Indicator and boundaries of financial stability
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* Views expressed are those of the individual author and do not necessarily reflect official positions of De Nederlandsche Bank.
Abstract
This paper presents an information variable for financial stability consisting of a composite index and its related critical boundaries. It is an extension of a Financial Conditions Index with information on financial institutions. The indicator is bounded, on one side, by the instability boundary which depends on the solvency buffers of the institutions and the stress level on financial markets. On the other side, the imbalances boundary signals when extreme imbalances accumulate. This concept is applied to the Netherlands and six OECD countries which experienced a financial crisis.

Key words: financial stability, indicator, crisis

JEL Codes: E44, G10, G12, G20
Quantifying financial stability

A clear understanding of financial stability requires a conceptual framework (see Houben et al, 2004). Such a framework is needed to structure and focus the analysis. For an objective and consistent assessment of financial stability, the framework must also be quantifiable: “...the concepts and definitions must have useful and policy relevant empirical counterparts” (Fell and Schinasi, 2005). Macro-prudential indicators, though useful, are mostly sector-specific, and therefore do not quantify the meta-concept of financial stability. Measures of financial stress usually also relate to a single segment of the system. There are, for instance, early warning indicators (EWI), which forecast a banking crisis on the basis of economic, market and banking sector variables. There are also EWIs for stock market, currency and debt crises (it appears that no EWIs have been developed for the housing market so far).

The indicator needed to quantify financial stability must be made up of different components of the financial system, as “financial stability can be seen as being consistent with various combinations of the conditions of its constituent parts...” (Fell and Schinasi, 2005). Such an indicator should contain information about financial institutions, markets and infrastructure. Several studies describe indices to measure stress within the financial system as a whole (for an overview, see Illing and Liu, 2003). These usually include variables for the stock, bond and currency markets, as well as, in some cases, for financial institutions. The problem is how to define financial stress: the dependent variable of the index. As developed economies, in particular, are rarely confronted with financial crises, quantitative references of such crises are usually lacking. Some EWI and stress indicators are therefore based on (subjective) assessments of crisis conditions by experts (Hanschel and Monnin, 2005).

From the perspective of financial stability, the risk of a crisis is relevant, but so is the well-functioning of the financial system under normal conditions. To this end, an index should reflect not just shock-resistance (buffers), but also the financial system’s functioning (intermediating savings and investment, and pricing and managing risks). Here, a major aspect is how the economy and the financial sector interact. Although the comprehensive nature of financial stability is hard to express in a single measure, a composite index could serve as an information variable for financial stability. Such an index shows how the system functions as a whole, with instability in one segment being compensated for by the well-functioning of another segment. This disaggregated information is provided by the index’s constituent parts. It is then possible to identify sectors with the highest risks, which is essential to policy aimed at financial stability. As a point of departure for an information variable for financial stability, the Monetary Conditions Index (MCI) and Financial Conditions Index (FCI), which perform a comparable function for monetary policy, are useful.
Index composition

In the 1990s, MCIs were developed by central banks to gain insight into monetary policy transmission. In these indices, short and/or long-term interest rates and the effective exchange rate are distinguished as transmission channels:

\[ MCI = w_r, r_t + w_e, r_{e_t}, \]  \hspace{1cm} (1)

\( r_r \) being the real interest rate, \( r_{e_t} \) the real effective exchange rate (both in terms of changes) and \( w_i \) the weighting factor of variable \( i \). The weighting factors are determined by the influence of interest rates and the exchange rate on GDP or inflation. MCIs are limited in that they do not make allowance for other transmission channels such as asset prices. Through their impact on stock and house prices, monetary policy adjustments may feed through to the economy and inflation (via credit demand, consumption and investment). That is why FCIs include asset prices:

\[ FCI = w_r, r_t + w_e, r_{e_t} + w_h, h_p + w_s, s_p, \]  \hspace{1cm} (2)

\( h_p \) being house prices and \( s_p \) stock prices, in real terms. In the literature, the variables are usually included in terms of changes or in deviations from trend. On the basis of equation 2, Goodhart and Hofmann (2001) find that, in the G7 countries, asset prices have a significant effect on the output gap and inflation, which makes them a useful addition to an MCI. In a comparable study, Mayes and Virén (2001) conclude that house prices have more explanatory power than stock prices. The inclusion of asset prices in FCIs is underlain by the discussion on whether stock and house prices are reliable indicators for monetary policy (Bernanke and Gertler, 2001). Although asset prices can contain information about (future) growth and inflation, a central bank which reacts with interest rate adjustments could ultimately damage the economy because interest rate movements may become more volatile (Filardo, 2001). Besides, the problem is how to identify the fundamentally correct level of asset prices. FCIs may, however, be useful for financial stability, because they can signal asset price developments which affect the economy. These could be unbalanced movements in stock and house prices, which might undermine the system’s stability. In order to take into account this risk in their policy considerations, central banks could include asset prices in their information set (Borio and Lowe, 2002).
Financial stability index

FCIs are a useful point of departure for a financial stability index because they are based on the influence of the financial sector on the economy. A strong positive (negative) influence could indicate an ample (tight) supply of finance relative to effective demand, resulting in over- or underproduction. An unbalanced asset price level - which determines decisions of lenders - could cause such an inefficient allocation of funds. An extreme negative impact of the financial sector on the economy usually relates to financial stress. In this respect, FCIs (where the business cycle is explained by financial variables) and EWIs (which forecast financial stress) complement each other. An advantage of FCIs is that, for the composition of the index, it is not necessary to make an assessment of stress, which is hard to make. However, FCIs have their limitations as stress indicator because they assume that shocks feed through in a linear and symmetric manner. This may not be the case in stress situations. Besides, FCIs are primarily information variables that summarise the transmission process and do not forecast like EWIs.

Usually, FCIs (in contrast to certain EWIs) do not include information about financial institutions. The position of the institutions does play a role in monetary transmission, however, notably in the credit view, which takes into account market imperfections (Kakes, 1999). In imperfect markets, monetary transmission depends in part on the position of borrowers and lenders. In the bank lending channel, for instance, the banks’ balance sheet position affects how interest rate adjustments feed through to the economy. As banks with insufficient liquidity or capital buffers react relatively more strongly to increasing interest rates - by reducing their lending - monetary transmission is intensified (Peek and Rosengren, 1995). In this way, the banks’ balance sheet position influences the economy. The same goes for pension funds and insurers, which steer their solvency position by adjusting contributions or benefit conditions, with possible economic effects. As the solvency ratio of financial institutions is dependent on the economic and financial cycle, financial institutions usually react pro-cyclically.

The balance sheet position of financial institutions can thus cause frictions which distort financial intermediation. In order to quantify the macroeconomic effects, some general equilibrium models include the position of financial institutions (Bank of England, 2004). This aspect should also be reflected in a financial stability index, for example, by incorporating variables of financial institutions. An FCI incorporating the position of financial institutions, in addition to the variables for the stock, housing, bond and currency markets, would cover almost the entire financial system. This enhances its usefulness as an information variable for financial stability. The underlying idea is that the variables included in the MCI and the FCI could be influenced by monetary policy and the variables in the Financial Stability Conditions Index (including the financial position of institutions) by policy aimed at financial stability.

1 The quality of the financial infrastructure (rules and regulations, payment and securities systems, etc.) is explicitly reflected in market and institutional data.
In this paper, an FCI for the Netherlands is extended with data on banks, pension funds and insurers, to construct a Financial Stability Conditions Index (FSCI):

\[ FSCI_t = w_1 r_t + w_2 r_{ee_t} + w_3 h_{t} + w_4 s_{p_t} + w_5 s_{olv_t} + w_6 v_{ol_t} \]  

$solv_t$ being the solvency buffer and $vol_t$ the volatility of the stock price index of financials (with the variables in terms of changes or in deviations from trend). The selection of the variables of financial institutions is based on EWIs for banks, which combine balance sheet data and market information. As a balance sheet variable, the institutions’ solvency is included, reflecting both the influence of the bank lending channel on financial intermediation (efficiency) and the buffer capacity for absorbing shocks (shock-resistance). Shocks are not just absorbed by financial institutions, but also by companies and households. This absorption capacity is reflected indirectly in the FSCI, since wealth losses incurred by businesses and households may feed through to institutions’ balance sheets. Next to balance sheet data, market data contains additional information about the risks run by institutions, and contributes to the leading character of a stress indicator (Gropp et al, 2002). Following Illing and Liu (2003), the stock price volatility of financials is included in the FSCI as market information. This is a measure of uncertainty and default risks.\(^2\) That is why market price volatility data is used as ‘financial soundness indicator’ in some studies (Worrell, 2004).

The FSCI corresponds to the indicator that we have developed on the basis of the Macrofinancial Risk model (Van den End and Tabbæ, 2005), as both are system-wide financial stability measures, incorporating the same information on financial institutions. Compared to the MfRisk measure, which is based on the Merton option model and hence on the default risk of financial sectors, the FSCI has a broader scope. It is based on the financial conditions in the system as a whole, covering both financial markets and institutions. The FSCI describes the development of the financial system’s stability and is in essence an (ex-post) information variable. It is not intended to forecast stability, although by taking into account asset prices and thereby possible financial imbalances, it contains information about future financial stability.

**Estimating weights**

The literature mentions several methods for determining the weights of the variables in an FCI. These are econometric estimations with a macroeconomic model, a reduced form aggregate

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\(^2\) The stock price volatility of financials differs from the movements in the broad share index which is also included in the FSCI. The correlation of these two variables is low for the Netherlands (correlation coefficient between y-o-y changes: -0.29). It may be noted that for pension funds, which are not listed, stock price volatility has been approximated, see footnote 4.
demand function (backward-looking IS curve), or a Vector Autoregression Model (VAR). The weights can also be determined by way of economic arguments, such as a variable’s importance for the financial system. Alternatively, every variable in the index can be given equal weights. In some studies, the above methods are combined (as in Goodhart and Hofmann, 2001 and Gauthier et al, 2004). This is also done to determine the FSCI for the Netherlands. The relationships between the financial sector variables and output (as estimated by the IS curve and the VAR model) fit into the definition of financial stability which states that “judgements about the performance of the financial system must be based on how well the financial system is facilitating economic resource allocation, the savings and investment process, and, ultimately, economic growth” (Schinasi, 2006). The IS curve and the VAR model are (partial) approximations of this definition of financial stability.

To begin with, the weights of the FSCI were determined by estimating the following IS curve,

\[
y_t = \alpha + \sum_{i=1}^{\omega_1} \beta_i \Delta y + \sum_{j=1}^{\omega_2} \beta_j \Delta rr + \sum_{k=1}^{\omega_3} \beta_k \Delta rer + \sum_{l=1}^{\omega_4} \beta_l \Delta hp + \sum_{m=1}^{\omega_5} \beta_m \Delta sp + \sum_{n=1}^{\omega_6} \beta_n \Delta solv + \sum_{o=1}^{\omega_7} \beta_o \Delta vol + \eta_t
\]

with the explanatory variables as year-on-year changes (IS_ch) and deviations from trend (IS_dev) to allow for unit roots. All variables have been converted into indices in logs. Here \(y_t\) is the seasonally adjusted index for GDP, \(rr\), the ten-year interest rate on Dutch government bonds, \(rer\), the euro’s effective exchange rate, \(sp\), the AEX share index and \(hp\), the house price. All these variables are in real terms, being deflated by the consumer price index (CPI). \(solv\) is an index of the solvency of Dutch banks, insurers and pension funds, weighted by these sectors’ balance sheet totals. The solvency of the pension and insurance sectors is based on pension and insurance liabilities at market value. \(vol\) is a weighted index of the volatility of the share indices of Dutch banks, insurers and pension funds.

The number of lags of the variables in IS_ch and IS_dev is chosen by a general-to-specific method. To start with, eight quarterly lags were included; the significant lags between the first lag and the last significant lag were maintained (as in Goodhart and Hofmann, 2001 and Gauthier et al, 2004). The estimation results are presented in Table 1.

3 Unit root tests indicate that all variables, except \(solv\), are nonstationary. The variables’ deviation from trend is determined by HP-filtered data.
4 The sectoral balance sheet totals are not entirely comparable due to the different underlying risk profiles, but the aggregate of the balance sheets is used to approximate the solvency of the financial sector.
5 The pension funds’ and insurers’ solvency has been approximated by adjusting provisions at book value (at a fixed actuarial interest rate) for the market rate, as in Van den End and Tabbae, 2005. \(vol\) has been determined as the standard deviation of the log equity return of the sectors on a daily basis, calculated in one-year moving periods, with the sectors’ balance sheet totals figure as weighting factors. The volatility of the pension funds’ equity has been derived from a ‘theoretical’ volatility of return on invested capital (as in Van den End and Tabbae, 2005).
Table 1, Estimation output, IS equations
Sum of estimated coefficients (lags between brackets)

<table>
<thead>
<tr>
<th>Variable</th>
<th>IS_ch</th>
<th>IS_dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>solv</td>
<td>0.026*** (1-8)</td>
<td>0.001** (1-7)</td>
</tr>
<tr>
<td>vol</td>
<td>-0.026*** (1-6)</td>
<td>-0.017*** (1-8)</td>
</tr>
<tr>
<td>sp</td>
<td>-0.027 *** (1-8)</td>
<td>-0.005*** (1-5)</td>
</tr>
<tr>
<td>hp</td>
<td>0.10*** (1-3)</td>
<td>0.054*** (1-6)</td>
</tr>
<tr>
<td>rr</td>
<td>-0.009*** (1-7)</td>
<td>-0.007*** (1-7)</td>
</tr>
<tr>
<td>reer</td>
<td>-0.171*** (1-7)</td>
<td>-0.045*** (1-7)</td>
</tr>
</tbody>
</table>

R2 adj 0.98 0.98
LM1 1.53
LM2 9.11**
ARCH 0.13
RESET (F-stat) 1.40
N 0.78

1) IS_ch is a single equation with explanatory variables as year-on-year changes of indices in logs.
2) IS_dev is a single equation with explanatory variables as deviations from trend, using HP-filtered data, lamba 129,600 (as in Gauthier et al, 2004).
*, **, *** indicate significance of coefficient with highest t-value or test-statistic at confidence level of 10%, 5%, and 1%. LM1 and LM2 are test statistics for autocorrelation with 1 and 2 lags, respectively. ARCH is an LM test for autoregressive conditional heteroskedasticity (ARCH) in the residuals. In the Ramsey RESET tests 1 fitted term is included in the test regression. N is a Jarque-Berra test for normality. There is an insufficient number of data to test for structural breaks.

Table 1 shows that the variables of financial institutions are significant, as are the stock and house prices, interest rates and the exchange rate. Moreover, the coefficients have the expected sign, which means that increasing solvency buffers contribute to, and rising stock price volatility detracts from real output. These relationships are indications of financial stability, according to the definition of financial stability specified above. Where the other variables in the FSCI are concerned, the sign of the coefficients usually corresponds with intuition as well (with rising house prices indicating easier, and rising interest rates and appreciation of the euro indicating tighter financial conditions), except for stock prices whose sign is negative. For an FSCI with variables in terms of deviations from trend, a negative sign can be explained because rising asset prices may lead to imbalances and potential instability. While the sign of stock prices is negative in IS_dev, the sign for house prices indicates that increasing price imbalances have a positive influence on output. This is contrary to intuition from the viewpoint that this would imply a positive contribution to financial stability (according to the definition above). Studies which also find a positive sign for house prices (Goodhart and Hofmann, 2001 and Montagnoli and Napolitano, 2004) use the FCI as an indicator for monetary conditions, where an imbalanced rise in house prices boosts GDP growth and inflation. In a financial stability index, however,
imbalances are expected to make a negative contribution. To find this relationship, house prices may have to be included in the FSCI with longer lags.

Next, a VAR model is estimated with the same explanatory variables (VAR_ch and VAR_dev) as in the IS curve. The VAR model takes into account the variables’ interdependence. For a financial stability indicator, the interaction between financial market prices, the economy and the financial sector has particular relevance. The VARs are estimated with six lags, which is the maximum number given the necessary degrees of freedom. LM tests indicate that with this number of lags the null hypothesis of no autocorrelation of the residuals is accepted. Normality tests indicate that the residuals are normally distributed. The effect of the variables in the VAR models shows up in the (generalised) impulse responses (Charts 1 and 2). Although the direction of the effects of the variables in the FSCIs is mostly plausible, the estimations need to be interpreted with caution. The volatility of stock prices and long-term interest rates turn out to have a significant effect (with confidence intervals different from zero); this is not evident for the other variables.

**Chart 1 Impulse responses VAR_ch**
The weighting factors of the FSCIs which are based on IS_ch and IS_dev are calculated by summing the coefficients of the lagged terms and expressing them as a ratio (as in Montagnoli and Napolitano, 2004):

\[
\text{Weight variable } X_i(W_i) = \frac{\sum \text{coefficient } X_{i,t-n}}{\sum \text{coefficient } X_{i,t-n}}
\]  

(5)

The weights of the FSCIs based on VAR_ch and VAR_dev are determined by the estimated cumulative impact of a shock (2*stdev) on the variables over a period of eight quarters (generalised impulses). This cumulative impact is also converted into a weight as in (5). The estimated weights of the variables of financial institutions are then scaled with the balance sheet total of the financial sector and the weights of the financial market variables are scaled with the capitalisation of the asset markets (see the Appendix). By this, both the importance of the various segments of the financial system and the changes of its composition are taken into account. In the Netherlands, the financial institutions make up more than half of the financial system (Chart 3).

6 Tests for the number of lags (sequential modified LR test statistic, final predictions error, Akaike information criterion, Schwartz information criterion and Hannan-Quinn information criterion) indicates that at least six lags have to be included.
Selecting an FSCI

The FSCIs whose weights are estimated by the IS curve and the VAR model, with variables in terms of year-on-year changes and deviation from trend, are shown in Charts 4 and 5. Chart 6 presents an FSCI whose weights are not estimated; here, every explanatory variable (in terms of changes) has an equal weight. These weights are scaled in the same way as above, by the importance of the system’s segments. Since the FSCI is not intended to forecast but primarily to describe the development of financial stability, the Lucas critique, which says that model parameters are unlikely to remain stable due to policy changes, is not relevant. The different FSCIs show roughly the same pattern. Chart 7 contains a disaggregated version of the index.

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7 Stock prices are not included in IS_ch and VAR_ch because their sign is contrary to intuition.
For selecting a certain FSCI, an (ex-post) analysis is applied to test how the various FSCIs reflect the realised risks within the Dutch financial system. Reference values for these risks preferably cover the whole financial system (including markets as well as financial institutions) and the main risk to its stability (i.e. default risk). For the Netherlands, sufficiently long data series of such indicators are available in credit spreads, credit ratings and failures of Dutch financial institutions (especially banks and insurers). Simple correlation analysis shows that the FSCI with equal weights and the explanatory variables in terms of year-on-year changes most adequately reflects the risks in the financial system (Table 2, line ‘Equal weights ch’). For this FSCI, the link with the reference series is the strongest and the signs of the correlation coefficients are correct. Rising spreads and failures go hand in hand with a declining FSCI (decreasing stability) and improving credit ratings with a rising FSCI (increasing stability). Moreover, the index is leading to realisations of risks in the financial system by three to four quarters in advance. The relatively good fit of the index with equal weights corresponds with Hanschel and Monnin (2005) who find that a stress index with equal weights is appropriate for the Swiss banking system.
Table 2 Correlation analysis

Correlation between FSCIs and reference values financial sector
Highest value at certain lead of the index (related lead in quarters between brackets, based on quarterly data 1988-2004)

<table>
<thead>
<tr>
<th>Form of FSCI</th>
<th>Spreads(^1)</th>
<th>Credit ratings(^2)</th>
<th>Failures(^3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IS(_{ch})(^4)</td>
<td>-0.42** (6)</td>
<td>+0.46** (4)</td>
<td>-0.59** (3)</td>
</tr>
<tr>
<td>IS(_{dev})(^4)</td>
<td>-0.50** (0)</td>
<td>+0.20* (3)</td>
<td>-0.06 (0)</td>
</tr>
<tr>
<td>VAR(_{ch})(^5)</td>
<td>-0.71** (2)</td>
<td>+0.31** (3)</td>
<td>-0.29** (0)</td>
</tr>
<tr>
<td>VAR(_{dev})(^5)</td>
<td>+0.50 (1)</td>
<td>+0.17* (3)</td>
<td>-0.13 (0)</td>
</tr>
<tr>
<td>Equal weights(_{ch})(^6)</td>
<td>-0.56** (2)</td>
<td>+0.60** (4)</td>
<td>-0.59** (3)</td>
</tr>
<tr>
<td>Equal weights(_{dev})(^6)</td>
<td>-0.49** (2)</td>
<td>+0.32** (2)</td>
<td>-0.46** (0)</td>
</tr>
<tr>
<td>Equal weights(<em>{ch})(</em>{exp})(^7)</td>
<td>-0.58** (2)</td>
<td>+0.52** (4)</td>
<td>-0.46** (2)</td>
</tr>
</tbody>
</table>

\(^1\) Spreads Dutch banks based on bonds issued by the banking sector (1990-2004, source: DNB), spreads Dutch insurance companies based on interest rate on bonds issued by individual insurers weighted by their market capitalisation (2000-2004, source: Bloomberg). Reference series of the spreads weighted by balance sheet total of both financial sectors. Credit spreads are derived from bonds with different characteristics and - like other market prices - do not always adequately reflect the fundamentals. These are the drawbacks of using them as a reference value.

\(^2\) Credit ratings long-term debt Dutch banks and insurance companies (1996-2004, source: Moodys), reference series weighted by balance sheet total of both sectors.

\(^3\) Failure rate of financial sector (1993-2003, source CBS). This series is dominated by small institutions and hence is not fully representative for the financial sector.

\(^4\) IS\(_{ch}\), resp. IS\(_{dev}\) is an FSCI with weights based on a single equation (IS) estimation with explanatory variables in terms of year-on-year changes, resp. deviations from trend, using HP-filtered data.

\(^5\) VAR\(_{ch}\), resp. VAR\(_{dev}\) is an FSCI with weights derived from a VAR-model estimation with explanatory variables in terms of year-on-year changes, resp. deviations from trend, using HP-filtered data.

\(^6\) Equal weights\(_{ch}\), resp. Equal weights\(_{dev}\) is an FSCI based on equal weights with explanatory variables in terms of year-on-year changes, resp. deviations from trend, using HP-filtered data.

\(^7\) Equal weights\(_{ch}\)\(_{exp}\) is an FSCI based on equal weights with explanatory variables in terms of year-on-year changes including an exponential adjustment for extreme changes, see Appendix.

*, ** indicate significance of coefficient at a confidence level of 10%, 5% respectively.

Once the FSCI based on equal weights has been chosen, it is adjusted to make allowance for possible non-linear relationships in stress situations. As the FSCI is based on a linear relationship between the economy and financial variables, it may not be representative of stress situations. In periods of financial stress, the effects on the economy emanating from the financial sector may be intensified. Such non-linear effects are taken into account by including extreme changes in the explanatory variables (more than two standard deviations) exponentially in the index ex-post (see the Appendix). This adjustment improves the correlation of the FSCI with credit spreads but reduces the correlation with ratings and failures (see Table 2, line ‘Equal weights\(_{ch}\)\(_{exp}\)’). Since non-linear effects most likely show up in market prices, the exponential adjustment of the variables in the FSCI suggests that its usefulness as a reflection of such effects is enhanced. To provide insight into the influence of the assumptions for the scaling of the estimated weights and for the adjustment for non-linear effects, a decomposition of the FSCI is shown in the Appendix.
Critical boundaries

A financial stability indicator is more meaningful when it has critical boundaries. This is in line with the concept of financial stability as a continuum moving within a corridor (Houben et al, 2004). The corridor is bounded by critical values at which the system ceases to function well. For the critical lower limit (instability boundary) of the FSCI, the indicator’s components may be presumed to assume the level of a stress situation. Stress depends not only on the institutions’ buffers, but, in a diversified financial system, also on price movements in the financial markets. Stress is therefore defined as a situation where the institutions’ buffers evaporate (solvency nil) and the financial market prices experience an extreme shock (a kind of stress test with a 2.5% probability of shocks in the market variables, see the Appendix). In the event of a systemic crisis, such outliers could coincide because interactions within the system will be reinforced. By defining that all market variables in the FSCI experience an extreme shock at the same time, it is implicitly assumed that there is full correlation between the variables. This is an appropriate assumption for stress situations. The distance between the FSCI and the critical instability boundary reflects the maximum stress that the system can bear (the stability corridor). The boundary changes with the level of the buffers of financial institutions. They represent a top-up layer in the stability corridor. The larger the buffers, the more stress the system is able to absorb. The upper limit for the FSCI is defined as a situation where basically favourable market price movements assume excessive proportions. Such movements could lead to an accumulation of financial imbalances. This might distort relative prices and lead to an inefficient allocation of resources, as a reflection of the malfunctioning of the financial system. Moreover, asset price imbalances might become unsustainable and their possible unwinding could threaten financial stability. For this risk we assume an imbalances boundary (the upper limit for the FSCI) at one-sided price movements which occur in 2.5% of cases, see the Appendix. This is a simple statistical method of setting the boundary, which is not based on the fundamental level of asset prices. As for the instability boundary, it is implicitly assumed that in this situation there is full correlation between the variables, based on the believe that major outliers can occur simultaneously in various asset markets as a result of interactions within the system. In between the instability and imbalances boundaries, the financial system is within the continuum of stability.

Applying the FSCI to the Netherlands

Chart 8 shows the development of the FSCI for the Netherlands, relative to the critical boundaries. The area between the instability boundary and the dashed fat line shows the level of the solvency buffers. The FSCI points at increasing instability (declining FSCI) during the stock
market crisis and the economic downturn of 2001-2003, and at a recovery (rising FSCI) thereafter. The deterioration of the FSCI at that time was accounted for by the decreasing buffers of pension funds and insurers, increasing volatility of financial institution’s stock prices, the appreciation of the euro, the rise in real interest rates due to the decline in inflation and the decelerating rise in house prices (see Chart 7). This combination of unfavourable developments made the FSCI decline to near the instability boundary. However, this critical threshold was not breached as there were still solvency buffers left at the institutions. The increase in stability since is accounted for largely by the decreased volatility of financial institution’s stock prices. The rise of the FSCI in 2004-2005, however, indicates a renewed increase of imbalances within the financial system, due to a combination of rising stock prices, declined bond yields and low volatility of stock prices. These imbalances could unwind at a later stage, for example if investors realise that they have underestimated the risks (for instance due to the search for yield).

Decreasing stability in 2001-2003 was preceded by a strong rise of the FSCI during the stock and house price boom at the end of the 1990s. Apparently, imbalances had grown to such proportions that the imbalances boundary was reached. The scissor movement of the FSCI (rising sharply in 1999-2001 and falling markedly in 2001-2003) illustrates that when basically favourable developments (such as rising asset prices and falling real interest rates) become excessive, they may become a source of instability. After all, excessively favourable financial conditions can generate an unbalanced rise in asset prices and debts, making the financial system prone to shocks. These may bring about a regime shift and instability. This means that both upward (potential build-up of imbalances) and downward (manifestation of instability) outliers of the FSCI are meaningful signals about financial stability.

Chart 8 FSCI Netherlands
FSCI based on equal weights and non-linear effects
Applying the FSCI to more countries

The advantage of a single-country model, such as the FSCI for the Netherlands, is that it can be tailored to that country’s characteristics. However, a disadvantage is that the model estimations are based on relatively normal conditions, because the past decades have not seen a financial crisis. In order to test the method’s use for those situations, an FSCI is constructed for a number of OECD countries which experienced banking crises in the 1980s and 1990s8 (the variables in the FSCIs have equal weights, see the Appendix).

Applying the FSCI to the US, Japan and four Nordic countries shows that, in most cases, the FSCI reached a low during the crisis (Charts 10a to f). At this point, usually the solvency buffers of the financial institutions were depleted. For the US and Sweden, the instability boundary was breached. Denmark is the only country for which no clear relationship is found. For the US, Japan and Norway, the FSCI reached a low at the beginning of the banking crisis. In Japan, Norway and Sweden, a sharp rise of the FSCI towards the imbalances boundary formed the run-up to the crisis. This shows that unbalanced asset price movements sowed the seeds for problems in the financial sector. And, indeed, in nearly all of these countries, the banking crisis was accompanied by a crisis in the stock or housing market. The pattern of a sharp increase of the index well before, a fall just before, and a sharp fall during the crisis appears to be typical for the countries which experienced a crisis (Chart 9).

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8 The identification and the length of the banking, stock market and housing market crises were derived from Kakes and Ullersma (2005). The countries were selected partly because of the availability of data. Owing to a lack of data on non-banking institutions, the buffer variable is based on the banks’ financial position only.
Conclusion

The multi-facetted concept of financial stability is by nature difficult to summarise in a single figure. Nonetheless, policymakers have a need for gauges that continuously provide structured information on the potential dangers of bubbles and instability within the financial system. Besides, such information variables or indicators would enhance the transparency of their assessments and policy measures if current updates are presented to the public, for instance via financial stability reports. The Financial Stability Conditions Index (FSCI) represents such an information variable for financial stability. In the FSCI, market and balance sheet information on financial institutions appear to have a significant contribution to a traditional FCI. By comprising information on markets and institutions, the FSCI covers almost the entire financial system. This enhances its usefulness as a measure of the broad concept of financial stability. An assessment of financial stability is more meaningful with quantitative references to critical states at which the system would not function well anymore. In this paper, this has been defined as an upper (imbalances) and a lower (instability) boundary of the FSCI. Movements of the index towards these boundaries provide relevant signals since they might point to the development of a boom/bust cycle. The application of the FSCI to the Netherlands and six other OECD countries shows that the index indeed reflects the typical boom/bust cycle which might be a harbinger of financial crises.
References


Appendix

Scaling weights
For the FSCIs of the Netherlands whose weighting factors were estimated, the weights of the variables of financial institutions, solv, and vol, were scaled with the ratio (balance sheet total institutions/total system) and the weights of financial market variables, rr, sp, and hp, with the ratio (capitalisation asset markets/total system). This assumes that the total system is the sum of the institutions’ balance sheet total and the capitalisation of the asset markets. It is acknowledged that summing balance sheet totals and market capitalisation is tricky because of differences in valuation and types of assets, as well as double counting (because institutions also operate in the markets). The coefficient of the exchange rate (reer) is not scaled because external assets may be ascribed to both institutions and markets.

For the FSCIs constructed by equal weights, the weights were scaled with a fixed ratio for the relative size of institutions and markets. To this end, a rough approximation was used by setting the scaling factor for the institution’s (market) variables at 0.5 (0.5, respectively) for market-oriented financial systems and at 0.7 (0.3, respectively) for bank-oriented financial systems. The distinction between bank and market orientation is based on Ludwig and Slok (2002), where the US, the Netherlands and Sweden have a market-oriented and Japan, Norway, Denmark and Finland a bank-oriented system.

Non-linearities
Allowance was made for non-linear effects on the economy emanating from the financial sector by including extreme changes in the explanatory variables (Xt) exponentially in the FSCI. In the case of a change of more than two standard deviations, the difference was squared and added to the change, as in 1.1.

\[
\Delta X_{t,x} = \Delta X_t + \left[ \text{MAX} \{\Delta X_t - 2^*s( X_{t,a});0\} \right]^2 + \left[ \text{MAX} \{-2^* s( X_{t,a})-\Delta X_t;0\} \right]^2
\]  

(1.1)

Influence of assumptions
To provide insight into the influence of the different assumptions applied to the FSCI (equal weights, scaling of weights and non-linear effects), the FSCI is decomposed in Table 1.1. It appears that applying equal weights has most influence, before the scaling by the financial system’s segments and the adjustment for non-linearities. The influence of 83% of equal weights means this weighting scheme changes the FSCI as composed by the sum of its individual components (year-on-year changes of indices in logs of \(y_t, \text{reer}_t, s_p, h_p, \text{solv}_t, \text{vol}_t\)) by 83%. In
this same way, the scaling by financial system segments changes the (raw data) FSCI by 51% and the adjustment for non-linearities by 14%.

**Table 1.1 Decomposition of FSCI**

Influence of assumptions (as a percentage of FSCI based on raw data, i.e. FSCI excluding weights, scaling and adjustment for non-linearities)

<table>
<thead>
<tr>
<th>Assumption</th>
<th>Influence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equal weights</td>
<td>83%</td>
</tr>
<tr>
<td>Scaling by financial segment</td>
<td>51%</td>
</tr>
<tr>
<td>Adjustment for non-linearities</td>
<td>14%</td>
</tr>
</tbody>
</table>

**Critical boundaries**

First, the critical instability boundary (lower limit) was determined by the difference between the actual solvency buffers (a weighted index of the capital ratio of banks and the funding ratio of insurers and pension funds) and a situation where these are nil (banks: BIS ratio of 8%; insurers and pension funds: funding ratio of 100%). Then the boundary was determined by an extreme one-sided shock in volatility, interest rates (both upwards), stock and house prices (both downwards) and the exchange rate (appreciation), at a confidence level of 2.5% (twice the standard deviation from long-term average price movements). The resulting difference in buffers and the extreme price changes were weighted with the weighting factors of the FSCI; this yielded the critical instability boundary. The imbalances boundary (upper limit) was determined by an extreme one-sided shock in volatility, interest rates (both downwards), stock and house prices (both upwards) and the exchange rate (depreciation), at a confidence level of 2.5% (twice the standard deviation of long-term average price movements).

**Data sources**

The source for the solvency of Dutch financial institutions is DNB, that for the solvency of banks in the multiple-country analysis the OECD. For interest rates, exchange rates and the share index in all countries, the source is IMF International Financial Statistics; for stock price volatility of the financials, it is Datastream. The source for Dutch house prices is the Dutch Land Register and for the multiple-country analysis the BIS.
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