given to the observations below the indicator's historical average and red to the observations among the 30 per cent highest. Observations between these are given the colour yellow. This allocation follows the colouring used by the ESRB.

A COMBINED APPROACH FOR SETTING COLOURS

Where we use both the conditional (Ferrari and Pirovano) and the unconditional approach for determining signals we need to combine these into a colour scheme. We do this in accordance with Figure 2 in the main text.

Appendix 3: Comparison between using the average bank and the weakest bank

The four major banks are each systemically important. This can justify using the weakest bank as an indicator. Moreover, it is reasonable to assume that a bank will make a considerable effort to avoid breaking a legal requirement, and that such a violation therefore is an indication of a potentially more serious problem than the breaking of any other non-legally binding threshold. Where there are legislative requirements – surplus buffer and LCR – we therefore use the bank that has the lowest observed value in each period as indicator. For the other indicators, which include the four major banks, we use the average of the banks. Figures 3.1 and 3.2 compare the results based on average and weakest bank respectively.

The weakest bank need not always have the lowest value. For ROE as a risk indicator, the weakest bank is the one that has the highest ROE, as high indicator values signal high vulnerability. The thresholds are the same for both heat maps.

Figure 3.1: Heat map for the average of the four major banks

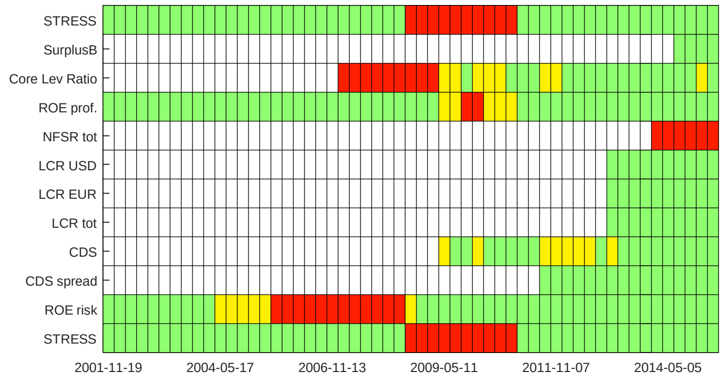
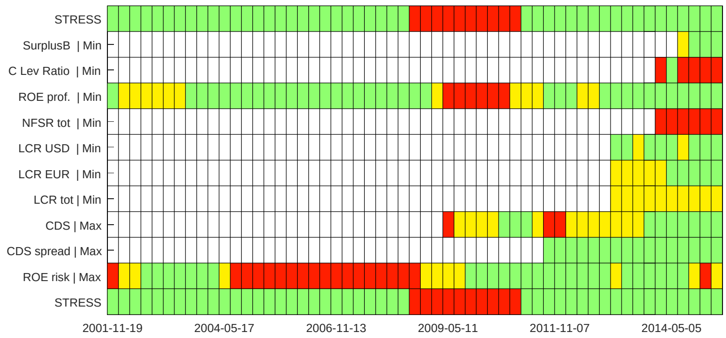


Figure 3.2: Heat map for the weakest of the four major banks



As expected, indicators based on the weakest bank signals more often than signals based on the average bank. The differences between the transformations we use and those we do not are not great; the averages of core leverage ratio and the ROE indicator, which are used in the article, gives no signals, whereas the weakest banks do (for these variables). Moreover the average of LCR in total currencies does not signal enhanced vulnerability while the weakest bank (which is used in the study) does.