COMESA MONETARY INSTITUTE

TOOLS FOR ASSESSING SYSTEMIC RISK IN DEVELOPING ECONOMIES: A GUIDE FOR COMESA MEMBER STATES

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1. Introduction

The global financial crisis brought on the realization that supervisory and regulatory frameworks lacked a "macro" dimension. Before the financial crisis of 2007-2011, regulators paid insufficient attention to the accumulation of risk at the level of the financial system as a whole, as opposed to individual financial institutions. Macroprudential oversight, focusing on systemic risk, is meant to fill this gap. It adopts a holistic perspective by focusing on the interactions between the components of the financial system.

Systemic risk is typically defined as the risk of disruption to financial services that is caused by an impairment of all or parts of the financial system, and that has the potential to have serious negative consequences for the real economy (IMF, BIS, FSB (2009)). Macroprudential oversight encompasses an analytical component that is aimed at detecting systemic risk, and a policy component aimed at mitigating it. Effective and timely mitigation of systemic risk starts with a rigorous analysis that informs policymakers when and where the most pressing risks to financial stability are building, and how to act on them.

Risks to financial stability are not easily measurable, and there is no widely accepted comprehensive model for measuring systemic risk. However, thanks to the overwhelming academic and regulatory response to the financial crisis, there is a corresponding diversity of models and measures that emphasize different aspects of systemic risk (Bisias *et al* (2012)). Therefore, to satisfy policymakers' demand, there is need to employ an effective macroprudential analysis framework, that encompasses tools that are tailored to the requirements of a given financial system.

2. Indicators of Credit Risk: The Credit-to-GDP Gap

Financial crises are usually preceded by private sector credit booms and so, this insight can be used to construct early warning indicators for crises. Due to non-linearity in the relationship between credit and financial stability, the assessment of credit risk should be conducted with different tools at different stages of financial development. This approach is particularly important for the activation and calibration of macroprudential tools such as the countercyclical capital buffer (CCB) (BCBS (2010)).

Excessive credit growth can be a source of risk in advanced economies as well low income countries (LICs). There are limits to a country's capacity to absorb financial deepening at each point in time. In countries with a developed financial system, rapid credit expansion frequently reflects systemic risk build-up. However, in LICs, fast credit growth is mainly connected to healthy financial deepening. Indeed, rapid credit growth may reflect healthy episodes of financial deepening rather than systemic risk build-up, making the nexus between credit and financial stability more complex. Therefore, investigating whether credit growth in LICs is indicative of financial deepening or poses risks to financial stability is a matter of importance in explaining banking crises and the calibration of macroprudential instruments in these countries. This issue is also relevant for the understanding of the relationship between financial stability and financial deepening.

Among indicators of credit booms, the literature on early warning indicators assigns a particularly prominent role to the ***credit-to-GDP gap***. Empirical research from the Basel Committee on Banking Supervision (BCBS) has shown that, indeed, this gap is a valuable leading indicator of systemic banking crises in advanced economies (Borio and Lowe, 2002; Drehmann et al., 2010). The credit-to-GDP gap ("credit gap") is defined as the difference between the credit-to-GDP ratio and its long-term trend. The trend is calculated using a one-sided Hodrick-Prescott (HP) filter[1] with a high smoothing parameter, taking account only of information up to each point in time.

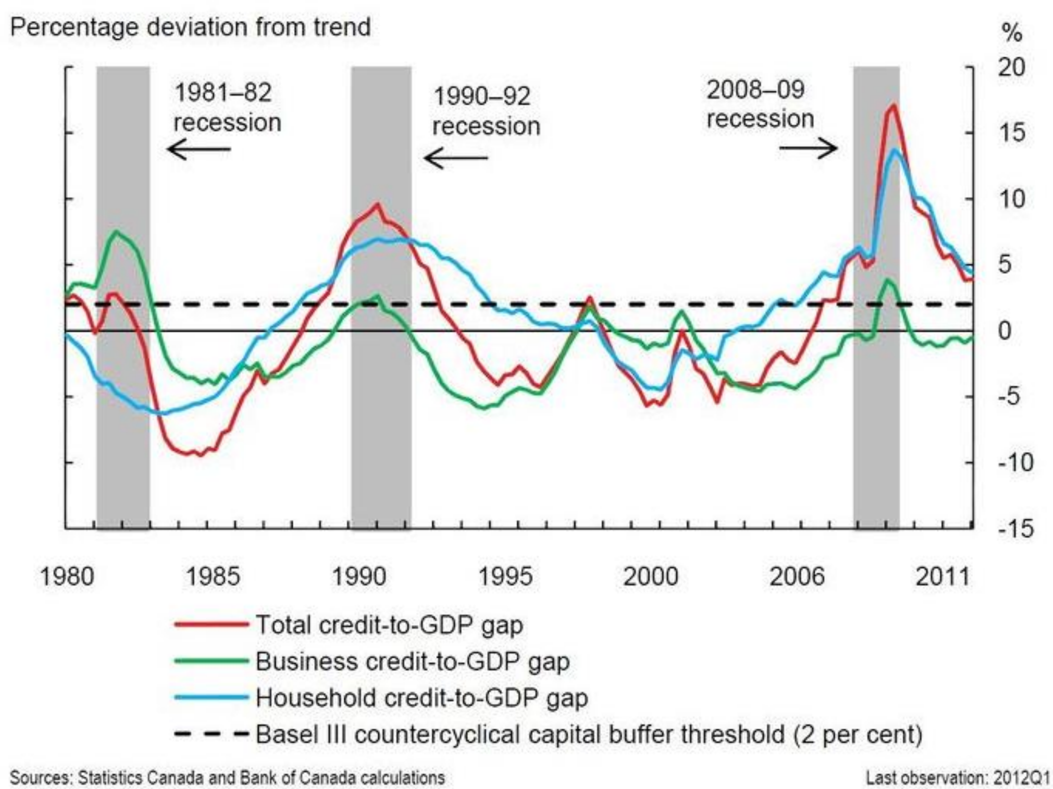
2.1. Data and computation considerations

The credit-to-GDP gap can be further improved by taking account of all sources of credit to the private non-financial sector, rather than just bank credit. A ratio based on all sources of credit is likely to provide a more accurate indication of impending systemic crises. Much of the work done on indicators such as the credit-to-GDP ratio is typically based only on credit granted by

[1] The HP filter is a decomposition that removes the cyclical component of a time series from a set of data, thus providing a representation of the time series more sensitive to long-term fluctuations. The technical literature suggests that the smoothing factor (i.e., the adjustment of the sensitivity of the trend to short-term fluctuations) is set according to the expected duration of the average cycle and the frequency of observation (Ravn, M. O. and H. Uhlig, 2002). They suggest the following as suitable smoothing factors, λ: 129,600 for monthly data, 1600 for data of quarterly frequency, and 6.25 for annual data.

domestic banks, with this aggregate excluding lending from non-banks or foreigners. However, such lending can be significant. As such, the credit series used should be defined by several characteristics, including, most importantly, the borrower, the lender and the financial instrument(s). The series should capture, as much as possible, all sources of credit, including borrowing by the private non-financial sector (i.e. households and non-financial corporations) and cover the same set of financial instruments, including loans and debt securities such as bonds or securitised loans. This goes well beyond the provision of credit by domestic depository corporations – such as commercial banks, savings banks or credit unions that are covered by traditional bank credit series – to include e.g. securitised credits held by the non-bank financial sector and cross-border lending.

Figure 1: Credit-to-GDP gap for Canada



In terms of computation, critics highlight two potential measurement problems that should be considered in the interpretation of the results. The first problem is linked to the stability of the HP filter's outcome as new data points become available. The second problem arises because structural breaks in the underlying series can have an important effect on the calculation of the trend. The filter is run recursively for each period, and the ex-post evaluation of performance of the credit gap is based on this recursive calculation. For instance, a trend calculated for, say, end-1988 only takes account of information up to 1988 even if this calculation is done in 2008 when more observations have become available. Hence, the HP filter also suffers from a well-known end-point problem. This means that the estimated trend at the end point (the most recent observation) can change considerably as future data points become available. A similar problem arises at the beginning of the time series used to compute the credit gap. Geršl and Seidler (2012) point out that the trend calculation can depend significantly on the starting point of the data. This is particularly important for short data series. Therefore, Borio and Lowe (2002) suggest that the practical rule of thumb is to use the credit gap only when at least 10 years of data for the credit-to-GDP ratio are already available.

2.2. Challenges and limitations

Emerging market economies (EMEs) are more likely to be undergoing a period of financial deepening which renders the specification of the trend for the calculation of the credit gap problematic. Economies that go through the process of financial development can experience prolonged periods of credit growth, to the extent that credit growth exceeds past norms. In these countries, a positive gap with respect to the long-term trend may reflect financial deepening instead of systemic risk build-up and, therefore, activating macroprudential tools based on this indicator might hinder financial development. Furthermore, for many EMEs, credit statistics are either not available for longer time spans to allow for proper assessment of the forecasting ability of the credit gap, or they are plagued by structural breaks which can strongly affect the credit gap calculation.

Historically, for a large cross section of countries and crisis episodes, the credit-to-GDP gap is a robust single indicator for the build-up of financial vulnerabilities. However, it may not be a good leading indicator of systemic risk build-up in countries at a low level of financial development. In particular, when the level of financial depth is low, traditional leading indicators of banking crises have poor predictive performance and so the analysis of systemic risk should be based on indicators that account for financial deepening while taking into consideration countries' structural limits. If financial deepening occurs at a steady pace, a gradual and persistent growth of credit will be embedded in the trend of the credit-to-GDP ratio and will not affect the gap (Drehmann and Tsatsaronis, 2014). By contrast, rapid expansions of credit are likely to be flagged by the credit-to-GDP gap as periods of financial vulnerabilities. The flip side of this is that a protracted credit boom will weaken the credit gap's signalling ability. A prolonged but large steady increase in the credit-to-GDP ratio will eventually lead to a lower credit gap without necessarily implying that financial stability risks have receded. These problems highlight the risk from a mechanical use of the credit gap. Policymakers have to assess whether in these situations credit levels are sustainable or whether they are a source of aggregate vulnerability.

The credit-to-GDP gap is a valuable early warning indicator for systemic banking crises, especially for advanced economies. As such, it is useful for identifying vulnerabilities and can help guide the deployment of macroprudential tools. Nonetheless, it is difficult to assert whether a positive credit-to-GDP gap is enough to raise expectations of future financial distress in LICs. Therefore, it may be worthwhile to consider whether an alternative measure of excess credit, which considers the structural characteristics of an economy, may stand as a better leading indicator of banking crises in countries at an early stage of financial development. In this respect, combinations of indicators could also act as benchmarks. Indeed, research points to composite indicators that statistically outperform the credit-to-GDP gap. A number of jurisdictions that have implemented the framework have made the case for using indicators that better capture the specific circumstances of their financial system. For instance, the Bank of England (2014) introduced a framework that is based on 18 core indicators, including the credit gap. Similarly, the Swiss National Bank (2013), the Central Bank of Norway (2013) and the Reserve Bank of India (2013) have explained that they monitor a small number of indicators in addition to the credit gap in evaluating aggregate vulnerabilities. For this reason, this paper offers alternative approaches to assessing systemic risk that involve the combination of various indicators.

2.3. Workshop V – Part I: The Credit-to-GDP Gap as an Indicator of Credit Risk

The credit-to-GDP gap is the difference between the credit-to-GDP ratio and its long term trend. By comparing the actual credit-to-GDP ratio with its long-term trend obtained using the statistical Hodrick-Prescott (HP) filter[2], we can then estimate whether or not the credit level is excessive. The credit-to-GDP gap suggests credit growth can be considered 'excessive' when the ratio rises significantly above its long-term trend, creating a large positive 'gap'.

Applying the Hodrick-Prescott (HP) filter

The technical literature suggests that the smoothing factor (i.e., the adjustment of the sensitivity of the trend to short-term fluctuations) is set according to the expected duration of the average cycle and the frequency of observation (Ravn, M. O. and H. Uhlig, 2002). They suggest the following as suitable smoothing factors, λ: 129,600 for monthly data, 1600 for data of quarterly frequency, and 6.25 for annual data.

Interpreting the credit gap

Thresholds are used to indicate when a positive gap might prompt policymakers to consider macro-prudential intervention. The BIS suggests the use of a range rather than point thresholds for policy purposes – 2-10 percent for the gap, depending on the country and policymaker's preference (Borio and Drehman, 2009). For an economy that is already highly indebted on a credit-to-GDP basis, a threshold closer to 2 percent is recommended. This method is used quite routinely in the literature (Borio and Lowe, 2002; Borio and Drehmann, 2009). Hilbers et al. (2005), for example, consider a credit-to-GDP gap of greater than five percentage points to be an indicator of excessive credit in the economy. A rise in credit relative to GDP can be a concern with international experience showing that rapid increases in the ratio often precede financial crises. However, there can also be reasons unrelated to system risk for increases in credit-to-income measures. For example, emerging countries have found that financial system liberalisation has been associated with a significant rise in the ratio.

A. Exercise

The purpose of this workshop is to determine whether or not there is a build-up of credit risk in the South African financial system. Participants are required to use the Hodrick-Prescott (HP)

[2] The Hodrick–Prescott filter (also known as Hodrick–Prescott decomposition) is a mathematical tool used in macroeconomics, especially in real business cycle theory, to separate the cyclical component of a time series from raw data. It is used to obtain a smoothed-curve representation of a time series, one that is more sensitive to long-term than to short-term fluctuations.

filter to derive the credit-to-GDP gap. This exercise is performed using the MS Excel worksheet titled "Workshop V_ex_VIdx.xlsx".

In the sheet labelled "Credit_Gap", you are provided with the quarterly time series of South Africa's ratio of private sector credit to GDP, for the period March 1992 to June 2017.

1. In E-Views, compute the credit-to-GDP gap for South Africa as at June 2017. Copy the results for both the trend and gap back into the "Credit_Gap" sheet.
2. Based on your results, what conclusions can be made about the level of credit for South Africa for the period ending June 2017? Depending on the size of the gap, what macroprudential policy recommendations can be made for South Africa?

3. Composite Indicators of Systemic Risk

Composite systemic risk indicators serve as a useful complement to the financial stability analytical toolkit by contributing to a more conclusive macroprudential analysis (Dijkman 2015). The use of indexes for purposes of monitoring financial stability was originally pioneered by the International Monetary Fund (IMF) in 2007 in the Global Financial Stability Risk Map. Several central banks have adopted these indices to monitor financial stability, including the Central Bank of Turkey, the Hungarian National Bank, the Norges Bank, and the Reserve Bank of New Zealand. The Central Banks of El Salvador and Costa Rica, with technical assistance from the World Bank, are in the process of developing these indices for their economies. In addition, the European Central Bank has developed a composite indicator for systemic stress on the basis of a series of high-frequency financial market indicators (Holló et al, 2012).

Composite indices address the time-dimension component of systemic risk. They are constructed on the basis of a range of supporting data series, with each composite index assessing a separate aspect of financial stability. With the use of carefully selected supporting indicators, a composite financial stability score is calculated. The score for each index is constructed by converting a range of indicators into percentile ranks based on the history of the series. The composite scores are tracked over time, and indicative stress levels are set; this is useful in informing policymakers as to when to act, communicating to the public about financial stability risks, and thereby serving as a useful supplement to the more qualitative aspects of financial stability analysis and reporting.

3.1. Types of financial stability indices

There are three different types of indices with different expected behaviour; ***a stress index***, ***a vulnerability index***, and ***a resilience index***. Each index measures a specific aspect of financial stability. During implementation, therefore, the appropriate selection of which index to adopt depends on the structural characteristics of the financial system and the authorities' preferences regarding comprehensiveness and coverage.

3.1.1. Stress index

The stress index is computed using a series of high-frequency financial market data, such as volatility in equity and fixed income markets, sovereign bond spreads, interbank lending spreads, credit default swap spreads of banks, and foreign exchange (forex) and interest rate swap spreads where available. The index may be constructed from three sub-indices which represent movements in local, regional and global financial markets respectively. For instance, the Board Options Exchange volatility index (VIX), also known as the 'fear index', is a relevant global indicator which denotes expected equity volatility. The JP Morgan Emerging Markets Bond Index Global (EMBI Global) is another indicator which tracks total returns for traded external debt instruments in the emerging markets. Additional indicators include the LIBOR-OIS[3] spread, measuring financial markets' perception of credit risk in the banking sector.

Country-level spreads are indicative of market perception about the riskiness of individual countries and regions. These indicators may be supplemented by volatility indexes for local capital markets and stock exchanges, provided that there is sufficient activity in these segments to warrant the monitoring of these indicators. Closer to the local banking system, it may also be useful to monitor interbank lending spreads, credit default swap spreads of (parent) banks, and foreign exchange and interest rate swap spreads, where available.

The stress index measures the degree of financial stress in the financial markets. Severe changes in the index signal turning points from "normal" to "crisis" mode, and vice versa. It usually

[3] LIBOR and OIS stand for London Interbank Offered Rate and Overnight Indexed Swap rate respectively.

shows rather low levels of stress and low volatility in normal times, but once a crisis strikes, it peaks very suddenly and becomes increasingly volatile.

Figure 2: Behaviour of a stress index

3.1.2. Resilience index

A resilience index measures the ability of banks and other financial entities to withstand adverse shocks. In the banking sector, this would cover a broad range of prudential indicators measuring capital, asset quality, and earnings indicators, as well as the liquidity outlook. A similar index may be created for non-deposit taking financial entities.

The New Economics Foundation[4] defines financial system resilience as the capacity of the financial system to adapt in response to both short-term shocks and long-term changes in economic, social, and ecological conditions while continuing to fulfil its functions in serving the real economy. Resilience is often implicitly equated with banks' capital positions – measured either in terms of risk-weighted capital ratios or simple leverage ratios. Ensuring that banks hold enough high-quality capital to withstand shocks has been a major focus of post-crisis regulation, particularly via the new Basel III capital and liquidity requirements.

Although banking system leverage is a key indicator of resilience, other factors relevant to financial system resilience must be explored. One factor to consider is the ***diversity of the financial system***; a lack of diversity is harmful for financial system resilience because similar institutions are likely to suffer from the same problems at the same time, exacerbating contagion

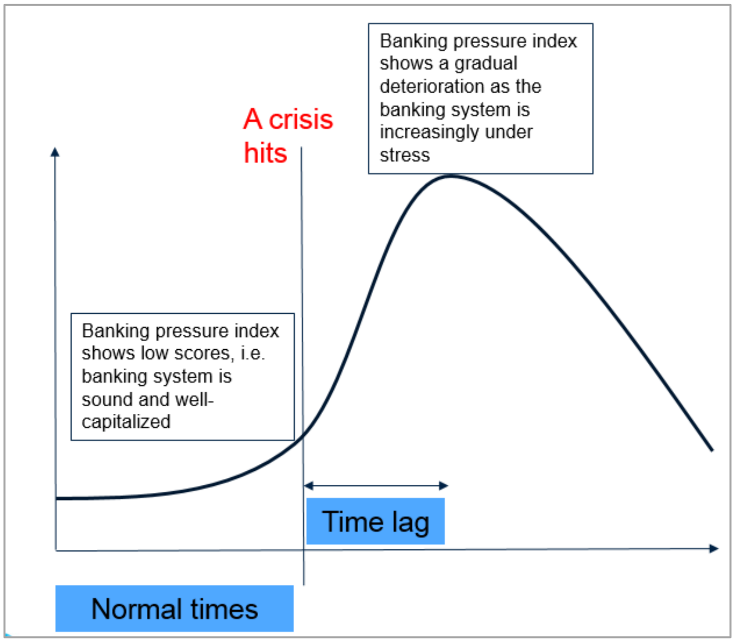
[4] New Economic Foundation (2014), 'Financial System Resilience Index"

effects and thus increasing the chance of a systemic crisis. ***Macro-financial linkages*** may also be relevant to resilience; financial system resilience is affected not just by the system's component parts or aggregate risk exposure, but also by the pattern of connections between institutions. There is also evidence that cross-border financial linkages may be more vulnerable in the event of shocks.

The ***composition of credit aggregates*** is significant for resilience because of the risks which bad debt poses to bank balance sheets. Excessive allocation of credit to financial or asset-market transactions enhances the risk of asset bubbles developing as increasing quantities of credit chase limited quantities of assets. Also, banks' ***liability composition*** is critical to their resilience, both individually and at a system level. Excessive leveraging and maturity transformation may expose banks to solvency and liquidity risks. Other relevant factors include the effects of political and regulatory reforms on the financial services industry.

Therefore, an effective resilience index should be able to capture all these factors and be able to capture levels of stress even in normal times. It is expected that after the outbreak of a crisis, stress levels slowly increase, but with a time lag as increases in delinquencies are increasingly being reflected in weakening of asset quality, and ultimately in capital. The length of the lag depends, amongst others, on regulatory/accounting/supervisory frameworks, particularly the dynamism of loan loss classification and provisioning.

Figure 3: Behaviour of a resilience index



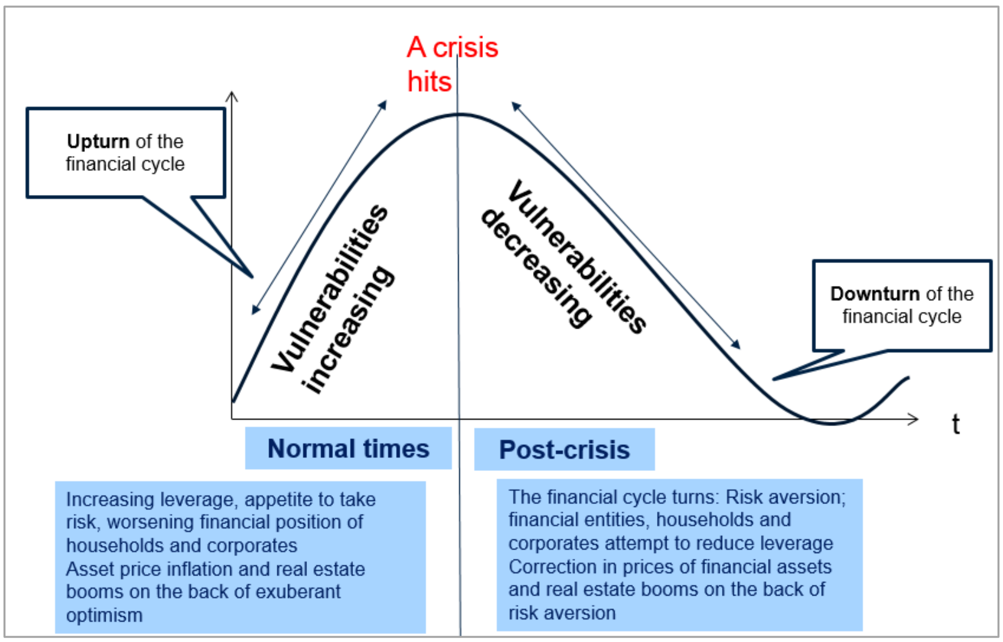
3.1.3. Vulnerability index

The vulnerability index is the most forward-looking of the three indices. It is designed to pick up on vulnerabilities and imbalances that, within the policy horizon (for example, one to two years), could translate into systemic threats. Ideally, it can provide early indications to market participants and policy-makers of emerging areas of weakness in the financial system, and help to inform corrective actions that could be taken to support financial stability and prevent losses in real economic activity.

Financial system vulnerabilities are conditions that make future financial system stress more likely. The degree of vulnerability may reflect, for example, the exposure of the financial system to particular risks. Imbalances create vulnerability by exposing the financial system to the risk of an abrupt correction and by reducing its ability to withstand other shocks. Assessment of financial system vulnerabilities may involve but is not limited to detecting imbalances, estimating the likelihood of future financial system stress, given the imbalances; and estimating the impact of a potential stress episode on the financial system and the real economy, should it occur.

In this regard, it is helpful to construct an index that tracks the financial cycle based on the behaviour of credit and asset prices, particularly property prices, considering that peaks in the financial cycle tend to be closely associated with systemic banking crises (Borio 2012). Once the financial cycle turns, credit availability becomes more constrained as the creditworthiness of borrowers worsens and collateral values deteriorate, and risk aversion increases. The pattern that is expected is thus that the vulnerability index will demonstrate increasing vulnerabilities in the upturn of the financial cycle, and that these vulnerabilities will gradually decrease once the financial cycle has turned.

Figure 4: Behaviour of vulnerability index



The vulnerability index can then be used to identify vulnerabilities in a financial system by comparing current economic and financial data with data from periods leading up to past episodes of financial stress. This type of assessment adds rigour to discussions on the evolution of imbalances by enabling more-precise comparisons with the past, thus allowing policy-makers to draw lessons from history. Specifically, indicators used in index can provide earlier warnings of imbalances. However, judgment is required in interpreting the index, which needs to be placed in the context of information from other complementary sources, including market intelligence gathered through discussions with participants and regular monitoring of economic and financial data.

3.2. Selection of indicators

Selection of the series of indicators that will be the basis for the construction of each composite index is a process that usually involves several iterations before a satisfactory specification is found. In deciding on the specification of any type of index, it is important to keep several considerations in mind:

a) *Unambiguous financial stability interpretation:* In selecting the indicators, it is important to ensure that each variable has an unambiguous relation to financial stability. The inclusion of variables that do not have such a clear-cut interpretation in terms of financial stability will obscure the composite indices, and will likely affect their accuracy in signalling episodes of financial distress.
b) *Sufficient data history and frequency:* The indicators need to have sufficient data history to allow for a proper time series analysis, ideally on the basis of through-the-cycle data, so that the long-term average sets a benchmark that is as reliable as possible. Ideally, this would call for at least sixteen years of data history, although this is not always realistic due to a combination of data availability issues and structural breaks in data series (e.g. due to changes in regulatory definitions). As a rule of thumb, it is advised that the data series be as long as possible, but with a minimum length of eight years. Similarly, it is important that data are available at least on a quarterly basis to ensure sufficient frequency.
c) *Avoiding trending:* Indicators that exhibit natural trending behaviour (such as the private-credit-to-GDP ratio) yield skewed outcomes and are therefore best replaced by logarithms or simple growth rates. It should also be noted that the trend behaviour of the data series implies that the latest observation tends to be in the tail end of the distribution; thus by default, it receives an extreme score.

3.3. Transforming indicators into an index

3.3.1. Changing indicators to scores

After selecting the indicators, it is necessary to establish a methodology for putting the “raw” indicators on a common scale before aggregating them into a composite index. There are several options for transforming a set of supporting indicators into scores; all have specific advantages and disadvantages. It is therefore worthwhile to explore alternative approaches to transforming data series into index scores.

It is necessary to bring the indicators to the same standard, by transforming them into pure, dimensionless, numbers. Another motivation for the normalization is the fact that some indicators may be positively correlated with the phenomenon to be measured, whereas others may be negatively correlated with it. We want normalize the indicators so that an increase in the normalized indicators corresponds to increase in the composite index. For example, when looking at capital adequacy in a resilience index, the ratio of tier 1 capital to risk-weighted assets has negative scores signalling high financial stability risk.

A. Standardization method

The standardization method transforms each indicator's time series into ***standard scores*** so that all the indicators included in the composite index can be compared on a similar scale. A standard score is the signed number of standard deviations by which the value of an observation or data point is above the mean value of what is being observed or measured. Standard scores are also called z-values, z-scores, normal scores, and standardized variables.

Computing a z-score requires knowing the mean and standard deviation of the complete population to which a data point belongs. The absolute value of z represents the distance between each data point and the population mean in units of the standard deviation. z is negative when the data point is below the mean and positive when above. In relation to financial stability indices, deviations from the mean signal higher or lower financial stability risk; positive scores that are higher than the historical averages signal high risk to financial stability, and the reverse holds for lower scores. A score of zero is deemed neutral and signal no change in the level of risk.

Standardization involves the following steps:

For each selected indicator that is to be included in the index;

- ***Step 1***: Transform the indicator such that a higher score for that indicator indicates higher financial stability risk. For example, since an increase in the ratio of tier 1 capital to risk-weighted assets means improved capital adequacy, the series would have to be transformed such that a positive change in the indicator signals high financial stability risk instead. The transformation is done by simply scaling the whole time series by -1.

- ***Step 2***: Calculate the average μ for the indicator. The average is computed as the sum of all the values x_n in the indicator's time series divided by the count N of all the values in the series:

$$\mu = \sum_{n}^{N} x_n$$

- ***Step 3***: Calculate the standard deviation σ for the indicator. Standard deviation is computed as the square root of the time series variance by determining the variation between each data point relative to the mean μ. If the data points are further from the mean, there is higher deviation within the data set:

$$\sigma^2 = \frac{\sum_{n}^{N}(x_n - \mu)^2}{N}; \qquad \sigma = \sqrt{\sigma^2}$$

- ***Step 4***: For each value x_n in the indicator's time series, compute the standardised score z:

$$z_n = \frac{x_n - \mu}{\sigma}; \quad n = 1, \cdots, N$$

3.3.2. Workshop III: Developing a Resilience Index using Standardisation

The purpose of this workshop is to develop a resilience index for a given banking system. This exercise is performed using the MS Excel worksheet titled "Workshop III_ex_ResIdx.xlsx".

Participants are provided with 10 banking sector variables that are grouped in four risk categories: ***capital adequacy, asset quality, earnings and profitability*** and ***funding and liquidity***. Quarterly aggregate data is provided from March 2001 to December 2015. It is assumed that each of the selected variables is an indicator of risk in the category to which they are assigned.

Table 1: Indicators selected for the resilience index

Category	Indicator
Capital adequacy	• Ratio of tier 1 capital to risk-weighted assets

Category	Indicator
	• Leverage ratio
Asset quality	• Ratio of non-performing loans to total gross loans • Ratio of large exposures to total gross loans
Earnings & profitability	• Return on average assets • Net interest margin • Ratio of overheads to income
Liquidity	• Ratio of liquid assets to total deposits • Ratio of total loans to total deposits • Ratio of short-term assets to short-term liabilities

1. In the spreadsheet “Workshop III_ex_ResIdx.xlsx”, the first sheet titled “INDICATORS” contains the aggregate time series of all the indicators laid out in Table 1. Perform a simple analysis of the data to determine the performance of the banking sector for entire time series.
2. In the sheet titled “STANDARD”, the indicators are transformed into z-scores using the standardisation method.
    - Recall that with the resilience index, a positive z-score means that the financial ratio is worse than the corresponding average over the period under review. We want normalize the indicators so that an increase in the normalized indicators corresponds to increase in composite index.

      To do this, at the top of the sheet along Line 2, fill out each cell corresponding to each variable with “1” or “-1”, depending on how each variable needs to be transformed to conform to the desired trend of the index.

    - In Lines 6 and 7 under the heading “Summary Statistics”, compute the mean and standard deviation for each variable for the length of the time series. Note that the mean also has to be transformed to follow the trend of the index.
    - Under the heading “Standardized Scores - z”, compute the z-scores for indicator as per the formula below:

$$z_t = \frac{x_t - \mu}{\sigma}$$

Here, z_t is the normalized (or z-score for) the financial ratio at time t; x_t is the financial ratio at time t; μ is the system mean of a particular financial ratio over the entire time series; σ is the system standard deviation of a particular financial ratio over the entire time series.

3. In the “RES_IDX” worksheet, we aggregate the scores to obtain a resilience index. The sub-indices and overall index are aggregated using the arithmetic mean.
    - Start by computing the sub-indices for each risk category. This is done by averaging over the scores of the indicators in each category to obtain one value at each time period.
    - In the column with the heading “Res_Idx”, the sub-indices are aggregated by using the arithmetic mean to obtain the final index score per time period.
4. Analyse the graphs of each sub-index as well as the overall resilience index. What conclusions can be made about the changes in the health of this banking system between 2001 and 2015?

    Using the radar chart feature of MS Excel, construct a cobweb diagram of the index for the period of December 2011 to December 2015. What does the diagram reveal about the changes in the banking system’s resilience during these time periods?

B. Empirical normalization

This approach is an alternative to the standardization method and is less sensitive to distributional properties of the data. However, some of the informational value of outliers gets lost.

The highest observed score receives a *z*-score of 1, which represents the highest financial stability risk. The lowest observed score receives a *z*-score of 0, which represents the lowest financial stability risk. The “neutral” score equals 0.5.

Empirical normalization involves the following steps:

For each selected indicator that is to be included in the index;

- ***Step 1***: Transform the indicator such that a higher score for that indicator indicates higher financial stability risk. This can be done by simply scaling the whole time series by -1.
- ***Step 2***: Identify the minimum and maximum values of the indicator and compute the range of the time series:

$$\text{range} = \text{maximum} - \text{minimum}$$

- ***Step 3***: For each value in the indicator's time series, compute the score *z*:

$$z_n = \frac{x_n - \min}{\text{range}}; \quad n = 1, \cdots, N$$

3.3.3. Workshop IV: Developing a Financial Stress Index using Empirical Normalisation

The purpose of this workshop is to develop a financial stress index for Brazil. This exercise is performed using the MS Excel worksheet titled "Workshop IV_ex_StressIdx.xlsx".

A. Background

Brazil's economy suffered its worst slump for quarter of a century in 2015 as a global commodity rout, a domestic political crisis and rising inflation forced businesses to slash spending and jobs. Brazil's economy had been hit hard by a collapse in commodity and oil prices in the past two years. The situation was made worse by the high debt levels, especially in foreign currency – essentially in US dollars. Problems of governance, corruption and political issues also created a perfect storm for continued political instability.

The country's growth rate decelerated steadily since the beginning of this decade, from an average annual growth of 4.5 percent between 2006 and 2010 to 2.1 percent between 2011 and 2014. GDP contracted by 3.8 percent in 2015. The economic crisis, as a result of the fall in commodity prices and an inability to make the necessary policy adjustments, - coupled with the political crisis faced by the country - contributed to undermining the confidence of consumers and investors.

The Brazilian banking sector's economic risk trend was viewed as negative, reflecting the country's low GDP per capita and political and economic challenges, which remain considerable. Brazilian banks are going through a correction phase, and both house prices and credit growth are contracting in real terms. The correction phase is expected to have a severe impact on Brazilian banks as a result of a prolonged recession.

The majority view among economists is that Brazil will emerge from recession in 2017, but at a very slow growth rate of 0.5 percent, which would be insufficient to reduce unemployment. The government has forecast growth of 1 percent. Recently-released data indicates that GDP grew for the first time in over three years in Q2 of 2017, confirming that the economy has turned a corner. The upturn was largely due to tailwinds to private consumption from falling inflation and a one-off decision allowing workers to make early withdrawals from a government severance fund. Export growth also accelerated in the quarter. The recovery remains tentative despite the good news.

B. Exercise

Participants are provided with eight financial markets variables that are grouped into four sectors: ***money market, equity market, external sector*** and ***real estate***. Monthly data is provided from June 2007 to March 2017. It is assumed that each of the selected variables is an indicator of risk in the category to which they are assigned.

Table 2: Indicators selected for Brazil's financial stress index

Category	Indicator
Money market	• Spread between the 10-year government bond yield and the key policy rate • Overnight interbank rate
Equity market	• Volatility of the Ibovespa[5] • VIX[6]
External sector	• Volatility of the Real/USD rate • Price of Brent crude oil, USD/barrel • Volatility of the Bloomberg Commodity Index[7]

[5] The Bovespa Index is designed to gauge the stock market's average performance tracking changes in the prices of the more actively traded and better representative stocks of the Brazilian stock market.
[6] VIX is the ticker symbol for the Chicago Board Options Exchange (CBOE) Volatility Index, which shows the market's expectation of 30-day volatility. It is constructed using the implied volatilities of a wide range of S&P 500 index options.
[7] The Bloomberg Commodity Index (BCOM) is a broadly diversified commodity price index distributed by Bloomberg Indexes. The BCOM tracks prices of futures contracts on physical commodities on the commodity

Category	Indicator
Real estate	• The BM&FBOVESPA Real Estate Index (IMOB)[8]

1. Provide a rationale for the indicators selected for use in the financial stress index.
2. In the spreadsheet "Workshop IV_ex_StressIdx.xlsx", the first sheet titled "INDICATORS" contains the aggregate time series of all the indicators laid out in Table 2. Perform a simple analysis of the data to determine the performance of the financial markets for entire time series.
3. In the sheet titled "EMPIRICAL", the indicators are transformed into z-scores using the empirical normalisation method.
   - Recall that with the financial stress index, a positive z-score means that the financial indicator is worse than the corresponding average over the period under review. We want normalize the indicators so that an increase in the normalized indicators corresponds to an increase in the composite index.

     To do this, at the top of the sheet along Line 2, fill out each cell corresponding to each variable with "1" or "-1", depending on how each variable needs to be transformed to conform to the desired trend of the index.

   - In Lines 6, 7 and 8 under the heading "Summary Statistics", compute the minimum, maximum and range for each variable for the length of the time series. Note that these statistics are also transformed to follow the trend of the index.
   - Under the heading "Normalised Scores - z", compute the z-scores for indicator as per the formula below:

$$z_n = \frac{x_n - \min}{\max - \min}; \quad n = 1, \cdots, N$$

markets. The index is designed to minimize concentration in any one commodity or sector. It currently has 22 commodity futures in seven sectors.

[8] The BM&FBOVESPA IMOB is designed to track changes in the prices of the more actively traded and better representative real estate sector stocks, so as to gauge average stock performance specific to the real estate sector, as encompassing stocks representative of the real estate intermediation and wider real estate exploitation subsectors, as well as the civil engineering and construction industry.

It must be noted that the z-scores must lie between 0 and one such that: the highest observed score receives a z-score of 1, which represents the highest financial stability risk; the lowest observed score receives a z-score of 0, which represents the lowest financial stability risk; and, the "neutral" score equals 0.5.

4. In the "Stress_IDX" worksheet, we aggregate the scores to obtain a financial stress index. The sub-indices and overall index are aggregated using the arithmetic mean.
    - Start by computing the sub-indices for each risk category. This is done by averaging over the scores of the indicators in each category to obtain one value at each time period.
    - In the column with the heading "Stress_Idx", the sub-indices are aggregated by using the arithmetic mean to obtain the final index score per time period.

    Analyse the graphs of each sub-index as well as the overall financial stress index. What conclusions can be made about the changes in Brazil's financial system between 2007 and 2017?

C. Order statistics

Order statistics have the advantage of being less sensitive to the distributional properties, but that comes at the price of losing some of the informational content of outliers. Transformation through order statistics does not require the raw data to be normally distributed. However, in the process of transformation, some of the information content of outliers gets lost, as the index's scores of outliers based on rankings will be somewhat subdued.

It is a relatively simple technique for transforming data series into an index score, and it involves the following steps:

For each selected indicator that is to be included in the index;

- ❖ ***Step 1***: Transform the indicator such that a higher score for that indicator indicates higher financial stability risk. This can be done by simply scaling the whole time series by -1.
- ❖ ***Step 2***: Sort the data series by magnitude, that is, from the smallest to the largest value.

- ***Step 3***: Assign each observation a rank, r (where $r = 0,\ldots.,N\text{-}1$). The smallest value is assigned rank, $r = 0$ and the largest value is assigned rank, $r = N\text{-}1$
- ***Step 4***: Calculate the ranking order score z, for each value, such that by construction, the lowest ranking observation has a score of 0 and the highest ranking observation has a score of 1:

$$z = \frac{r}{N-1}; \quad r = 0, \cdots, N-1$$

For financial stability monitoring purposes, the latest observation of any data series is the most relevant. In the process of adding new observations, the sample is expanded, one observation at a time. The indicator is thus transformed into an index recursively over an expanding sample.

A related but simpler alternative is the construction of a predefined number of equal-sized intervals, a methodology that is applied by the Norges Bank (Dahl et al 2011). The data are ranked in such a way that the higher-ranking observations correspond to higher risk to financial stability. Subsequently, the data series is divided into a number of intervals, in such a manner that each interval contains an equal number of observations. By adding the latest observation for a particular indicator to the ranked data, it can fall into a particular interval, each of which corresponds to a financial stability score.

3.3.4. Workshop V – Part II: Developing a Vulnerability Index using Order Statistics

The purpose of this workshop is to develop a vulnerability index for South Africa. This exercise is performed using the MS Excel worksheet titled “Workshop V_ex_VIdx.xlsx”.

A. Background

South Africa‘s gross domestic product (GDP) declined by 0.7 percent during the first quarter of 2017 after contracting by 0.3 percent in the fourth quarter of 2016. Economic activity contracted over a wide range of sectors, including construction, manufacturing and transport. Only mining and agriculture made a positive contribution to output growth. This reflects subdued demand throughout the South African economy. The data on the first quarter showed that demand is down and that business conditions are tough.

Low growth has led to the stagnation of GDP per capita, and persistent high unemployment and inequalities. The economy faces many structural challenges while high inflation limits room for monetary policy support and high public debt constrains public spending. The central bank revised down its growth forecasts for country; it estimates 2017 full year GDP growth of 0.5 percent, down from 1 percent. Underlying demand in South Africa's economy is extremely weak, and it is unclear whether any drivers of economic growth will emerge in the absence of structural initiatives that would reduce uncertainty and boost confidence.

However, some investors are still choosing to invest in the region. For instance, the South African MSCI index remains a top performer among global emerging markets. Assets under management grew by 5.9 percent in the week to July 19, compared to 2.9 percent from emerging markets as a whole. The broad recovery in commodities this year boosted South African miners. The key risk for investors is political instability. Heightened uncertainty caused business confidence to plummet to an over 30-year low in August, despite the recent revival in growth.

B. Exercise

Participants are provided with eleven variables that are grouped into four categories: ***macroeconomic conditions, financial markets, credit conditions*** and ***external sector***. Quarterly data is provided from March 1992 to June 2017. It is assumed that each of the selected variables is an indicator of risk in the category to which they are assigned.

Table 3: Indicators selected for South Africa's vulnerability index

Category	Indicator
Macroeconomic conditions	• Annual GDP growth • Ratio of gross government debt to GDP • Business confidence index[9]
Financial markets	• 10-year government bond yield • Average interbank rate
Credit conditions	• Ratio of private sector credit to GDP • Ratio of household debt to GDP

[9] The business confidence index (BCI) is based on enterprises' assessment of production, orders and stocks, as well as its current position and expectations for the immediate future. Opinions compared to a "normal" state are collected and the difference between positive and negative answers provides a qualitative index on economic conditions.

	• Ratio of corporate debt to GDP
External sector	• Nominal effective exchange rate • Ratio of current account balance to GDP • World Bank all-commodities index

1. Provide a rationale for the indicators selected for use in the vulnerability index.
2. In the spreadsheet "Workshop IV_ex_VIdx.xlsx", the first sheet titled "INDICATORS" contains the aggregate time series of all the indicators laid out in Table 3. Perform a simple analysis of the data and describe the overall macrofinancial conditions for South Africa for the length of the time series.
3. In the sheet titled "ORDERSTATS", the indicators are transformed into z-scores using the order statistics approach.
   - Recall that with the vulnerability index, a positive z-score means that the indicator is worse than the corresponding average over the period under review. We want normalize the indicators so that an increase in the normalized indicators corresponds to an increase in the composite index.

     To do this, in section 1 titled "TRANSFORM", at the top of the sheet along Line 3, fill out each cell corresponding to each variable with "1" or "-1", depending on how each variable needs to be transformed to conform to the desired trend of the index.
   - In section 2 titled "RANK", we rank each observation of each indicator as required by the order statistics approach. Specifically, assign each observation a rank, r (where r = 0… N-1). The smallest value is assigned rank, r = 0 and the largest value is assigned rank, r = N-1.
   - In section 3 titled "Z-SCORES", Calculate the ranking order score z, for each value, such that by construction, the lowest ranking observation has a score of 0 and the highest ranking observation has a score of 1:

$$z = \frac{r}{N-1}; \quad r = 0, \cdots, N-1$$

4. In the "V_Idx" worksheet, we aggregate the scores to obtain a vulnerability index. The sub-indices and overall index are aggregated using the arithmetic mean.

- Start by computing the sub-indices for each risk category. This is done by averaging over the scores of the indicators in each category to obtain one value at each time period.
- In the column with the heading "V_Idx", the sub-indices are aggregated by using the arithmetic mean to obtain the final index score per time period.

5. Analyse the graphs of each sub-index as well as the overall vulnerability index. What conclusions can be made about evolution of risks and vulnerabilities in the South African economy?

Using the radar chart feature of MS Excel, construct a cobweb diagram of the index for the following periods: June 2008, June 2011, June 2014 and June 2017. What does the diagram reveal about the changes in the vulnerabilities during these time periods?

3.3.5. Creating the composite index

Once the raw data has been transformed into a common scale, the next step is to convert them into the composite index. Aggregation of the individual indicators is the combination of all the components to form one or more composite indices. Different aggregation methods are possible. The most used are additive methods that range from summing up unit ranking in each indicator to weighted average of the supporting indicators or time-varying weights, by applying portfolio theory to the aggregation of the individual indicators (as is done in Holló, Kremer, and Lo Duca 2012).

4. BHI: A Bank Health Assessment Tool

The Bank Health Index (BHI) was developed by Ong *et al* (2013). The tool is based on simple CAMELS[10]-type ratings for each bank, including systemically important ones. It is simple to use and update and provides a measure of relative (but not absolute) health of a banking system. System-wide health, vis-à-vis a global peer group of banks such as the G-SIBs, can also be assessed by taking the aggregate of each variable for all banks in the system to derive system-wide BHIs, or by inputting system-wide ratios.

[10] "CAMELS" integrates ratings from six component areas: Capital adequacy, Asset quality, Management, Earnings, Liquidity, and Sensitivity to market risk.

The BHI, albeit simple, can be useful for initial identification of relative bank soundness and is also able to identify more specific areas of vulnerability. Banks' financial statements data (preferably audited) are required for calculating the BHI. As a rough and ready measure of individual banks' health, we calculate simple CAMELS-type ratings for each institution in the defined sample. A BHI is subsequently derived from the ratings and a heat map is generated to provide a snapshot of a particular bank or banking system.

4.1. Methodology

For each bank, five financial ratios are calculated, one in each category of capital adequacy, asset quality, earnings and profitability, liquidity and leverage (see Table 4).

Table 4: Indicators selected for the Bank Health Index

Category	Indicator
Capital adequacy	Ratio of total equity or tier 1 capital to risk-weighted assets
Asset quality	Ratio of non-performing loans (less of provisions) to total gross loans
Earnings & profitability	Return on average assets
Liquidity	Ratio of liquid assets to customer deposits and short-term funding
Leverage	Ratio of tangible common equity to tangible assets

Then, each financial ratio is normalized around the system-wide (or all sample banks') mean and standard deviation to facilitate comparability, such that:

$$z_{i,t} = \frac{x_{i,t} - \mu}{\sigma}; \quad i = 1, \cdots, N$$

$z_{i,t}$ is the normalized (or z-score for) the financial ratio of bank i at time t; $x_{i,t}$ is the financial ratio of bank i at time t; μ is the system mean of a particular financial ratio over the three periods to time t; σ is the system standard deviation of a particular financial ratio over the three periods to time t. The system means and standard deviations are calculated over three periods in order to provide a sufficiently large sample size, incorporate both the time and cross-sectional dimensions, and ensure that any deterioration during the crisis period is adequately captured.

The *z*-score provides an indication of a bank's performance in particular areas relative to its peers. With the exception of the asset quality measure (NPL ratio), a positive *z*-score means that the financial ratio of a particular bank is better than the corresponding average across its peer group over three periods. In the case of the asset quality measure, the NPL ratio *z*-score is multiplied by -1 so that any increase in that score would be represented as an increasingly negative development.

An overall relative health score for each bank at a particular point in time can be estimated by summing up the *z*-scores for each of the financial ratios, such that:

$$z_{bank,t} = z_{capital,t} + z_{asset,t} + z_{earnings,t} + z_{liquidity,t} + z_{leverage,t}$$

Here, $z_{capital,t}$ is the *z*-score for capital adequacy at time t; $z_{asset,t}$ is the *z*-score for asset quality at time t; $z_{earnings,t}$ is the *z*-score for earnings at time t; $z_{liquidity,t}$ is the *z*-score for liquidity at time t; and $z_{leverage,t}$ is the *z*-score for leverage at time t. Hence, the sum of the five standardized financial ratios $z_{bank,t}$ is a bank's BHI, relative to its peers. It essentially represents a relative overall measure of health for a particular bank in the defined peer sample. The BHI for a country‘s banking system compared to a global peer group would give the relative health of a banking system.

One can then generate heat maps of the BHI to visually differentiate the overall relative soundness of individual banks, as well as the individual constituent components of the Index, for a particular period and over time. Details of constructing a heat map are laid out in Section 5 below.

4.2. Considerations

As with all indicators and tools, specific limitations that are attached to the use of the BHI should be taken into consideration in any analysis. The BHI should be complemented by an analysis of its individual constituent components. The Index comprises aggregated z-scores, which provide an overall measure of bank health but which may also hide valuable information about particular aspects of individual banks' performance. Furthermore, the BHI only shows the relative health of banks within a chosen sample. The Index is a relative rather than an absolute indicator, i.e., a particular bank is merely the "healthiest" or "weakest" bank in the peer group sample, not necessarily in absolute terms. A comparison on absolute terms would require the inclusion in the sample of a peer institution that is known to be a representative global benchmark for financial strength.

The BHI does not adjust for nuances associated with heterogeneity across banks. It should ideally be applied in a homogeneous environment, i.e., to institutions with similar business models and subject to the same regulatory requirements, to facilitate consistency in comparisons. Where this is not the case, any analysis of the resulting BHI should take differences into consideration.

Also, comparisons over a longer time period may be affected by the method of calculating the *z*-scores. The system means and standard deviations are calculated over three periods on a rolling basis, which means that the *z*-scores for any one period are based on different means and standard deviations than for other periods, and the differences may be quite significant over an extended period.

5. Assessing Early Warning Properties of Systemic Risk Indicators

5.1. Validation of indicators

Predicting banking crises is an exercise in compromise and usually consists of several iterations. The process involves the analysis of the historical behaviour of risk indicators to ascertain whether they behaves as expected, signalling previous episodes of financial distress or the build-up of imbalances. For instance, the typical pattern of a composite index that consists of stress indicators is that it will likely signal relatively low levels of financial stability risk in the upturn of the financial cycle, but may spike suddenly in the face of financial distress. By contrast, vulnerability indices that are based on indicators that measure levels of indebtedness, leverage, or the evolution of asset prices will likely display rising levels of financial stability risk in the upturn of the financial cycle, followed by gradually decreasing levels of risk in the downturn. Lastly, resilience indicators tend to follow the financial cycle indicators, but with a significant lag. It usually takes several iterations before a satisfactory specification has been found.

The ideal indicator would signal all impending crises and never crises that fail to materialise. All known early warning indicators (EWIs) fall short of this ideal, and hence they must be evaluated on the basis of how they trade off the rate of missed crises against the rate of false positives (i.e.

the percentage of signals they emit for crises that do not happen). This evaluation depends on policymakers' preferences concerning these two types of error.

Good EWIs must fulfil a number of additional requirements that go beyond statistical accuracy. Drehmann and Juselius (2014) propose three such requirements in the context of macroprudential policymaking. The first is timing: EWIs must provide signals early enough for policy measures to take effect. For instance, the Basel III guidance states that "the indicator should breach the minimum [critical threshold] at least 2–3 years prior to a crisis" (BCBS (2010)). The second requirement is stability: the indicator should not flip-flop between signalling a crisis and being "off". EWIs that issue stable signals reduce uncertainty regarding trends and allow for more decisive policy actions. The final requirement is interpretability. Forecasts and signals that policymakers find hard to understand and interpret are likely to be ignored. This puts a premium on simplicity and ease of communication, making single indicators with robust performance particularly appealing.

One way to determine the predictive power of a risk indicator is by using the ***noise-to-signal ratio*** which was built on work by Kaminsky and Reinhart (1999). This approach monitors the evolution of an indicator such that a deviation from the normal "level" beyond a certain prescribed threshold is considered a warning signal about a possible crisis. This approach requires for crises to be clearly defined and works best with indicators or indices that are forward-looking. In addition, a signalling horizon has to be determined to represent the time period within which the index is expected to anticipate a crisis. In practice, the 24 months is considered as an ideal signalling horizon. Therefore, a signal is considered "true" if a stress episode follows in the next 24 months and "false" if a stress episode does not follow in the next 24 months. For any given threshold, the performance of the indicator can be judged using the categories as presented in Table 5.

Table 5: Assessment of true and false signals of stress episodes

	Crisis	**No crisis**
Signal was issued	A	B
No signal was issued	C	D

A = Number of months with true crisis signal
B = Number of months with false crisis signal
C = Number of months with false no-crisis signal
D = Number of months with true no-crisis signal

A perfect indicator would have no observations in categories B and C; A would equal the total number of pre-stress months, and D the total number of normal months in the sample. However, an index with observations in categories C and B would present "Type I" and "Type II errors" respectively.

The method is simple: for each period, a signal is calculated. The signal takes the value of 1 (is "on") if the indicator exceeds a critical threshold; it is 0 ("off") otherwise. A signal of 1 (or 0) is judged to be correct if a crisis occurs (or does not occur) at any time within the signalling horizon, allowing the fraction of correctly predicted crises as well as incorrect calls to be calculated. Hence, the noise-to-signal-ratio is the proportion of false crisis signals in normal periods (the noise) divided by the proportion of true crisis signals among the pre-stress periods:

$$\frac{B/(B+D)}{A/(A+C)}$$

An indicator is deemed useful if its noise-to-signal ratio is less than 1.

5.1.1. Workshop II: Indicator Validation Using the Noise-To-Signal Ratio

The purpose of this workshop is to use the noise-to-signal ratio (NSR) as a method of assessing early warning properties of selected indicators. This exercise is performed using the MS Excel worksheet titled "Workshop II_ex_NSR.xlsx".

Participants are provided with macroeconomic data for 11 countries in the sub-Saharan region that have experienced a banking crisis, a currency crisis or both. For each country, we have the following indicators on annual basis for the period 1980 – 2015: ***GDP growth, inflation*** and the ***current account balance-to-GDP ratio***. It is assumed that each of these indicators can be used as early warning indicators for crises.

1. In the spreadsheet "Workshop II_ex_NSR.xlsx", the first 11 sheets contain data and graphs for selected individual countries. The charts report both the variables of interest and the timing of systemic banking or currency crises (red bars). By simply looking at the data, try to gauge which macroeconomic indicator best signals the occurrence of a crisis.
2. Next, we construct crisis indicators for each of the three variables. This is done using the sheets labelled "SIGNALS" and "NSR".
   a. First, we set crisis thresholds for each variable in the table "CRISIS THRESHOLDS" in the "NSR" sheet. This is considered the threshold above or below which the macroeconomic variable signals a crisis.
   b. In the sheet "SIGNALS", all the countries' data is combined to provide a larger sample from which to draw reliable signal performance. In columns I, K and M, we assign a signal to each data point. For each macroeconomic variable, if the data point in the previous year exceeds the threshold prescribed in step 2a above, it is assigned value "1" to indicate a crisis, and value "0" otherwise.
   c. In columns J, L, and N, it is determined whether the signal is true, or if its type-I or type-II error.
3. In the "NSR" sheet, we compute the noise-to-signal ratio for each macroeconomic variable.
4. Determine which variable performs best as an early warning indicator.

Repeat the exercise for different threshold levels and compare the results.

5.2. Graphical representation using risk diagrams

Systemic risk indicators can be graphically summarized using visual analytics. Applying visual analytics tools to macroprudential supervision is a multi- and interdisciplinary exercise, requiring a clear understanding and definitions of: 1) supervisors' analytic concepts, tasks, and mental models; 2) data; and 3) the visual analytics requirements. Success in developing visual analytics tools is typically achieved through repeated interactions with visual representations of data. Through this iterative process the interactive techniques of visual analytics help evoke novel insights from data.

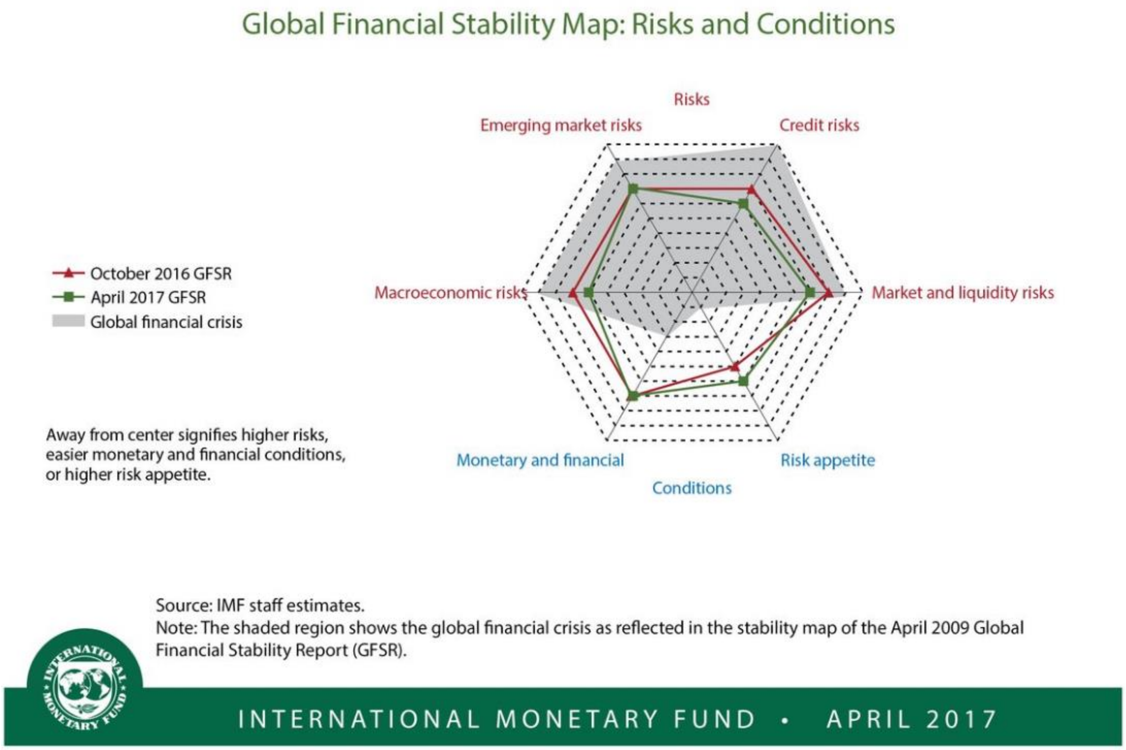
Visual analytics is only part of the toolkit that macroprudential supervisors will need to transform data into actionable knowledge. Visual analytics does not replace the need for statistical tools, which may be preferable for tasks or phenomena that can be structured with limited dimensionality and that recur frequently enough to provide a reliable sample. Visual analytics seeks to couple interactive visualization tightly with data analysis. Because visual analytics strongly emphasizes comparisons and relationships among empirical data, it is important to define clear, measurable, meaningful abstractions that capture the relevant data semantics and are comparable when applied across the financial system.

5.2.1. The cobweb diagram

After the introduction of the Global Financial Stability Map in 2007 (IMF (2007)) and its regular publication in the Global Financial Stability Report to provide a graphical presentation of risks and conditions affecting financial stability for communication purposes, risk diagrams became a more popular tool for monitoring and assessing financial stability and for communication.

Following the approach in the IMF’s Global Financial Stability Map, a radar/ cobweb-style diagram can be constructed, wherein each axis represents a risk category (Figure 5). The diagram usually has 5–6 axes onto which the assessment of the selected risk categories or conditions (e.g. the credit risk, monetary and financial conditions, etc.) is marked. The category assessment in the centre of the diagram corresponds to a very low level of risk while the closer the risk assessment is to the external border of the diagram, the higher the risk. Risk assessments of two or three periods are usually included in the risk diagram for comparison purposes. Risk category indices over time are often shown in separate charts. The risk diagram development methodology, as well as the selection of risk categories and indicators included in the diagram, is country-specific. The selection of indicators and risk categories is determined by distinctive features of each country's financial system and factors affecting financial stability, as well as by data availability for their assessment. The process of selecting indicators and risk categories should follow the criteria laid in Section 3.2 above.

Figure 5: The IMF Global Financial Stability Map

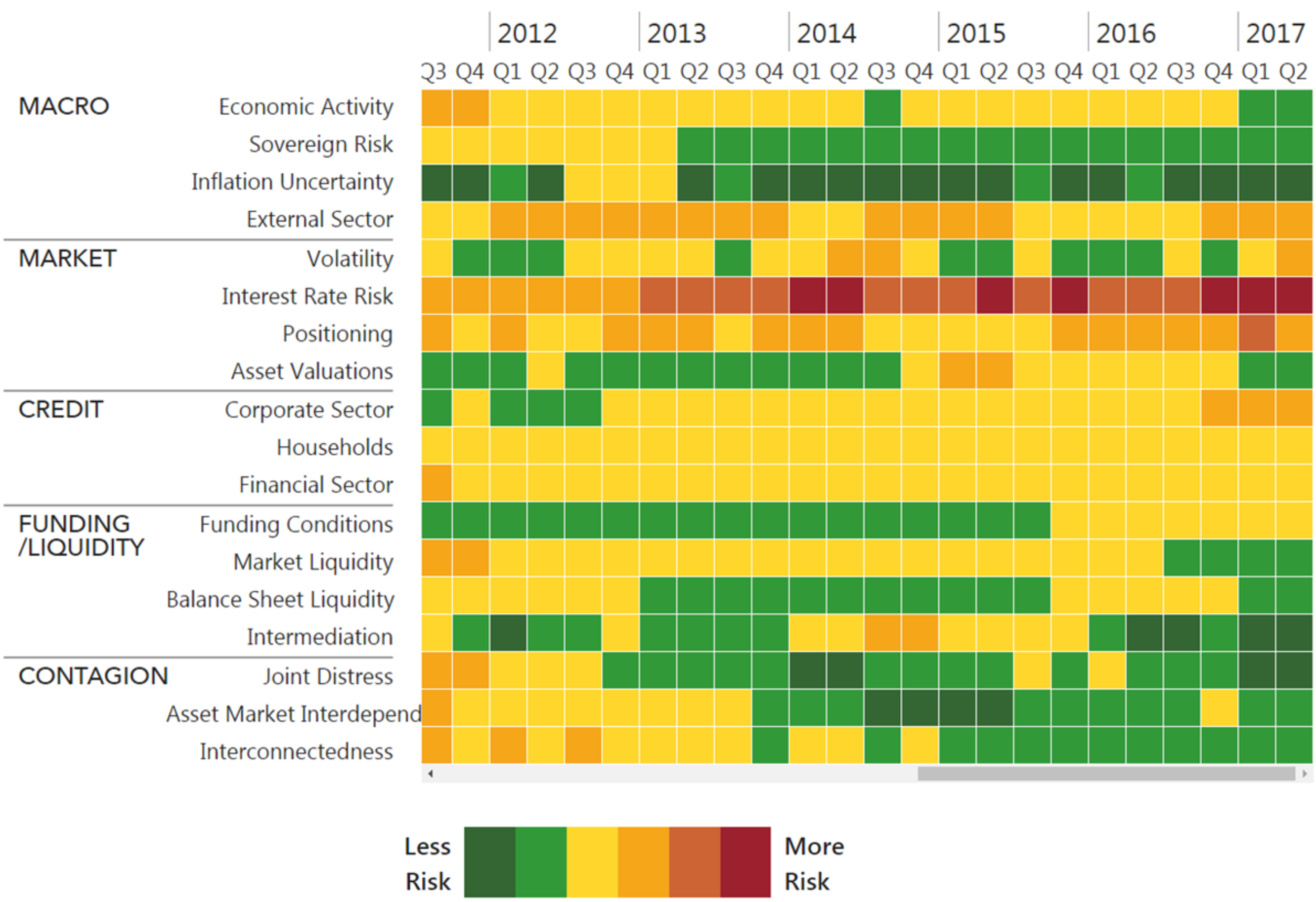


As an example the IMF Global Financial Stability Map as presented in their Global Financial Stability Report for 2017 provides a summary of the changes in key global financial conditions and risks. It can be seen that near-term macroeconomic risks reduced between October 2016 and April 2017, and this was explained by ***monetary and financial conditions*** which remained highly accommodative. The Report goes on to further explain how the increase in ***risk appetite*** occurred against this stronger economic backdrop. ***Market and liquidity risks*** eased from elevated levels as risk premiums fell and volatility remained subdued. Steeper yield curves helped banks enhance profitability, while tighter corporate bond spreads, low rates, and ample market access reduced refinancing risks, leading to a reduction in ***credit risks***. Lastly, although emerging market economies continued to enhance their resilience, higher inflation volatility in some countries and rising financial vulnerabilities in China left ***emerging market risks*** unchanged.

5.2.2. The heat map

A heat map is a two-dimensional representation of data in which values are represented by colours. A simple heat map provides an immediate visual summary of information. The heat map adds particular value when used to present the historical evolution and movement across a large number of time series. Ideally, a heat map displays a snapshot of weaknesses in the financial system based on prescribed risk categories. It is not designed to predict the timing or severity of a financial crisis but to identify underlying vulnerabilities that may predispose the system to a crisis.

Figure 6: A financial stability heat map for the U.S. by the Office of Financial Research



The reliability of any heat map depends on well-defined scaling criteria. This includes the development of qualitative and quantitative criteria outlining the thresholds that need to be exceeded for a particular occurrence of financial stress to be labelled "systemic." This applies not only to the overall systemic assessment, but also to the assessed impact of the financial disturbance on the individual components of the financial system and the real economy (which subsequently feed into the overall assessment). In other words, appropriate scales with corresponding trigger points need to be established as a basis upon which authorities can assess whether a particular financial stress situation constitutes limited, moderate, serious, or very severe risks. In order to make for a more disciplined assessment, authorities may choose to represent the outcomes of their systemic risk assessments on a numerical scale

To this end, appropriate scaling criteria need to be established; this is more of an art than a science. It involves not only establishing indicative quantitative trigger points, but considering qualitative elements, as well. As an illustration, the extent of the disturbance of financial institutions may be assessed on the basis of the estimated loss of capital for the banking system and its impact on the available solvency buffers. Assuming a scale that ranges from 0 ("negligible") to 3 ("very severe"), estimated losses that bring the capital adequacy ratio (CAR) of a significant part of the banking system close to or below the statutory minimum may be considered "very severe" (3). Significant losses that still leave part of the existing solvency buffers above the statutory minimum intact (more than 3 percentage points above the statutory CAR, for example may be considered "serious" (2). Smaller losses with limited impact on existing solvency buffers may be "moderate" (1) or "negligible" (0). Each value on the scale is assigned a colour that represents the intensity of the threat on the heat map.

6. Mapping Interconnections in the Financial System: The Contagion Matrix

Identifying interconnections within the financial system and from the financial system to the real economy gives a notion about the contagion effects that are likely to occur in the event of a financial crisis. The contagion channels between each of the constituents of the financial system can be summarized in a contagion matrix. The contagion matrix primarily concentrates on real contagion channels: that is, direct exposures and interconnections. The main purpose of the matrix is to provide authorities with a concise overview of the main interdependencies in the financial system. The matrix indicates the transmission mechanisms of financial shocks through the financial system that can arise as a result of direct exposures. In a crisis situation, this provides authorities with a frame of reference with which to identify the most likely contagion effects of an actual financial shock, thereby giving them an opportunity to conduct a quicker and more disciplined assessment of systemic risk. The content of the matrix should be adapted in the light of country-specific characteristics.

6.1. Contagion within the financial system

While real exposures can in principle be mapped before a crisis, certain categories of information become available only in the context of the actual crisis. This obviously includes the specific characteristics of the triggering event, but also the information the authorities need in order to assess contagion effects through the information channel. The direction and intensity of contagion effects through the information channel ultimately depend on economic agents' behavioural response to the disclosure of financial distress and—are therefore noticeably more difficult to contemplate in advance than contagion through real exposures. In this context, it is relevant to take the state of the business cycle and the prevailing financial market conditions into consideration. As a general rule, contagion via the information channel can be expected to be more serious if the crisis coincides with a trough in the business cycle or unsettled financial market conditions.

Contagion via the information channel also depends on the collective policy response by the authorities. Ill-conceived or poorly coordinated responses are likely to increase uncertainty and may result in loss of confidence. Also, informational contagion to financial institutions may be of special concern if their financial resilience is perceived to be weak or if particular institutions demonstrate special vulnerabilities to the triggering event (such as heavy reliance on wholesale funding after a sharp deterioration of liquidity conditions).

Figure 7: A summarised contagion matrix

	Contagion to			
		Institutions	**Markets**	**Infrastructure**
Contagion from	**Institutions**	- Credit risk exposures - Shareholder links - Guarantor/provider of contingent credit lines - Deposit insurance (through financing funding shortfalls or replenishments) - Access provider to financial infrastructure	- Market maker for derivatives - Underwriter of CDSs - Fire sales of financial assets	- Operational disturbances
	Markets	- Investment losses on available for sale assets/trading portfolio - Revenue channel - Funding/liquidity management	- Information channel	- Coverage for counterparty exposures with collateral (margin calls)
	Infrastructure	- Overdue incoming and outgoing payments	- Trading platforms and clearing and settlement systems	- Supporting services, technical links, and connected ICT systems

6.1.1. Contagion between financial institutions

- ***Credit risk exposures***. Financial institutions can be linked in a great number of ways, which may lead financial problems to spread from one institution to another. Credit risk exposures are an obvious contagion channel, with the failure of one institution to honour its debt obligations imposing financial damage on another.
- ***Cross-border participation and shareholder links***. Many financial systems are characterized by a high degree of cross-participations between financial institutions, both nationally and internationally. In order to offer a broad range of products, for instance, banks may have significant stakes in insurance companies, investment firms, and other kinds of financial institutions. Similarly, cross-border integration has progressed steadily over the past 15 years, with many financial institutions owning significant stakes in overseas subsidiaries. While

cross-participations may have diversification benefits, they also create a contagion channel through which severe difficulties of subsidiaries or branches can spread to the group level.

- ***Liquidity management***. Banks rely to a large extent on the key funding markets for liquidity management. Rumours about financial difficulties (such as an upcoming downgrade) may lead to deterioration in the terms of interbank market access for the affected banks. In extreme cases, the interbank markets may close for the affected institution, which necessitates rapid activation of alternative liquidity sources (such as selling assets, perhaps at fire sale prices, or use of the emergency liquidity assistance window of the central bank).
- ***Deposit insurance***. Deposit insurance helps to mitigate adverse wealth effects from bank failures and prevent contagious bank runs. It therefore reduces the likelihood of banking crises and also contributes to damage control when banking crises occur, provided that coverage is sufficient and funding is credible. Nonetheless, deposit insurance can sometimes cause contagion effects, especially in countries that do not have prefunded regimes (or where the arrangement is significantly underfunded). Under such circumstances, the remaining banks usually pay for the costs of activating the deposit insurance fund after the crisis has struck, which may entail substantial costs (depending on the coverage of the deposit insurance arrangement, the deposit base, and the share of insured deposits of the affected institution). Even in countries with prefunded deposit insurance regimes the remaining banks may be faced with steep increases in insurance premia in order to replenish the fund.
- ***Access to payment services***. Larger banks often provide smaller banks (and other financial institutions) with access to key payment services. They may act as system operators (beneficiary and payer service providers), provide correspondent banking services (a domestic banking institution that handles payments on behalf of a foreign financial institution, through so-called Vostro or nostro accounts), and custodian banking services (a bank that safe-keeps and administers securities for its customers and often provides various other services, including clearing and settlement, cash management, foreign exchange, and securities lending). Disruptions at the level of the access providers may leave the end-users cut off from effective payment services, especially in absence of back-up providers.

6.1.2. Contagion from financial markets to institutions

- ***Investment losses***. Adverse price developments in financial markets can expose financial institutions to investment losses. As a general rule, an institution's vulnerability to adverse market developments depends largely on the size and riskiness of its investment activities. Losses on the investment portfolio are an important channel through which financial market corrections affect financial institutions. The trading portfolio is the greatest source or risk, as it needs to be valued mark-to-market according to International Financial Reporting Standards (IFRS) and most other accounting regimes, with losses passing through the profit and loss account. In principle, this risk may be mitigated by hedges and other safeguards, but these may break down in times of severe crisis.
- ***Exposure through the revenue channel***. Financial institutions are also exposed to losses through the revenue channel. Banks, especially investment banks, often actively trade stocks, bonds, options, commodities, derivatives, or other financial instruments for their own account (proprietary trading, as opposed to trading on their customers' account). Deteriorating financial market conditions may be associated with decreasing profitability of proprietary trading, and may also reduce fee income that financial institutions receive for undertaking financial market transactions for their clients, as clients may be less inclined to invest in bear markets. Share and debt issues and major acquisitions may be postponed, too.
- ***Funding/liquidity management***. As many banks have become more dependent on wholesale funding (as opposed to deposits), banks' reliance on a smooth functioning of the interbank markets has also increased. Interruptions in the key funding markets can therefore be associated with severe liquidity stress in the banking system. This was illustrated in the summer of 2007, when uncertainty about the distribution of subprime losses caused banks to hoard liquidity, with the main funding markets charging prohibitive spreads and coming to a near-standstill.

6.1.3. Contagion from financial infrastructure to institutions

- ***Overdue payments***. Disturbances in the smooth functioning of financial infrastructure are most likely to affect financial institutions through delays in: incoming and outgoing payments; or deliveries or receipts of securities. Delays in incoming payments may in turn cause liquidity difficulties, while a failure to ensure that outgoing payments are processed in a timely manner may expose financial institutions to reputational damage or legal risk. Risk mitigants such as real time gross settlement (RTGS), delivery-versus-payment, collateralization, and margining help to limit counterparty risk.

6.1.4. Contagion from institutions to markets

- ***Market maker for derivatives***. Financial institutions, including non-bank institutions such as hedge funds, can play an important role as market makers for derivatives (swaps, options, futures, warrants). These instruments serve as key hedging instruments, especially for managing interest rate and exchange rate risk. A shock that affects a large number of market makers at the same time (such as a simultaneous failure of a large number of hedge funds) could impede the proper functioning of these derivatives markets, which in turn may have an impact on the capacity of financial and non-financial companies to manage financial risk effectively.
- ***Fire sales of financial assets***. Disturbances at financial institutions may also spill over to financial markets through the risk of fire sales of financial assets. Weak institutions may seek to generate liquidity by liquidating assets at fire sale prices, which may disturb the market for the specific asset category. Fire sales may also occur when secured lenders to defaulting banks sell the assets pledged by the bank as collateral. Disturbances in financial markets created by fire sales may in turn inflict damage on financial institutions as IFRS requires mark-to-market valuation of the trading portfolio.

6.1.5. Contagion in financial markets

- ***Information channel***. A sudden loss of confidence in one market may limit the willingness of intermediaries to trade, thus reducing overall market liquidity and affecting the price formation process. Unexpected disturbances in one market may also lead to an overall reappraisal of risk-return assessments through the information channel. This may cause sudden price corrections (such as a flight to quality) as investors seek less risk in exchange for lower profits. This may lead investors to sell what are perceived to be higher-risk investments and purchase safer investments (government bonds, gold).

6.1.6. Contagion from financial infrastructure to markets

- ***Trading platforms and clearing and settlement systems***. Financial markets rely on the smooth functioning of the supporting financial infrastructure, including trading platforms and clearing and settlement systems. Operational disturbances may impede the timely processing of financial market transactions, which can cause market liquidity to dry up and distort the price formation process.

6.1.7. Contagion from financial institutions to infrastructure

- ***Operational disturbances***. Most modern payment systems contain safeguards such as real time gross settlement (RTGS), delivery-versus-payment (dvp) for securities settlement, and payment-versus-payment (pvp) for foreign exchange payments. In addition, some derivative and securities settlement systems reduce counterparty and credit risk through central counterparties. These safeguards mitigate the risk that failure of a major player (typically a financial institution) jeopardizes the functioning of the key payment and clearing and settlement infrastructure. In the absence of such safeguards, failure of an important financial institution can cause serious operational disturbances in financial infrastructure, with broader systemic repercussions.

6.1.8. Contagion from financial markets to infrastructure

- ***Coverage for counterparty exposures with collateral (margin calls)***. Corrections in financial markets can cause a decline in the value of collateral. As a result, the participant in a collateralized payment or settlement system may find it hard to obtain the necessary collateral. Margin trading (buying securities with cash borrowed from a broker, using other securities as collateral), for instance, relies heavily on the use of collateral. Corrections in financial markets can cause the value of the collateral to fall short of the maintenance requirements, in which case the trader either must pledge additional collateral or close out the position. This can be done by selling the securities, options, or futures if they are long and by buying them back if they are short, making up for possible shortfalls. If the trader does not take any of these steps, the broker can sell its securities or other assets to meet the margin call from the clearing house. If this occurs on a sufficiently large scale, financial asset prices may come under pressure.

6.1.9. Contagion in financial infrastructure

- ***Supporting services, technical links, and connected ICT systems***. Disruptions in a critically important system can spread through several technical links that exist between different systems. The large value wholesale payment systems often function as a basis on which other systems—including retail and stock exchange settlement systems—are constructed. While the large value wholesale systems are mostly based on real time gross settlement, the dependent systems are often netted only once a day by adjusting the position of the respective players in the wholesale system. Payment systems also rely on a smooth functioning of ICT systems, including SWIFT for communication.

6.2. Contagion from the financial system to the real economy

In the absence of a cohesive conceptual framework that has been thought-through in advance, assessing the effect of financial disturbances on the real economy is rather challenging. Most of the literature on the interconnections between the financial system and the real economy typically focuses on the transmission of real-to-financial sector shocks, rather than the other way around. Following the methodology of the Bank of England, two contagion channels from the financial system to the real economy can be identified: financial losses incurred by non-financial economic agents; and restricted access to financial services.

The *financial losses channel* essentially relates to negative wealth effects for households, non-financial corporations, and the government that arise as a direct result of the particular crisis event. In the case of the bankruptcy of a financial institution, households and non-financial corporations may have uninsured deposits that can only be partially recovered. Households' financial wealth or disposable income may also have a considerable exposure to financial markets developments: for example, through defined contribution pension systems or through unit-linked insurance policies.

The *restricted access channel* relates to disturbances in the supply of financial services to the real economy that can be attributed to the financial disturbance. In a state that is commonly referred to as "financial stable," the financial system supports real economic activity in three main ways: by allocating financial resources efficiently between activities and across time; by assessing and managing financial risks; and by absorbing economic shocks. The capacity of the financial system to fulfil these functions can be severely affected in the context of a systemic crisis. Contagion through the restricted access channel may also arise in the case of failure of niche players, whose functions or geographic coverage cannot readily be taken over by alternative suppliers. Contagion through the restricted access channel may also occur in case the financial disturbance narrows the range of available financial products, thereby preventing households and enterprises from finding products with an appropriate risk profile.

As was the case with contagion within the financial system, amplification may take place through the information channel. Contagion through the information channel may arise if the financial shock has a material impact on saving, investment, and consumption decisions by economic agents. Such amplification may arise if a severe financial shock triggers a generic reappraisal of the economic outlook, with consumers and non-financial businesses raising their savings at the expense of current investment and consumption expenditure. Again, contagion to the real economy through the information channel will be more difficult to predict than contagion through direct linkages.

6.3. Relevant information needs

Performing a systemic risk assessment in the context of an actual crisis requires that before the crisis, authorities have identified their data requirements and have put in place appropriate procedures to ensure that these data can be produced at short notice. The list that follows presents some indicators that authorities may take into consideration when establishing the extent to which a particular crisis causes damages to financial institutions, financial infrastructure, financial markets, and the real economy.

6.3.1. Financial institutions

Key quantitative indicators to assess the extent of the disturbance in financial institutions include:

- ***Shortages in liquidity***. This could be reflected in several indicators, including an unusually high amount of pending payments (inability to settle payment systems obligations in a timely manner; backlogs in transaction confirmations), unusually high spreads on interbank loans, deposit withdrawals, lack of liquid assets, and a low volume or lack of undrawn interbank credit lines.

- ***Loss of (core) capital***. Losses may arise due to credit, market and operational risk. It is helpful to differentiate the losses according to the extent that they are irrevocable (write-downs of delinquent loans as losses versus market valuation losses, which can be booked as unrealized losses, for example).
- ***Fall in expected future profits***. This relates to the effect on the institution's future income generating capacity (and its loss absorption capacity over time). Examples are lower volume of business or lower margins.
- ***Risk mitigants***. These include the institution's solvency (overall solvency ratio, Tier 1 ratio) and profitability (return on equity) and liquidity buffers (liquidity ratio; quick or acid test ratio; and the like). The presence of legal (guarantees, collateral, netting) and institutional safeguards (deposit insurance) help to mitigate the impact of the disturbance on the affected institution, but these safeguards may also function as contagion channels to other parts of the financial system.

6.3.2. Financial infrastructure

The effect of the disturbance on financial infrastructure can be assessed on the basis of the following indicators:

- ***Volume and value of pending transactions***. The main factor in assessing the potential for a payment system to trigger or transmit systemic disruptions is the volume and value of payments that the particular system processes—either in aggregate or individually—relative to the resources of the system's participants and in the context of the financial system more generally. In this context, the extent of the disruption of payment systems may be assessed on the basis of the volume and value of pending transactions. The damage may be aggravated by long expected recovery times and lack of back-up systems.
- ***Critical dependency of other systems and/or markets***. In assessing the extent to which the proper functioning of financial infrastructure is impaired, authorities may also consider whether the affected part of financial infrastructure is used to settle other payment systems or financial market transactions.
- ***Risk mitigants***. These include the presence of readily available back-up systems, the use of collateral, guarantees, netting and central counterparties, and effective oversight.

6.3.3. Financial markets

Financial markets contain a wealth of information that is helpful not only in assessing the extent of the disturbance in individual markets, but that in the event of a crisis is also highly informative about market perceptions about systemic risk; such information, in turn, gives valuable guidance about the intensity and direction of contagion through the information channel. The following indicators are relevant in this context. Their availability may be problematic, especially in countries that are in their initial stages of financial market developments.

- ***Spreads***. Spreads contain a lot of information about market perceptions on risk and returns. The total spread on a bond is the sum of the inherent risk profile of the underlying obligation and market factors, such as liquidity and the efficiency in executing transactions. Ideally, these elements should be disentangled. Bid-ask spreads denote the price difference between a quote of a market maker for immediate sale (bid) and an immediate purchase (ask). The level of the bid-ask spread is a common measure of the liquidity of the market. In developing countries, the accuracy of the bid-ask spread as an indicator for market liquidity depends on the efficiency of financial markets.
- ***Volatility indices***. Volatility indices are common indicators of the general level of risk aversion in markets. Most volatility indices calculate implied volatility on the basis of option prices.
- ***Market turnover data***. These constitute a basic indicator of overall liquidity conditions for a particular financial asset or asset class.
- ***Risk mitigants***. These include safeguards in the market: both legal (collateral, guarantees, netting) and institutional (central counterparty, regulation/supervision).

6.3.4. The real economy

- ***Financial losses for households and non-financial corporations***. Relevant indicators include the amount of uninsured deposits and possible shortfalls in the deposit insurance fund (which may need to be borne by taxpayers, depositors, and others). The expected pay-out time for the deposit fund is also relevant, as negative wealth effects may be amplified in case depositors lose access to their accounts for a prolonged period. In case of a crisis involving financial markets, households and non-financial corporations may be facing losses due to ownership of financial assets. This includes not only direct ownership but also indirect ownership: for example, through participation in life insurance and pension funds.

- ***Restricted access to financial services***. Relevant indicators include sectoral and regional lending concentrations of banks. The banking system's capital adequacy ratio may also be taken in consideration, as this gives a sense about the financial capacity of banks to provide the real economy with loans.
- ***Consumer and business confidence indicators***. These may give a notion about the risk that the financial disturbance causes economic agents to reappraise the economic outlook, with postponements of consumption and investment expenditure. In this context, the strength of the balance sheets of households and nonfinancial corporations may also be relevant.

On the whole, the contagion matrix is a convenient tool to map interconnections in the financial system, which in times of financial crisis may function as contagion channels. Filling in the cells of the contagion matrix before a crisis erupts has the advantage of providing the authorities with a frame of reference in contemplating the most likely contagion effects of an actual financial shock, hence allowing for a quicker and more disciplined systemic risk assessment. The content of the cells depends crucially on country-specific characteristics, including the stage of financial development.

7. Implementing Systemic Risk Assessment Tools: Examples

7.1. A Financial Stress Index for South Africa

The Reserve Bank of South Africa (RBSA) developed a Financial Stress Index (FSI) which uses five broad indicators as a base to create a general and simple index to quantify vulnerability in a financial system. They recognise that although a single aggregate indicator such as an FSI will never be sufficient on its own, it can be a useful tool for policymakers to analyse developments in financial stress in various parts of the financial system.

Besides being a stress testing tool, the FSI represents a single quantitative measure that can be used to forecast instability. Consistently high levels of the FSI could be indicative of deterioration of stability of the financial system.

Table 6: Variables selected for calculation of the RBSA FSI

Markets	Variables	Comments
1. Funding	1. Government bond spread 2. Interbank liquidity spread 3. Cost of borrowing 4. Treasury yield spread	1. The 10-year non-government bonds yield (OTHI) less government bond yield (GOVI) 2. Jibar less yields on 3-month Treasury bills (TBs) 3. Repo less the yields on 3-month TBs 4. Moving average of 3-month TBs minus yield on 10-year bonds
2. Equity	1. CMAX[60]: All-share Index 2. VIX	1. The extent to which the All-share Index has dropped over a year before 2. Uncertainty in share prices
3. Foreign exchange	1. US dollar/rand volatility index 2. Euro/rand volatility index 3. Sovereign bond spread	1. Uncertainty in value of rand relative to US dollar 2. Uncertainty in value of rand relative to euro 3. South African bond yield minus US bond yield
4. Real estate	1. CMAX: Absa House Price Index 2. CMAX: Commercial real property prices	1. The extent to which property prices in the real Absa House Price Index have deteriorated in the past year 2. The extent to which listed commercial property prices have declined over the past year

The FSI is derived from five financial markets which are important sources of funding for banks; ***funding, equity, foreign exchange*** and ***real estate***. These markets are represented by a selection of variables as laid out in Table 6. The selection of these variables was guided by theoretical and empirical considerations as well as the availability of data in the analysed period. The FSI is computed on a monthly basis.

The aggregated index involves a two-level construction process that use variance-equal weight techniques across indicators. The first level is concerned with the transformation of variables using empirical normalisation in order to eliminate disparity in units of measurement among variables as well as indexing with respect to a tranquil period. The next level involves aggregating the variables by variance-equal weights. The index is mean-reverting and, therefore, its level provides more useful information than its growth rate because the focus is on stress above the mean (normal stress level). Also, since each variable in the FSI is normalised, the level of stress for a current event can be compared only with that of an historical event in terms of its deviations from the mean. Moreover, a value of the index is likely to change when the sample period and the tranquil are altered, but the ordinal ranking of two events should remain the same.

7.2. The Norges Bank's Composite Indicator of Systemic Stress

The Norges Bank's Composite Indicator of Systemic Stress (CISS) is an example of a stress index and is centred on Norway's financial markets, financial intermediaries and financial infrastructure.

A. Selection of indicators

The indicators selected for the construction of the index are categorised into five sectors; ***money market, bond market, equity market, financial intermediaries and external sector***. Sub-indices are developed to measure stress levels in each of the five market segments, representing the severity of financial market stress. Each sector is included in the index for the following reasons:

- As a primary source of short-term funding, the ***money market*** is non-negligible when assessing the functioning of the financial system.
- The ***bond market*** is a source of funding for large corporations and the government. Variations in bond yields affect household balance sheets through pension funds and other instruments. Therefore, development in the bond market is important for the evaluation of systemic stress.
- Stress in the ***equity market*** erodes funding to firms as well as returns to investors, hurting both the supply and demand side of the real economy; furthermore, it spreads easily to the rest of the financial system and is often the trigger of financial. These profound effects are closely linked to the definition of systemic stress.
- External shocks can have significant impacts on both financial markets and the market for goods and services. Foreign counterparties represent a source of funding for firms, and a reduction in these inflows could impose important limitations to economic activity. Moreover, movements in the prices of export goods will have a significant and direct impact on the national income and government revenues. Uncertainty in the ***external sector*** can thus increase systemic stress.

The indicators included in the CISS are detailed in Table 7. The Norwegian Interbank Offered Rate (NIBOR) is supposed to reflect the interest rate on short-term unsecured interbank. Higher volatility of the 3-month NIBOR reflects higher uncertainty in the Norwegian interbank market. Uncertainty often results in flight to quality (e.g. secured lending or riskless bonds) and/or flight to liquidity (e.g. central bank deposits) due to increasing asymmetric information. This could increase systemic stress.

Table 7: Norges Bank CISS Indicators

Sector	Indicator
Money Market	Realised volatility of the 3-month NIBOR
	Interest rate spread between 3-month NIBOR and 3-month Norwegian Treasury bills
	Spread between 3-month NIBOR and the key policy rate
Bond Market	Realised volatility of the Norwegian 10-year benchmark government bond yield
	Yield spread between investment-graded non-financial corporations (utilities) and government bonds (5-year maturity)
	10-year interest rate swap spread
Equity Market	Realized volatility of the Oslo Stock Exchange Benchmark Index (OSEBX)
	CMAX[11] for the Oslo Stock Exchange Benchmark Index (OSEBX)
	Amihud illiquidity measure for the Oslo Stock Exchange Benchmark Index (OSEBX)
Financial Intermediaries	Realized volatility of the idiosyncratic stock returns of the banking sector – Oslo Stock Exchange Equity Certificate Index (OSEEX)
	Yield spread between investment-graded financial and non-financial corporate bonds (5-year maturity)
	CMAX interacted with the inverse price-book ratio for the financial sector equity market index
External Sector	Exchange rates (USD/NOK and EUR/NOK) volatilities
	Oil (Brent Crude) price volatility

The spread between the NIBOR, an indicative market rate, and the essentially risk-free T-bills is often used as a proxy for counterparty risk and liquidity risk. In the face of higher uncertainty, banks charge higher interest for unsecured loans, while at the same time rushing to first-rate collateral such as Treasury bonds, driving down their yields. The first effect captures flight to quality, and the latter flight to liquidity. Both effects contribute to widening the spread in times of crisis.

[11] CMAX stands for maximum cumulative loss

Money market spreads like that between the 3-month London Interbank Offered Rate (LIBOR) and the federal funds rate reflect counterparty risk and liquidity risk. In the case of Norway, this spread also demonstrates the close link between the liquidity situation of the dollar market and that of the Norwegian money market, as Norwegian banks commonly use a liquid swap market for Norwegian kroner against US dollar in their liquidity management. Monetary policy has an important influence on financial markets and therefore should not be ignored when evaluating systemic stress. Lowering the key policy rate by injecting liquidity should help to ease stress in financial markets by lowering the funding costs for banks in distress, even if the extent to which central bank liquidity measures can reduce money market spreads has proven to be limited by the recent crisis.

Just as in the bond market, higher volatility in the stock market reflects increased uncertainty about fundamentals as well as the behaviour of other investors. Stock prices are typically more volatile than bond prices. Therefore, only prolonged periods of large declines can be seen as true equity market crises. In good times, the Oslo Stock Exchange Benchmark Index (OSEBX) will be close to zero, as prices generally move up. Since market risk is taken care of by volatility of the stock market benchmark index, only risks attributed to bank-specific events are included in the financial intermediaries sector.

B. Standardizing the indicators

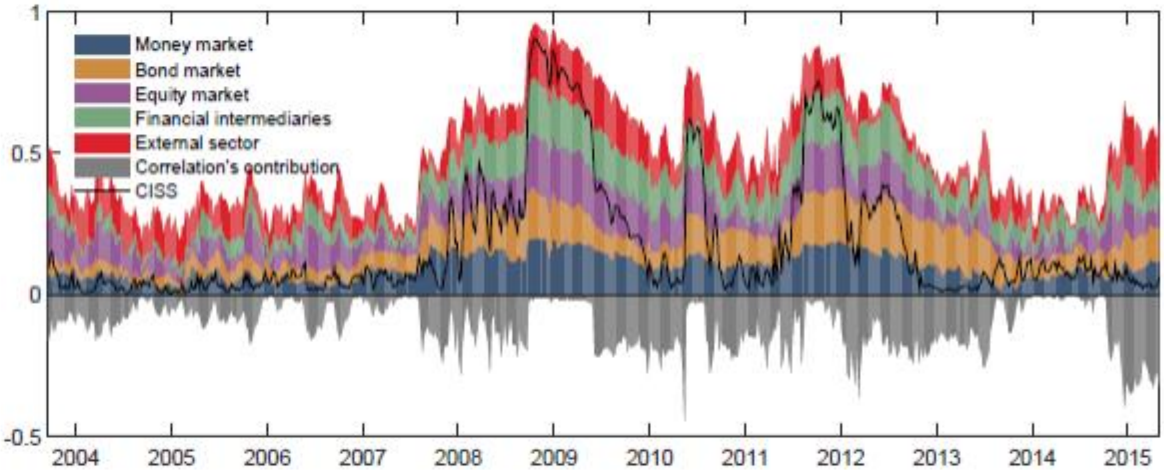
The indicators are standardized using order statistics since the classical standardization is sensitive to outliers and will lead to significant revisions of the resulting sub-indices and the final indicator as time evolves. As a policy tool, the systemic stress indicator should be rather robust against outliers, to make recent measurements comparable to past episodes.

C. Index aggregation

Each sub-index is composed of three indicators, and dynamic cross correlations are estimated. The average stress index is weighted by the resulting correlation matrix. Correlation measures how stresses in different markets linearly relate to each other. If the stress level in different financial markets are highly correlated, when one market is suddenly under distress, instability could quickly spread to other markets, increasing systemic stress.

Therefore, the CISS indicator takes into account both the severity and span of stress in different financial markets. This index is such that at a glance, the Norges Bank is able to detect in which markets stress has arisen and how widespread it is, as illustrated in Figure 8.

Figure 8: Decomposition of the Composite Indicator of Systemic Stress for Norway



D. Index validation

The systemic stress indicator for Norway is evaluated through: robustness checks by recursion; comparing the Norwegian CISS with that of other Scandinavian countries and the Eurozone; event identification with the recursively estimated real-time CISS; and, investigating the relationship between the Norwegian CISS and Norway's real economy. Overall, the Norwegian CISS is considered robust and viewed as a reliable indicator of financial stress.

7.3. A Financial System Resilience Index for the UK

The New Economic Foundation developed the Financial System Resilience Index (FSRI) to compare the financial system resilience of the UK with that of the G7 countries over time. The comparative index allows for the analysis of the G7 major economies: the United States, Canada, Japan, Germany, France, the UK, and Italy.

To construct the index, they identified indicators for each of six resilience factors shown in Figure 9 that are available for all the G7 economies. They also included the leverage ratio as a final indicator, because this has been a major focus of regulatory reform to increase the resilience of banks, making seven factors in total. In all cases, these indicators are ratios rather than absolute numbers in order ensure cross-economy comparability.

Figure 9: Factors that affect the resilience of the financial system

Resilience factor	Potential sub-factors/indicators	Rationale
1. Diversity	'D-Index': ownership structure, market concentration, funding model, geographic spread	Diversity known to enhance resilience of complex systems
2. Interconnectedness/ network structure	Concentration of systemically important financial institutions (SIFIs), intra-financial system concentration, cross-border exposures, repo, securitisation	Pattern of connections affects transmission of shocks through financial network – for example large 'super-spreaders' connected to everyone else
3. Financial system size (relative to domestic economy)	Bank assets/GDP, debt/GDP, debt/ income, 'too-big-to-fail' subsidy	High indebtedness increases fragility to shocks; v large financial sectors may become 'too big to save'
4. Asset composition	Real economy lending ratio, finan-cialisation of credit, stranded asset holdings	Excessive non-GDP credit creation inflates asset bubbles; specific risks attach to particular assets (e.g. fossil fuels, mortgages)
5. Liability composition	Leverage ratio, liquidity risk, foreign bank exposures and funding risks	High leverage and excessive reliance on short-term wholesale market fund-ing increases fragility
6. Transparency/complexity	Securitisation, derivative exposure	Risk of mispricing, exacerbates confidence shocks and procyclicality

The FSRI combines all seven resilience factors, giving equal weight to each. The indicators are then standardised using order statistics, assigning each indicator a score on a scale of 1—100, the worst (least resilient) score across all countries for all years is equal to zero and the highest score is equal to 100.

Figure 10: Country ranking of the Financial System Resilience Index (2012)

Country	Rank	Resilience Rating (max=100)
Germany	1	73
Japan	2	71
France	3	66
Italy	4	63
Canada	5	62
USA	6	56
UK	7	27

The composite index reveals that, based on data up to the year 2012, the UK's economy, compare to other G7 countries, was highly exposed to vulnerabilities in the financial system while, conversely, the financial system was not performing well in terms of its basic social and economic functions. It was concluded that the UK currently had the least resilient financial system of any G7 country.

7.4. Bank of Canada's Imbalance Indicator Model

The Bank of Canada's Imbalance Indicator Model (IIM), though not an outright index, could serve well as an example of an indicator of financial system vulnerability. The model proves useful for isolating historical imbalances that could be indicators of financial system vulnerabilities. It complements other sources of information, including market intelligence and regular monitoring of economic and financial data.

In order to identify critical thresholds, the Bank of Canada uses data on only advanced economies. This is because the number of stress episodes experienced by any one country is typically small, and using a broad sample of countries allows the use of others' experiences to identify the critical thresholds, as well as to test the validity of the model. The decision to use only data from advanced economies is so as to increase comparability in economic and structural aspects. The data are monthly and the model is estimated for 17 advanced economies over the period from December 1980 to December 2009. To ensure that the exercise is relevant for informing preventive policy actions, a variety of indicators are considered for each sector that could be expected to signal a stress episode up to two years before the event.

In the model, an indicator signals future stress when it rises above a threshold level that tends to be associated with historical stress episodes, suggesting an imbalance. Several possible values of the threshold are considered for each indicator, and the one that simultaneously minimizes two errors, the error of failing to signal before stress occurs and the error of signalling an imbalance even when stress does not subsequently occur, is chosen. This approach helps to identify the best threshold for each variable and to determine the most robust predictors of stress episodes (that is, those with the lowest error rates). Extracting signals from these indicators on a regular basis can highlight changes in existing imbalances and detect potential imbalances that merit more-intensive analysis or debate.

Figure 11: Results from Bank of Canada's Imbalance Indicator Model

	Threshold	Noise-to-signal ratio	Pre-dot-com crash 1998–99				Pre-financial crisis 2005Q3–07Q2				Recent period 2010–11				Current period 2012–13Q2			
			CA	US	UK	AU	CA	US	UK	AU	CA	US	UK	AU	CA	US	UK	AU
Broad leverage																		
Credit-to-GDP gap (percentage points)	4.7	0.50						100%	100%	88%	88%		38%	13%	67%			
Ratio of household debt to GDP (per cent)	70.9	0.43			13%		50%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Deviation of ratio of household debt to GDP from 10-year moving average (per cent)	10.9	0.52				100%	100%	100%	100%	100%	100%		25%	75%	100%			
Asset prices																		
Equity prices, 3-year real growth (per cent per year)	7.5	0.62	88%	100%	100%	63%	100%	100%	100%	100%	13%				17%	33%	17%	
House prices, 5-year real growth (per cent per year)	6.9	0.45					75%	75%	100%	63%								
House-price gap	12.6	0.27					63%	100%	100%		13%			25%				
Ratio of house prices to income (index, long-term average = 100)	110.5	0.18					38%	88%	100%	100%	100%		100%	100%	100%		100%	100%
Banking sector																		
Deviation of return on equity for banks from 10-year moving average (per cent)	17.1	0.47	38%		50%		63%	50%	100%	63%								
External sector																		
Current account deficit (per cent of GDP)	4.8	0.22				63%		100%		100%				13%				
Deviation of real effective exchange rate (REER) from 10-year moving average (per cent)	20.2	0.12			13%		100%			100%	75%			100%				100%

Legend

- Indicator does not exceed threshold (no signal).
- X% Indicator exceeds threshold for one or two quarters in the time frame (weak signal).
- X% Indicator exceeds threshold for three or more quarters in the time frame (strong signal).

CA = Canada
US = United States
UK = United Kingdom
AU = Australia

The indicators included in the model cover four key areas of potential vulnerabilities: *broad leverage*, *asset prices*, *the banking sector* and *the external sector*. Within each category, indicators were selected based on their performance in signalling stress events, while also reflecting judgment on the range of sectors in which financial stress would materialize.

The results of the model are presented in Figure 11. The second column in the table reports the threshold estimated for each indicator using cross-country data, and the third column indicates its accuracy, as measured by the adjusted noise-to-signal ratio (the lower, the better). The row for each indicator reports the percentage of quarters during the selected period that the indicator exceeded its estimated threshold. The cells are shaded red if the variable exceeds the estimated threshold for at least three quarters during the selected period, and yellow if the indicator breaches the threshold for one or two quarters.

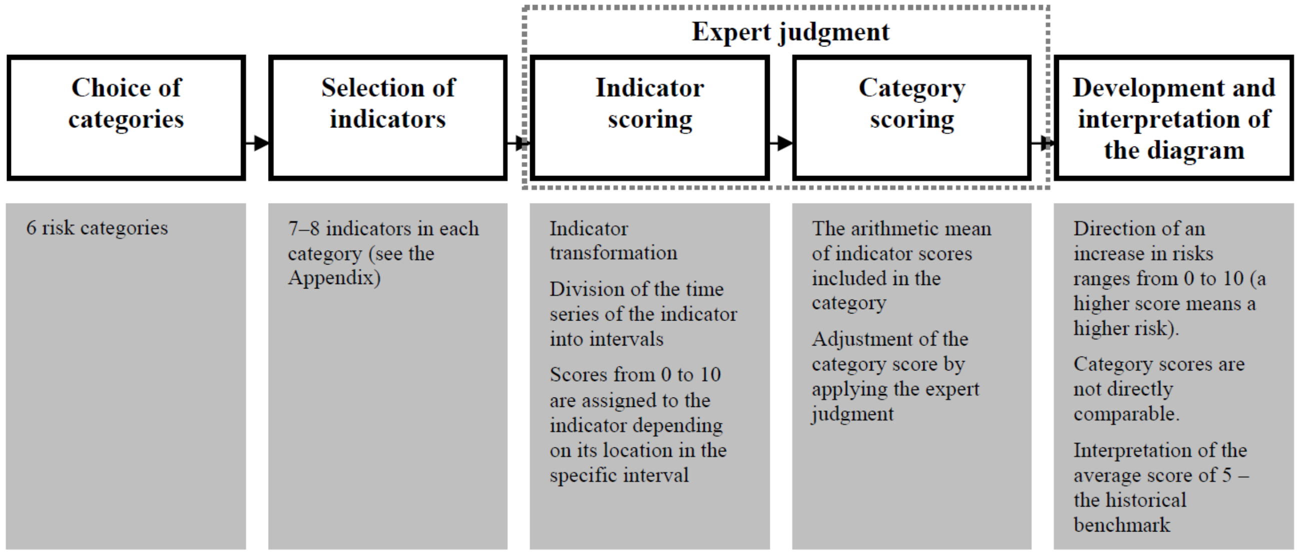
These results indicate that the signals of imbalances are persistent and that policy-makers could have warnings more than a year before a stress episode. Bank of Canada's results are broadly consistent with results in the literature early warning indicators, which has found excessive leverage and elevated asset prices to be key leading indicators of financial system vulnerabilities in advanced economies. Finally, these models are statistical and reduced-form in nature, which means that they will not be able to fully account for the impact of changes in economic structure or in the financial system (either through innovation or regulation). For these reasons, the indicator signals should not be interpreted mechanically. Rather, information about underlying trends in these and other indicators as well as policy-makers' judgment are crucial to translating signals into an assessment of vulnerabilities.

7.5. Bank of Latvia's Financial Stability Risk Diagram

In 2013, based on the experience of the IMF and the central banks of other countries, the Bank of Latvia developed the risk diagram as an additional analytical tool for financial stability risk monitoring and assessment in Latvia. The aim of this risk diagram is to present the most important financial stability risks and the direction of their changes in a single chart.

Figure 12 presents the process of the risk diagram development for Latvia. It shows that the risk diagram is not quite a technical tool, since the expert judgment plays an important role in scoring each indicator (by choosing the way of transformation of indicator data and by determining the division into intervals) and far less frequently in scoring risk categories (if factors, which are difficult to assess by using quantitative methods, substantially affect the risk category assessment during the period considered).

Figure 12: Development process of Latvia's risk diagram



A. Selection of risk categories and indicators

Six risk categories were defined: ***external macrofinancial risks, domestic macroeconomic risks, non-financial corporation credit risk, household credit risk, liquidity and funding risks of credit institutions,*** and***, solvency and profitability risks of credit institutions***. Each risk category comprises 7–9 indicators that best describe trends and changes of the specific risk.

Risks of the ***external macrofinancial environment*** are linked to external shocks (e.g. the slowdown of economic growth in the main trade partner countries, turmoil in foreign financial markets, deterioration of the fiscal situation in the EU countries), which might have a negative impact on the domestic macroeconomic environment and thus also on the quality of credit institutions' assets and profitability. Changes in foreign demand are characterised by imports in the main trade partners. In the light of the strong impact of the EU economic growth on economic processes in Latvia, several aggregate indicators describing the economic and fiscal situation in the EU countries are included in the category of external macrofinancial risks. The composite indicator of systemic stress (CISS) developed by the ECB is used for assessing the financial market situation.

Changes in the ***domestic macroeconomic environment*** affect the condition of financial stability in different ways, mainly causing changes in borrowers' solvency, thus affecting the quality of the credit institutions' loan portfolio and their profitability indicators. Economic activity indicators, the job seekers' ratio, consumer price inflation and current account balance of Latvia are employed for the assessment of the domestic macroeconomic situation. Taking account of the fact that the effect of the macroeconomic situation on financial stability is stronger in an unfavourable fiscal situation and in conditions of a high private sector debt burden, indicators of the debt level of the public and private sectors are also used for the assessment of the risk category changes.

In the assessment of the ***credit institutions' credit risk***, taking account of the role of household and non-financial corporations' credit risk, as well as differences in development of lending to households and non-financial corporations in Latvia, credit risks of households and non-financial corporations are assessed in separate risk categories. Profitability and interest coverage ratio of non-financial corporations are included in the credit risk category of non-financial corporations for the assessment of borrowers' creditworthiness, while indicators of the quality of the loan portfolio are incorporated therein for the analysis of the effect of changes in borrowers' creditworthiness on balance sheets of credit institutions. Several indicators, e.g. the debt-to-equity ratio, credit-to-GDP ratio and credit-to-GDP gap have been employed for the assessment of the burden of liabilities incurred by non-financial corporations. To measure the possible risk concentration in a particular industry (e.g. the real estate market), the Herfindahl–Hirschman Index is calculated for non-financial corporations. The real net wage, job seekers' ratio and the ratio of interest payments to disposable income are employed for the assessment of household creditworthiness. The ratio of household debt to disposable income and its gap are used for the assessment of the household debt burden. The housing affordability index is included in the household credit risk category. Indicators of the loan portfolio quality are also analysed in the household credit risk category to assess the impact of changes of borrowers' creditworthiness on credit institutions' balance sheets.

The category of ***liquidity and funding risks*** assesses the effect of the availability of funding provided by credit institutions and changes in funding costs on financial stability. In addition to the traditional liquidity and funding risk assessment indicators, e.g. deposit growth and the credit-to-deposit ratio, some specific indicators for assessing risks of Latvian credit institutions are used. Considering the significance of non-residents' deposits in funding of some Latvian credit institutions and the related potential risks to Latvia's economy and the credit institution sector (e.g. an increase in short-term external debt, the reputation risk), this category also includes an indicator reflecting a share of residents' assets financed by other financial resources (residents' deposits and other liabilities to residents, gross funding of parent banks and capital).

The assessment of ***credit institutions' solvency and profitability risks*** reflects the ability of credit institutions to absorb shocks and raise adequate capital for absorbing losses when necessary. The return on equity (ROE), overall interest rate margin and net provision expenditure are used to assess credit institutions' profitability in the risk diagram for Latvia. The indicators describing the Latvian credit institutions' capitalisation level, the provisioning ratio and the ratio of net loans past due to capital are employed for solvency risk analysis.

B. Assessment and interpretation of indicators and risk categories

Quarterly data, starting with 2002 (or from the moment data become available) are used in calculations. The choice of the above period is determined by the significant structural changes in Latvia's economy and the financial sector in the 1990s, stabilisation of development following essential and frequent fluctuations and increased availability of the number of indicators. Each indicator is assessed by using one of the three methods depending on the statistical distribution of the indicator time series and its economic interpretation. If data are not very asymmetric and their empirical distribution has no heavy tails, a standard method is used, i.e. the indicator values sorted in an ascending order are divided into 11 intervals with an equal number of observations (percentiles). Each percentile group corresponds to one of the risk scores ranging from 0 to 10; the middle interval contains the median of the series and corresponds to the score of 5.

If the distribution of an indicator is very asymmetric or has heavy tails, an alternative method based on the median is used. The middle interval contains the median and corresponds to the score of 5, other observations are divided into 10 intervals so that the length of intervals starting from the minimum value of the indicator and spreading to the beginning of the middle interval differs from the length of intervals starting from the end of the middle interval and spreading to the maximum value of the indicator.

The expert judgment supplements the assessment of many indicators. If a decrease in the value of an indicator results in a higher risk score, the values used in calculations are multiplied by –1. Taking account of the fact that relationship between some indicators and financial stability risks is non-linear (e.g. both a very rapid GDP growth and its sharp drop suggest threats to financial stability), deviations of these indicators from the predefined level are used.

Before obtaining an overall assessment of the risk category, each indicator is scored in the range from 0 to 10 (a higher score means a higher risk). A score of 5 shows the historical benchmark of observations, and does not automatically correspond to a "normal" risk or vulnerability level. In certain cases indicator scoring could be adjusted by the expert judgment. The overall score of the category is the arithmetic mean of indicator scores included in the category (all indicators of the category have an equal weight). The assigning of different weights would require the assessment of the importance of indicators and degree of their impact on financial stability, thus reinforcing subjectivity. Furthermore, the significance of each indicator changes with time; therefore, risk category evaluation would not be fully comparable over time. It is only the CISS developed by the ECB that has more weight than other indicators in the external macrofinancial risk category in the risk diagram for Latvia, since this indicator assesses the stress situation not in one but in several important segments of the financial system of the euro area: money, bonds, equity and currency markets, as well as in the financial sector.

Figure 13: Financial stability risk diagram for Latvia

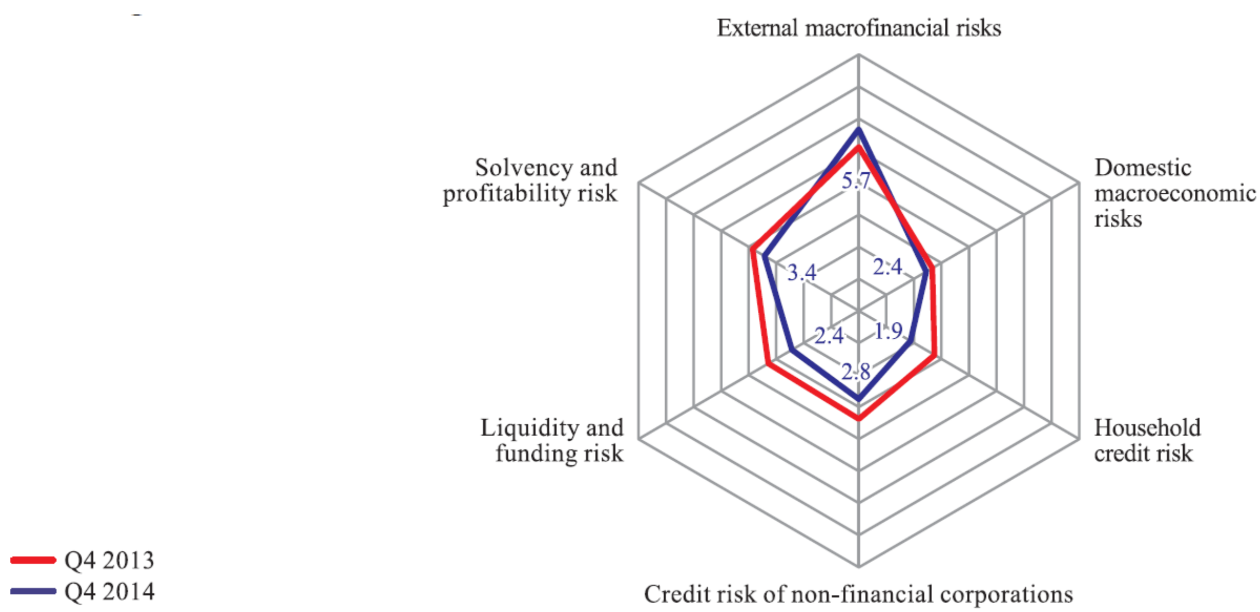
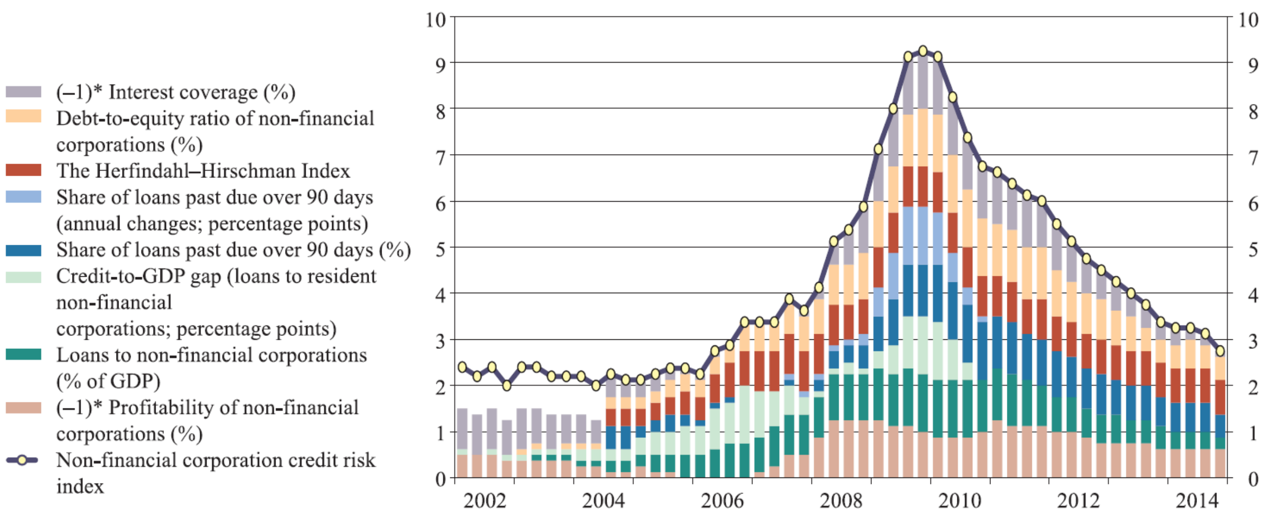


Figure 13 shows a summary of Latvia's financial stability risk assessments. Proper interpretation of the assessments depicted in the risk diagram is important. A category score of 0 is in the centre of the diagram, but a score of 10 is on the outer border (a higher category score means a higher risk). A score of 5 shows the historical benchmark of observations. It cannot be automatically considered a "normal" assessment of the risk or vulnerability level, and it cannot be interpreted as a long-term equilibrium level either. The risk diagram does not assess the absolute degree of risk in the specific period. Risk categories are assessed in comparison with retrospective historical values. Thus, risk levels are assessed only in relation to their historical benchmark or compared to the selected period (the previous quarter, the respective period of the previous year, etc.). This means that the risk diagram does not determine the absolute level of financial stability but the direction of its change. When the latest indicator observations are released, category assessments (including their historical benchmarks) are recalculated.

Figure 14: Dynamics of Latvia's non-financial corporation credit risk index and its components



To expand the applicability of the risk diagram, the assessment of each risk category is also depicted as an individual index (Figure 14). The depiction of the contribution made by individual indicators in the overall category score helps to understand the key factors explaining the main changes in the risk assessment.

7.6. A Bank Health Index for Spain

Ong et al (2012) developed a Bank Health Index for selected Spanish banks using end-2011 data. The heat map that was subsequently generated (Figure 15) showed clear differentiation in the soundness of banks within the system, as well as the evolution of the financial health of these institutions over time. The heat map showed system-wide distress in 2008, especially concentrated at the mid-sized to smaller banks.

Figure 15: Heat map of BHI for selected Spanish banks

Institution	Cajas de Ahorros	Total Assets	Overall Bank Health					
		(In millions of euro)	Pre-Restructuring				Post-Restructuring	
		Latest	2006	2007	2008	2009	2010	2011
1 Santander S.A.		1,292,677	0.95	0.38	1.83	3.66	5.18	3.63
2 BBVA		622,359	2.81	2.88	1.08	2.19	4.94	3.48
3 BFA- Bankia		321,188			-3.92	-2.58	-4.48	-7.66
	Caja Madrid		0.62	5.13	-3.57	-3.02		
	Bancaja		0.29	-0.91	-4.26	-1.81		
	Caiza Laietana		-4.28	-8.04	-5.38	-4.34		
	Caja Insular		-2.88	-2.89	-4.73	-3.76		
	Caja de Avilla		-0.66	1.80	-4.23	-2.45		
	Caja Segovia		-0.81	-1.74	-4.09	-1.28		
	Caja Rioja		-0.94	-0.58	-1.16	-0.90		
4 Caixa Banca		281,554					2.46	1.92
	La Caixa		4.60	4.58	1.71	2.79	3.31	1.98
	Caixa de Girona		-0.10	-2.01	-3.88	-2.38		
5 Catalunya Caixa		77,049					-5.24	-7.41
	Caixa Catalunya		1.15	-2.01	-5.58	-4.01		
	Caixa Tarragona		-2.03	-3.53	-6.05	-4.15		
	Caixa Manresa		-1.43	-1.21	-3.45	-2.98		
6 Nova Caixa Galicia		76,133					-6.00	-4.37
	Caixa Galicia		0.18	-1.07	-4.55	-3.36		
	Caixanova		1.65	-0.83	-3.25	-2.33		
7 Unicaja	Unicaja	40,214	6.07	4.45	3.42	5.30	5.67	4.70
	Caja de Laen		1.94	1.81	0.76			
8 Unnim		28,924					-6.30	-6.02
	Caixa Sabadell		-3.39	-4.67	-5.00	-3.02		
	Caixa Terrassa		0.73	-0.43	-2.51	-3.51		
	Caixa de Manlleu		-6.55	-6.51	-6.09			
9 Kuxta		20,016	7.25	8.19	2.62	2.65	1.71	1.47
10 CAM	Caja Mdeiterraneo	74,478	-2.55	-2.91	-4.11	-1.92	-4.37	

8. Practical Considerations for Implementing Systemic Risk Assessment Tools

8.1. Institutional arrangements

Besides establishing the analytical foundations of financial stability monitoring, policymakers also need to give some thought to more practical aspects. Responsibilities for conducting macroprudential analysis need to be assigned to specific agencies. In addition, macroprudential analysis needs to be embedded in an institutional framework, aimed at ensuring that the outcomes of the analysis are translated into effective risk-mitigating policies. The authority responsible for conducting macroprudential analysis should also give thought as to how the outcomes of the exercise are to be communicated.

The presence of a robust institutional framework is key to translating macroprudential analysis into policymaking. The literature on the topic has expanded rapidly in the last few years. While a detailed discussion is beyond the scope of this paper, Nier et al (2011) list a number of institutional requirements of an effective macroprudential policy framework.

The designation of a single macroprudential authority or group of authorities is a core element of the institutional framework. In practice, the central bank is the most common authority of choice, either as the single macroprudential authority or as the lead authority in a multiagency, committee arrangement. Committee structures can be especially helpful in jurisdictions where regulatory responsibilities are dispersed. The main rationale for providing central banks a central role is that they are relatively shielded from political and industry pressures, and that in their capacity as monetary authority and payment systems overseer—and often also as a prudential supervisor, they have an important advantage in developing a system wide perspective. In addition, in their capacity as monetary authority, they are well-placed to assess the interaction between macroprudential and monetary policy.

The macroprudential authority needs to be provided with a clear mandate and adequate powers, matched with strong accountability. The macroprudential authority needs a strong mandate to conduct unbiased risk assessments and to empower it to pursue unpopular lean-against-the-wind policies in the upturn of the financial cycle. In order to truly adopt a system-wide perspective, the macroprudential authority's monitoring powers need to cover the bulk of the financial system. The macroprudential authority should also have sufficient powers to propose risk-mitigating measures, including for entities and sectors that are not directly under its purview. It should have powers to monitor compliance and to enforce measure in case follow-up is unsatisfactory. These broad powers should be balanced with strong accountability, wherein the macroprudential authority not only communicates about the financial stability outlook, but also reports about the effectiveness of measures that have been undertaken as part of its macroprudential mandate.

The responsibility for conducting macroprudential analysis is usually assigned to central banks, often with a central role for dedicated financial stability departments. Many central banks have set up dedicated financial stability departments, which are a natural point for anchoring responsibilities for financial stability surveillance. Even so, the involvement of other departments including the research, monetary, financial market, and payment systems departments, is highly desirable. In countries where the central bank is not responsible for prudential supervision, the responsibility for macroprudential analysis may be shared with the prudential regulator.

8.2. Availability of data

The team responsible for macroprudential analysis needs access to a broad range of data. Macroprudential analysis is a very data-intensive exercise, and data availability is often a constraining factor in strengthening macroprudential analysis. A thorough stocktaking of data availability is therefore a useful starting point for establishing a framework for macroprudential analysis. This can be helpful in identifying gaps and prioritizing measures to address them. An area where data gaps often occur is the non-bank financial institutions (NBFI) sector, where the frequency of prudential reporting tends to be lower and the lags in producing data longer than for the banking sector. In addition, the analysis of the financial position of the household and enterprise sector is often impeded by lack of available data. For these sectors, it is likely that external sources will need to be used. A potential data source is the credit reference bureau, which may contain relevant information about the leverage, indebtedness, assets, income, and liabilities of households. Even when data are available, adequate access needs to be ensured. It may be particularly challenging to obtain access to confidential microprudential data, particularly if the central bank does not undertake supervisory responsibilities.

Another decision relates to the periodicity of macroprudential analysis. The analysis of the time series dimension of systemic risk needs to be conducted most frequently. In practice, most countries undertake the assessment twice a year and report on the outcomes in a financial stability report at least once per year.

Overall, the staffing and resource implications of putting in place a robust framework for macroprudential analysis are considerable, but still worthwhile. The significant investment requires a strong commitment on behalf of the implementing country. It is important that the implementation costs are seen against the background of the potential costs of financial crises, which can undo years of economic growth and progress in fighting poverty. This implies that any policy that contributes to reducing the likelihood of a crisis and enhancing the quality of the crisis response is likely to be cost-efficient.

9. References

- **Basel Committee on Bank Supervision. 2010**. "Guidance for national authorities operating the countercyclical capital buffer"
- **Bisias, D., M. Flood, A. W. Lo, and S. Valavanis. 2012**. "A Survey of Systemic Risk Analytics." Working Paper 0001, Office of Financial Research, U.S. Department of Treasury, Washington, DC.
- **Borio, C. 2012.** "The Financial Cycle and Macroeconomics: What Have We Learned?" Working Paper No. 395, Bank for International Settlements, Basel, Switzerland.
- **Borio, C. and Lowe, P. 2002.** "Asset Prices, Financial and Monetary Stability: Exploring the Nexus." BIS Working Papers No. 114
- **Committee on the Global Financial System. 2010.** "Macroprudential Instruments and Frameworks: A Stocktaking of Issues and Experiences." CGFS Paper No. 38, Committee on the Global Financial System, Bank for International Settlements, Basel, Switzerland.
- **Dahl, G. A., T. B. Kloster, U. Larsen, K. J. Rakkestad, R. Reisvaag, B. D. Syversten, and C. B. Træe. 2011**. "A Cobweb Model of Financial Stability in Norway," edited by Magdalena D. Riiser. Staff Memo No. 15/2011, Norges Bank, Oslo, Norway.
- **Dattels, P., R. McCaughrin, K. Miyajima, and J. Puig. 2010**. "Can You Map Global Financial Stability?" Working Paper WP/10/145, International Monetary Fund, Washington, DC.
- **Djikman, M. 2010**. "A Framework for Assessing Systemic Risk." The World Bank Policy Research Working Paper WPS5282
- **Dijkman M. 2015**. "Monitoring Financial Stability in Developing and Emerging Economies: Practical Guidance for Conducting Macroprudential Analysis." Policy Research Working Paper 7248, Finance and Markets Global Practice Group, World Bank, Washington, DC.
- **Dijkman M., Yejin C. L., 2016.** "Uganda: An Analytical Framework for Assessing Systemic Risk," Draft Report. First Initiative Mission, World Bank, Kampala, Uganda.
- **Drehmann, M., and Juselius, J. 2014**. "Evaluating Early Warning Indicators of Banking Crises: Satisfying Policy Requirements." International Journal of Forecasting, 2014, vol. 30, issue 3, 759-780
- **Drehmann, M and Tsatsaronis, K. 2014.** "The Credit-To-GDP Gap and Countercyclical Capital Buffers: Questions and Answers." BIS Quarterly Review, March 2014
- **Drehmann, M., Borio, C., Gambacorta, L., Jiménez, G., and Trucharte, C. 2010.** "Countercyclical capital buffers: exploring options." BIS Working Papers No. 317

- **Geršl, A and Seidler, J. 2012**. "Credit Growth and Countercyclical Capital Buffers: Empirical Evidence from Central and Eastern European Countries." Institute of Economic Studies, Faculty of Social Sciences, Charles University in Prague. Working Paper: 3/2012
- **Holló, D., M. Kremer, and M. Lo Duca. 2012**. "CISS–A Composite Indicator of Systemic Stress in the Financial System." Working Paper No. 1426, European Central Bank, Frankfurt am Main.
- **International Monetary Fund, Bank for International Settlements, and Financial Stability Board. 2009**. Guidance to Assess the Systemic Importance of Financial Institutions, Markets and Instruments: Initial Considerations. Report to G20 Finance Ministers and Governors.
- **Kaminsky, G., and Reinhart, C. 1999**. "The Twin Crises: The Causes Of Banking And Balance-Of-Payments Problems"
- **Nier, E., J. Osiński, L. Jácome, and P. Madrid. 2011.** "Towards Effective Macroprudential Policy Frameworks: An Assessment of Stylized Institutional Models." Working Paper WP/11/250, International Monetary Fund, Washington, DC.
- **New Economic Foundation (2014)**, 'Financial System Resilience Index"
- **Ong, L., Jeasakul, P., and Kwoh, S. 2013.** "HEAT! A Bank Health Assessment Tool." IMF Working Paper WP/13/177
- **Pasricha G., Roberts T., Christensen I., Howell B., 2013.** "Assessing Financial System Vulnerabilities: An Early warning Approach." Financial Stability Department, Bank of Canada.
- **Ravn, M. O. and H. Uhlig, 2002**. "On Adjusting The Hodrick-Prescott Filter For The Frequency Of Observations"
- **Wen, Y. 2015**. "A composite indicator of systemic stress (CISS) for Norway – A reference indicator for the reduction of the countercyclical capital buffer." Staff Meme No. 4, Norges Bank.