

Measuring and forecasting stress in the banking sector: evidence from Switzerland

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1. Introduction

Central banks and supervisory authorities regularly assess the situation in the banking sector, which is a vital element in the financial system. Two main questions are at the centre of such assessments: what is the present condition of the banking sector, and how will it evolve in the medium term? The first aim of this paper is to develop a “stress index”, summarising the current condition of the Swiss banking sector in one single measure. The second goal is to forecast the stress index with the information drawn from the economic environment and macroeconomic imbalances, which have the potential to influence the condition of the banking sector in the medium term.

Banking crises and their determinants have been the subject of widespread empirical research in the last few years. Binary variables, which signal whether a banking sector is in a crisis or not, are frequently used in the literature to describe the condition of banking sectors in emerging markets.² But, as banking crises are rare birds in industrialised countries, binary variables are less suitable to depict the condition of their banking sectors. Yet, the absence of full-blown crises does not mean that the condition of the banking sector is always equally sound and stress-free.

The index developed in this paper is an attempt to discern the fluctuations in the banks’ stress. The index represents a continuum of states, describing the banking sector’s condition ranging from low levels of stress, where the banking sector is tranquil, to high levels of stress, where the banking sector is in a severe crisis. To our knowledge, it is the first time that a stress index focusing exclusively on the banking sector has been developed. Four different types of variables are used to build the stress index: market price data, balance sheet data, non-public data of the supervisory authorities, and other structural variables. The stress index for Switzerland is calculated on a yearly basis for the period from 1987 to 2002. The final stress index shows two episodes of high stress: at the beginning of the 1990s, when the industry saw major restructuring and takeovers among regional banks, and in 2001-02, during the stock market crash. Financial experts in Switzerland generally agree that these two episodes were the most stressful in the period under consideration. We also find that indices based only on one single type of variable do not detect all stress episodes. This suggests that several variables should be incorporated in the stress index in order to capture the different ways in which a banking crisis can show up.

After computing the stress index, we explore the impact of the economic environment and macroeconomic imbalances on stress. Previous studies on early warning systems (EWSs) for banking crises have empirically established a link between the real economy and the financial sector. This suggests that the economic environment corresponds to a common risk to all financial institutions and that it has the potential to forecast the stress. Thus, if macroeconomic imbalances are prevailing and the economy is weak, the banking system is more prone to experience crises or stress in the near future.

Instead of taking the level or the growth rate of the variables, as most previous studies do, we use deviations from their longer-term trend, ie so-called gaps. The advantage of the gaps is that they underline the cumulative process of the imbalances: a large trend deviation can develop either in one period with strong above (or below) trend growth or through a sequence of years with above (or below)

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² See, for example, Goldstein et al (2000).

trend growth. To calculate the trend, we apply a “rolling” technique taken from Borio and Lowe (2002a). Hence, we only use information that was available to the policymakers at each point in time and we do not take advantage of the information contained in the full sample. The future value of the stress index is then regressed on the gaps. Our results confirm that macroeconomic imbalances explain a substantial part of the future stress in the Swiss banking sector. After checking the robustness of our model, we find that there is some multicollinearity and that the forecasts vary significantly with the specification of the model. One reason could be that the number of observations for the stress index in our sample is limited.

The outline of the paper is as follows. Section 2 gives a definition of the stress index. The stress index is then computed with data for Switzerland, and its validity and robustness are discussed. Section 3 briefly outlines which macroeconomic imbalances can serve as early warning signals for future stress in the banking sector of developed countries. The method for calculating the gaps is also presented. In Section 4, we forecast the stress index for Switzerland. Finally, Section 5 concludes and highlights open issues for future research.

2. Measuring stress in the Swiss banking sector

Usually, one expects the central banks’ assessment of the banking sector to be a condensed judgment, ie is the situation good, bad, better/worse than in the last quarter? Ideally, the answer to this question should be a single indicator, which summarises the global condition of the banking industry. In this section, we develop such an indicator and estimate it for the case of Switzerland.

2.1 Which measure best describes the condition of the banking sector?

When we look into the literature for an indicator that describes the condition of the banking sector, we usually find binary indices, which indicate whether the banking sector is in crisis at a given point in time or not. The literature on banking crises devotes great attention to the identification and description of such crises. Unfortunately, this kind of information is not very useful for depicting the situation in most developed countries, where banking crises are rare, if not inexistent. Nevertheless, even if these countries do not experience crises, it does not mean that their banking sector remains constantly sound and stable; their banks also go through good and bad periods, where they suffer greater or lesser degrees of stress. Therefore, a measure of the banking sector’s stress probably gives a better picture of the banks’ condition than a simple binary crisis indicator. Furthermore, to differentiate crises from tranquil periods, critical values must be arbitrarily chosen. Stress indices, on the other hand, are continuous, which means that they do not require the definition of critical values. This eliminates part of the arbitrariness.

2.2 Definition of stress in the banking sector

The stress indicator represents a continuum of states which describe the banking sector’s condition at a given point in time. The stress level is measured on a scale ranging from tranquil situations, where stress is quasi-absent, to extreme distress, where the banking sector goes through a severe crisis. It is important to distinguish the banking sector’s stress from its fragility. Stress emerges from the combination of exogenous shocks and fragilities in the banking system. A fragile banking sector does not systematically suffer stress if it benefits from a quiet and stable environment. Conversely, a solid banking system can undergo stress if it experiences extreme exogenous shocks. The interaction of the shock’s magnitude and the banking system’s fragility determines the stress level.

2.3 How to measure stress in the banking sector

To our knowledge, there is no continuous measure in the literature which specifically focuses on estimating banking sector stress. One should, however, mention the study by Illing and Liu (2003), who build a subindex for the banking sector (by estimating the beta of a bank’s stock portfolio) and use it in a general financial stress index. Another study, by Bordo et al (2000), proposes a global financial condition index without concentrating on the banking sector.

We base our stress index on the observation of crisis symptoms in the banking sector. Typically, several symptoms signal banking crises (bank run, fall in the banks' stock price, bank failures, etc). To measure the stress level, we estimate the gravity of the different crisis symptoms at a given date. If the symptoms are present and acute, the banking sector is likely to be in a crisis situation and, therefore, the stress is likely to be high.

There is an extensive literature focusing on the definition and identification of banking crises. We rely on it to define a set of variables representing crisis symptoms. We then measure their intensity and aggregate them to form our final stress index. Researchers generally agree that banking crises show up in many different ways and that identifying them implies a certain degree of subjectivity. This conclusion suggests that a single variable cannot capture the complexity of crises. To detect the many forms that a banking crisis can take, we build a stress index, which combines several types of variables (ie market prices and balance sheet data). The next section lists the variables included in our index. Most of them have been suggested by earlier studies, but some are specific to our index.

2.4 Variables included in the stress index

Since our goal is a quantitative and continuous index, we only consider quantitative variables. Each variable reflects a potential symptom of banking stress. Due to the annual frequency of some series, we compute a yearly index for the Swiss banking sector from 1987 to 2002. We use four types of information: market prices, aggregate balance sheet data, non-public information, and other structural data.³

Market price data

The first selected variable is the banks' stock price index. When the banking sector goes through a crisis, its intrinsic value diminishes and, subsequently, banks' stock prices fall. A period of high stress should therefore be characterised by a decreasing banking sector stock price index. This criterion has been previously used by Vila (2000) and Illing and Liu (2003) to define stress and crisis events. In order to detect falling stock prices, we look at the biggest decline in 12 months observed during the year.⁴ This measure allows sharp falls to be exhibited more clearly than with the raw data (Vila (2000)).

The second market price variable used in our index is the yield spreads for bank-issued bonds. The spread reflects the risk that investors associate with the banking sector. During a crisis, a higher spread should be observed. Illing and Liu (2003) suggest this variable. We use the average spread over one year in our index.

Balance sheet data

A typical banking crisis symptom is a sudden drop in deposits, which reflects the loss of confidence on the part of depositors in the banking system (bank run). This criterion is widely used to identify banking crises (eg Kaminsky and Reinhart (1996, 1999), Demirgüç-Kunt and Detragiache (1998) and Vila (2000)). To detect this phenomenon, we incorporate the total interbank deposits in our index. We think that bank runs should be well reflected in this variable since interbank deposits are relatively liquid and very partially insured. Furthermore, we can assume the banks to be more informed on the situation of their rivals than the public.

As the fourth variable, we use the return on assets of the banking sector. Although this variable is, to our knowledge, not used in the literature, we think that it is a relevant criterion for developed countries. It seems plausible that a non-profitable banking sector is a sign of trouble and that it should be associated with high stress.

³ See the appendix for the data sources.

⁴ This measure is called CMAX and is computed with the following formula: $CMAX_t = \text{index}_t / \text{maximum index over the last 12 months}$.

The fifth variable is the variation in bank capital. This variable has been used by Caprio and Klingebiel (1996) and González-Hermosillo (1999) to identify systemic banking crises. If a bank is in trouble, its capital will tend to shrink and, therefore, a banking sector in crisis should experience a decrease in total capital.

Another sign of crisis is found in the banks' evaluation of their own situation. This is reflected in banks' provisions, since, if a bank thinks that its situation is deteriorating, it should accumulate provisions. To take this information into account, we integrate the banking sector's provision rate into our stress index. Unfortunately, provisions are not an unbiased signal of crisis because, in stress periods, the banks' capacity and incentive to raise provisions might be reduced. González-Hermosillo (1999) uses a similar measure, namely the loan reserve coverage of non-performing loans.

Non-public data

The Swiss Federal Banking Commission, the banking supervisory authority of Switzerland, maintains a list of banks that are under special scrutiny. A bank appears on this list if it is experiencing unusual problems. We use the total assets of the banks on this list to estimate the share of the banking sector considered to be in trouble by the banking supervisory authority. During a crisis, this share should increase. One might think that this variable represents the "true" value of banking system stress since the supervisory authority has broader access to banks' information than the public. Unfortunately, this is not the case because: (1) only banks with unusually large-scale problems, or a high degree of stress, are registered and, therefore, the list does not show minor episodes of stress; and (2) the authority might sometimes miss problems, or detect them with a delay. However, the evolution of the banks under special scrutiny is certainly correlated with stress in the banking sector.

Other structural variables

Finally, we consider the variation in the number of bank branches. This variable takes into account the possibility of bank failures or reorganisation in the banking sector. This criterion is used by Bordo et al (2000), who consider the bank failure rate, and by Kaminsky and Reinhart (1996, 1999), who look at the closures, takeovers or mergers in the banking sector, to define crises. Our hypothesis is that bank failures or, at least, bank mergers or reorganisations are more likely to occur in periods of stress.

Variables not taken into account in the stress index

Information about non-performing loans is also a variable which appears frequently in studies on banking crises. Demirgüç-Kunt and Detragiache (1998), Corsetti et al (1998) or González-Hermosillo (1999) use the ratio of non-performing loans as a sign of crisis. Bordo et al (2000) prefer the loan loss rate. Unfortunately, the data on non-performing loans for the Swiss banking sector are only available since 1999.

2.5 Construction of the index

We combined the variables described above into one single stress index. At this stage, the choice of weighting method is crucial, since it determines the impact of each variable on the final stress index. We choose the variance-equal weight method to compute our index. This technique is the most common in the literature.⁵ It consists, first, in standardising the variables to express them with the same units and, second, in aggregating them using identical weights. The index formula is the following:

$$I_t = \sum_{i=1}^k \frac{X_{i,t} - \bar{X}_i}{\sigma_i}$$

⁵ There are other techniques to construct an index. Unfortunately, we were not able to find an alternative weighting scheme which would naturally fit in the context of a banking stress index. For example, we tried to apply the factor analysis technique, but this method does not yield meaningful results in the Swiss case, since the variables do not move together.

where k is the number of variables in the index, \bar{X}_i is the mean of the variable X_i and σ_i its standard deviation. We also standardise the final index to express it in terms of deviations from its mean.

2.6 How to assess the plausibility of the stress index

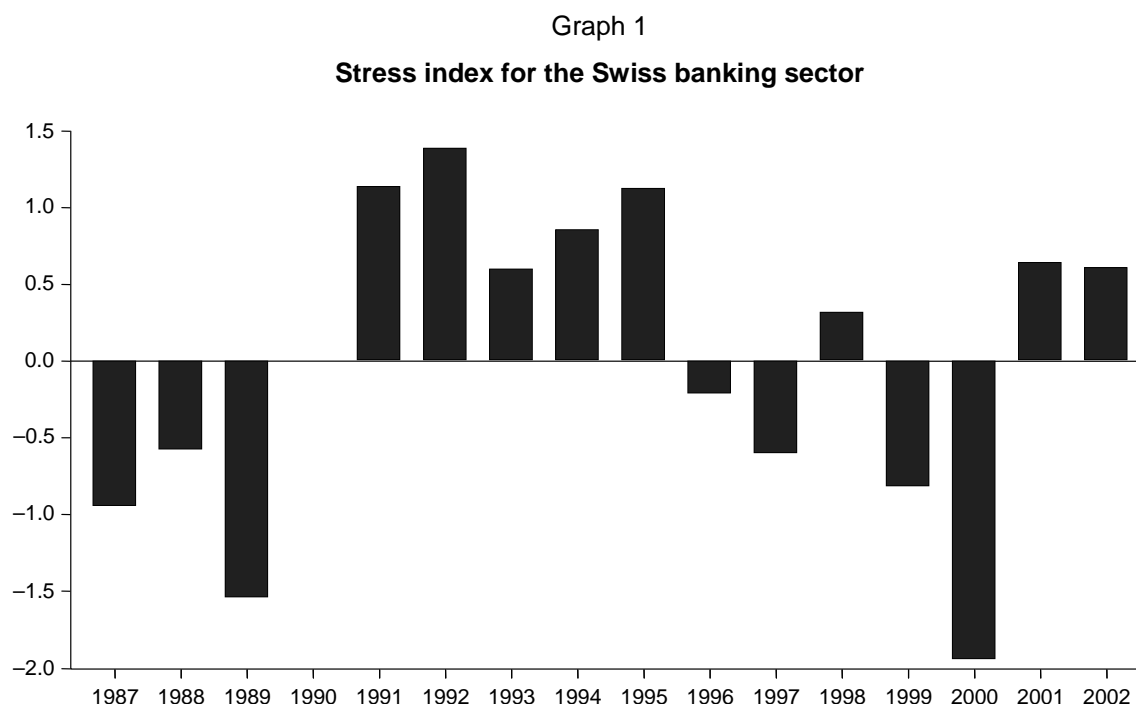
Assessing the plausibility of the stress index is probably the most problematic step of the process, since, by definition, the real stress sequence is not known. Illing and Liu (2003) suggest comparing the computed index with the results of experts' description and evaluation of the historical stress level. Identifying crises by using experts' assessments is relatively common in the literature. Caprio and Klingebiel (1996), Dziobek and Pazarbasioglu (1997), Bordo and Eichengreen (1999) and Lindgren et al (1996), for example, have used this technique. Unfortunately, the detected crises may vary from one expert to the other. After comparing several studies, Frydl (1999) and Eichengreen and Arteta (2000) conclude that the timing of crises differs significantly from one study to the next. Experts' opinions can obviously not be taken as the "true" value of stress, but they can still be used to assess the plausibility of our results.

For the Swiss case, it is generally agreed that, in the last 20 years, the banking sector has known two periods of high stress: at the beginning of the 1990s, when the industry went through a period of major restructuring and takeovers among regional banks, and in 2001-02, during the stock market crash. A shorter period of stress is also likely to have occurred in 1998, with the Russian and the LTCM crises.

2.7 Results for the Swiss case

Estimation of the stress index

Graph 1 shows the evolution of the computed stress index for the Swiss banking sector between 1987 and 2002. A level above zero means that the stress is higher than average. The index is expressed in terms of standard deviations from its mean.

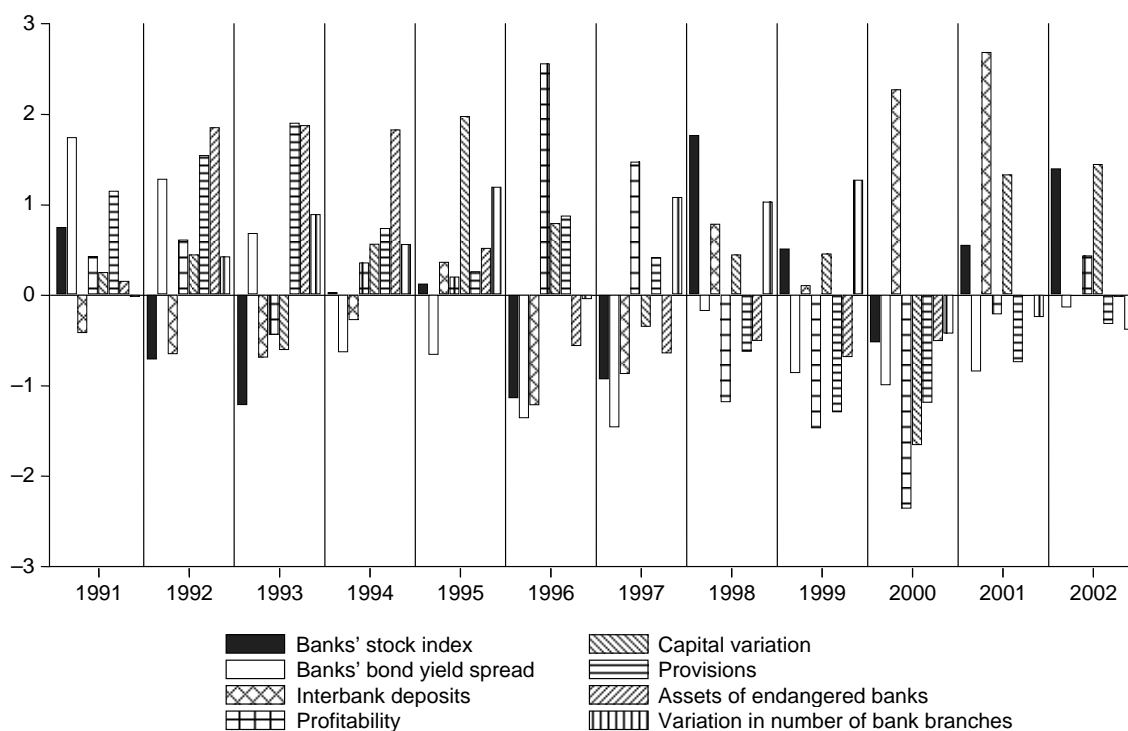


The index identifies three periods where the stress is above average: from 1991 to 1995; in 1998; and in 2001-02. This corresponds to the description of the Swiss banking sector that is commonly given by experts. The highest degree of stress is observed in 1992 and, globally, the beginning of the 1990s was the worst period for Swiss banks. The stress in 1998 was less intense than in the two other stress periods. Conversely, the year 2000 was the least stressful for the banking system in Switzerland.

Decomposition of the index

It is possible to decompose the stress index and isolate the contribution of each factor to global stress. Graph 2 presents the decomposition of our index. A positive (negative) value indicates that the variable is above (below) its sample mean and that it indicates more (less) stress to the system than it does on average.

Graph 2
Decomposition of the stress index (1991-2002)



The decomposition shows that the stress at the beginning of the 1990s is reflected in most of the variables: between 1991 and 1995 (with the exception of 1993), there are always at least six variables out of eight that indicate more stress than the average. The most recent stress period (2001-02) is the reflection of a decrease in banks' stock prices and in their capital (plus a drop in interbank deposits for 2001).

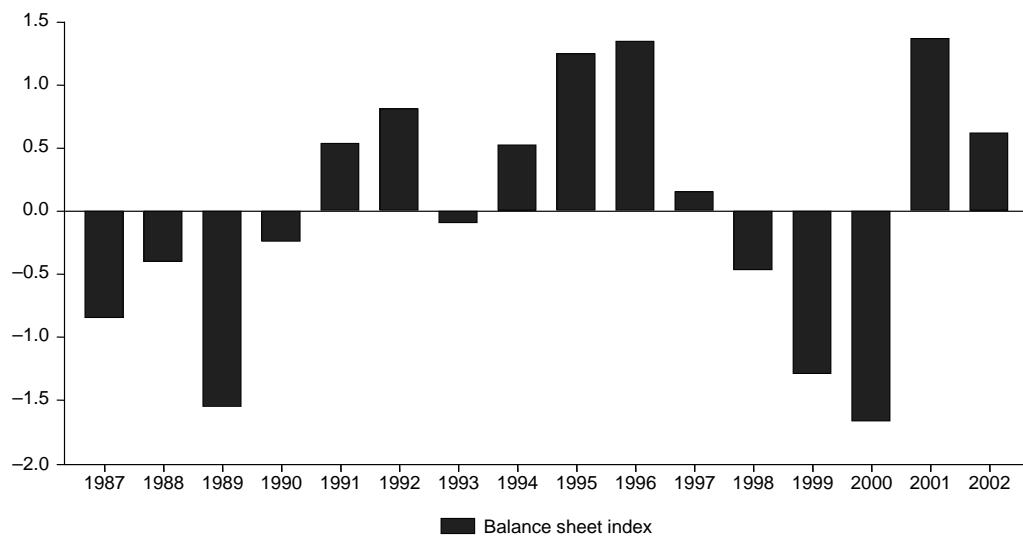
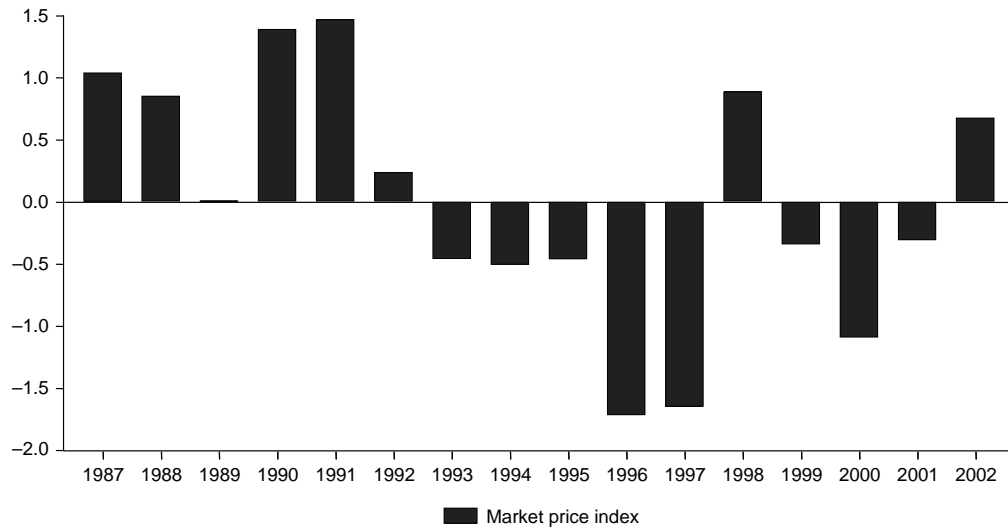
Market prices vs balance sheet data

In the literature, two types of information are commonly used to identify banking crises: market prices and balance sheet data. Indices usually rely upon either one type of variable or the other. Graph 3 presents the results for our stress index when only market prices or balance sheet data are used respectively.

Graph 3 clearly shows that the identification of stress periods largely depends on the type of variables used. The "market price index" shows four periods of stress (1987-88, 1990-91, 1998, and 2002), with the highest value for the years 1991 and before. The stress in 1998 is also important. The "balance sheet index" spots the beginning of the 1990s, with a maximum in 1996 and a break in 1993, and the years 2001-02, with an overall maximum in 2001. With the exception of 1991 and 2002, the two indices differ significantly. They also fail to give a stress pattern that fits the story related by experts. This result suggests that market prices and balance sheet data each provide only one part of the general picture. For example, the market price index, which reflects the situation of the quoted institutions, does not detect the stress at the beginning of the 1990s, which affected mostly non-quoted regional banks. Thus, combining both sources of information improves the index by allowing several symptoms of stress to be identified.

Graph 3

Market price index vs balance sheet index

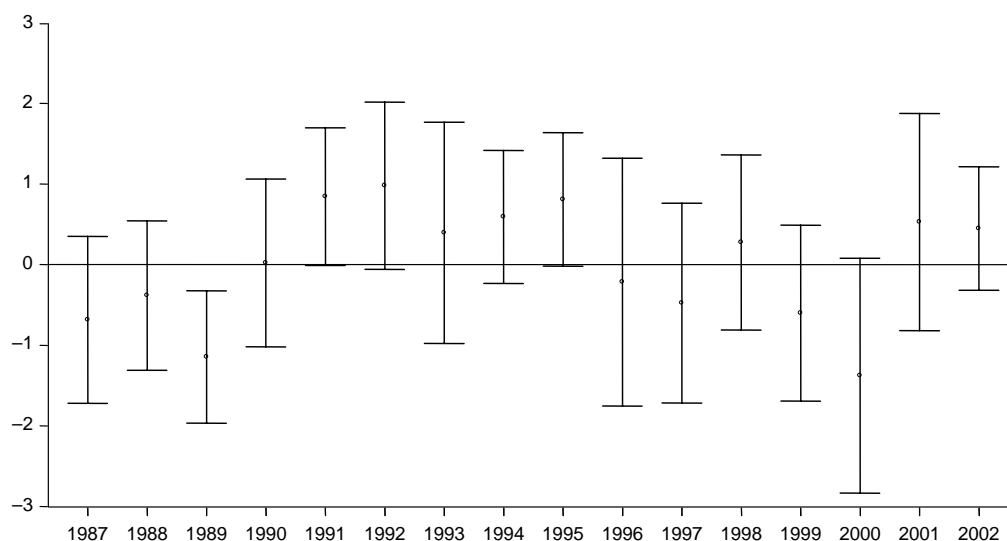


Robustness of the index

To check how sensitive our results are to the choice of variables, we computed indices using all possible variable combinations. This shows whether the results of the different combinations gather around the same value or whether they are widely spread. Graph 4 shows the truncated ranges of these indices (for each year, we exclude the highest and lowest 5% of values).

The index value seems to depend relatively strongly on the mix of the variables, as the results concerning market prices and balance sheet data in Section 2.7 have already suggested. However, globally, it is still possible to distinguish a higher level of stress at the beginning of the 1990s, in 1998 and in the last two years.

Graph 4
Robustness of the index



2.8 Limitations of the index and possible improvements

The principal limitation of our stress index is its low frequency. Unfortunately, most of the balance sheet data are collected annually and, therefore, the index can only be updated on a yearly basis. Furthermore, some of our data are only available since 1987, which makes our series relatively short. The lack of sufficient observations is problematic for the forecasts, as we will see in Section 4. However, our index is probably able to capture significant stress episodes even with an annual frequency, since, according to Frydl's (1999) survey, banking crises last on average between two and a half and four years.

The weight attributed to each variable in the final index is another controversial point. We give an equal weight to all variables, but one could argue that some variables are more relevant for stress than others and, therefore, that they should have a larger weight in the index. Unfortunately, we did not find an alternative weighting scheme that is economically more appropriate.

Another technical shortcoming of our approach is that it does not take into account the skewness of some variables for their standardisation. A potential improvement would be to use a standardisation method which incorporates this characteristic. Bordo et al (2000) propose a measure based on the median rather than the mean, and Illing and Liu (2003) mention a method based on the observed quantiles. These options should be explored in future studies.

Finally, it is also possible to refine the definition of the variables included in the stress index. As an example, Illing and Liu (2003) use a measure of banks' share price relative to the overall stock price in order to distinguish idiosyncratic shocks from economy-wide shocks. The authors also exploit GARCH techniques to take into account the serial correlation of many price series. This method is probably less useful for yearly variables, as the serial correlation tends to decrease with frequency for financial data. In any case, one should carefully consider the opportunity of pure technical improvements, as they tend to complicate the interpretation of the index.

3. Macroeconomic imbalances as early warning signals

Once the level of stress in the banking sector is assessed, another challenging question arises: is it possible to predict stress in the banking sector? A reliable estimate of future stress or at least of its variation - whether the stress will increase or decrease in the medium term - could represent a useful input for periodical assessments of the banking sector's condition. If the stress can be predicted, the

supervisory authorities and the central banks might consider actions to prevent serious problems in the banking system.

In the last couple of years, a vast literature has emerged on the so-called early warning systems (EWSs). There are two distinct types of model.⁶ The first type of model is based on the “micro” approach and typically projects individual bank failure. The data used for the micro approaches stem from individual banks’ balance sheets: they generally include indicators for capital adequacy, asset quality, earnings and profitability, liquidity, and sensitivity to market risk. The second type of EWS model is based on a “macro” approach and aims at the early detection of systemic banking crises. The data used in the macro EWSs are essentially macroeconomic variables. More recently, financial and political indicators have also been included in the estimations of macro approaches. Because our stress index is defined to reflect the stress of the overall banking sector, and not the stress of individual institutions or certain bank categories, the macro EWS approaches seem to be more suitable in our case.

Two findings of the macro EWS models are worth mentioning. First, the models have established empirical evidence of the link between the real economy and the financial system. In other words, the economic environment and prevailing macroeconomic imbalances can, to a substantial degree, influence stress in the banking system. Demirgüç-Kunt and Detragiache (1998) conclude, in a study on both developing and developed countries, that banking crises tend to emerge when the economic environment is weak. Second, the variables reflecting a weak economic environment and the build-up of imbalances seem to have the power to predict the condition of the banking sector. These two findings motivate our choice to rely on the economic environment and imbalances to forecast the stress index.

3.1 Macroeconomic imbalances and available information

Traditionally, researchers use macroeconomic variables in levels or their growth rates to predict banking crises. We rather focus on macroeconomic imbalances, which can be considered as a common risk exposure of financial institutions, and which have the potential to create stress in the future. We use the gap approach developed by Borio and Lowe (2002a). Technically, a macroeconomic imbalance is the gap between the original series and its trend. A positive (negative) deviation means that the actual series lies above (below) its trend. We assume that the trend is the proxy for the longer-term fundamental value of a variable, around which the actual series fluctuates. Admittedly, the assumption that the fundamental value can be “correctly” determined is controversial. We believe that even with a pragmatic approach to calculate the trend, we should still be able to broadly observe the imbalances, which usually follow cycles of several years.

Using gaps puts the focus on cumulative processes, since macroeconomic imbalances can build up either through a strong above (below) trend growth one period or through a sequence of years with small above (below) trend growth. The larger and more numerous the macroeconomic imbalances are in an economy at the same time, the more likely it is that the stress in the banking sector will rise later. It is important to note that it is not the build-up of imbalances but their sudden unwinding which can cause disruptions in the economy leading to higher stress for the banking sector.

To calculate the trend and the gap at time t , we use only the information that was available at that particular point in time (ie the gap for 1990 is estimated with the data for 1990 and the preceding years). This means that we place ourselves in the position of the policymakers at time t and we do not take advantage of the information contained in the full sample. The estimation of the trend is revised every year as new information is added to the sample.

3.2 Choice of explanatory variables

The list of macroeconomic variables used in earlier studies to predict banking crises is rather long. In order to choose the “right” indicators that could best predict the stress index for Switzerland, the variables should have a significant influence on the condition of the banking sector and should have

⁶ See, for example, Bell and Pain (2000) for a survey of the two groups of models.

proved to be robust across a number of other studies. Moreover, the variables should be related to typical macroeconomic imbalances in industrialised countries.⁷ The variables we selected in this respect are the following: the share price index (SP), the housing price index (HP), the credit ratio (CRR) (private credits/GDP), the investment ratio (INVR) (investments/GDP), the gross domestic product of Switzerland (GDP) and euro area GDP (GDP Europe). All variables in our data set are nominal and on an annual basis. The data were collected for the period between 1970 and 2002.⁸ In the following paragraphs, the main intuition for the impact of each variable on the stress is given and earlier studies that include these variables are mentioned.

Share price index and housing price index

A steep rise in asset prices (both share and housing prices) may trigger a wealth effect, which fuels consumption and subsequently leads to stronger economic growth. But when asset prices suddenly swing back, negative consequences for the banks have to be expected. The stress index could rise, especially when the banking system is already weak.

In the context of falling share prices, banks' profitability will most likely decrease, for example because commission and trading income sink and profits from the banks' own asset holdings will be lower. In the wake of falling asset prices, the balance sheets of firms and households will become weaker too. For the banks this means that more loans could end up non-performing. The banks' capital position will become weaker because of higher non-performing loans, but also because of a reduction of the value of the banks' own share holdings. Borio and Lowe (2002a,b) note that share price booms predict banking crises in a sample of 32 countries, including the G10 countries.

Households and firms typically hold a large fraction of their wealth in real estate. During a housing price boom, the debt capacity (in terms of mortgage loans) rises. Perhaps the banks' willingness to lend will also be greater. A decline in housing prices reduces the value of loans collateralised with real estate. Consequently, a higher number of defaults by mortgage-financed real estate owners will increase the number of non-performing loans for the banks. As in the case of declining share prices, an increasing amount of non-performing loans means that the profitability of the banks will be lower, and accordingly the stress will be higher.

Credit ratio

For an economy that is growing, it is normal that credits are increasing. But if credits grow much faster than GDP, this could mean lower lending standards on the part of the banks, ie loan applications are not adequately analysed. A rise in the credit ratio, which is the amount of credits to the private sector divided by GDP, could be associated with higher risk-taking by the banks in their lending business. The imbalance will start to unwind when borrowers find it more difficult to service their debt (for example because of a rise in interest rates or because the economy enters a recession). The more and the longer the credit ratio deviates from its longer-term trend - and assuming that the banks cannot fully hedge the credit risk - the more likely a rise in stress in subsequent periods. Borio and Lowe (2002a) point out that credits are a good indicator for crisis prediction. Eichengreen and Arteta (2000) conclude that rapid credit growth is among the most robust causes for banking crises, but their sample contains mostly emerging market countries.

Investment ratio

Investments have less frequently been used in macro EWS models. Nevertheless, we decided to use the investment ratio in our forecast of stress as it gives us a broader view of possible prevailing macroeconomic imbalances in the economy. Overinvestment can lead to losses for corporations and also for banks when the projects do not achieve their planned return on investment. Hardy and Pazarbasioglu (1999), in a study on leading indicators for the Asian crisis in the 1990s, include the

⁷ For simplicity, we use the term macroeconomic imbalances in this paper, although some of the imbalances (eg in asset prices) are sometimes referred as financial imbalances.

⁸ For more details, see the data sources in the appendix.

investment ratio in their data set. Unfortunately, as mentioned for example by Borio and Lowe (2002a), the variable is not always robust.

GDP and GDP Europe

The evolution of GDP reflects the general condition of an economy. If the performance of the economy is weak, the credit standing of borrowers deteriorates. The number of corporate and private defaults rises during a recession and leads to an increase in the share of non-performing loans and in risk provisioning for banks. Especially for banks that are strongly engaged in the lending business, a deep and long-lasting recession could lead to higher stress. Demirgüç-Kunt and Detragiache (1998) find in a sample of 65 and 45 countries respectively that low real GDP growth increases the probability of a banking crisis in the period between 1980 and 1994. Eichengreen and Arteta (2000) conclude that GDP growth rates generally decline before a banking crisis. The evidence is somewhat weaker when the authors limit their sample to OECD countries.

For Switzerland, being a small open economy, the business cycle is influenced to a considerable degree by the international environment. For this reason, we include euro area GDP (GDP Europe) in our data set. Swiss banks are directly affected by the European business cycle, as part of the banks' income is generated in that region. Indirectly, Swiss banks are affected by the impact of the European business cycle on domestic prospects. A recession in Europe could lead to a deterioration in economic conditions in Switzerland and thus reinforce a recession in Switzerland with the consequences described in the paragraph above.

For equity and housing prices and for credit and investment ratios, a positive gap is a priori expected to predict stress. The assumption for the GDP and the GDP Europe gap differs from the assumption for the other gaps as a recession is associated with a negative gap. One could also argue that a positive GDP gap might be an early warning signal for stress, indicating that the economy is on an unsustainable expansion path. The unsustainable expansion will sooner or later have to be corrected, which could lead to a rise in stress for the banks. From the empirical literature on banking crises, however, it is known that banking crises tend to occur when there is a recession (Borio and Lowe (2002b)).

3.3 Method for calculating gaps

For each series (GDP, GDP Europe, SP, HP, CRR and INVR), we take logs and calculate a rolling Hodrick-Prescott filter (HPF) trend. We use a "rolling" filter because we only rely on information that was actually available at each point in time. The gap is the actual series of a variable minus the trend. All gaps are then standardised in order to measure their relative size:

$$s_gap_t = \frac{g_t}{\sigma_t}$$

The standardised gap (s_gap_t) at time t is equal to the gap (g_t) at time t divided by the standard deviation (σ_t) of g . The standard deviation corresponds to the standard deviation from the starting date (1970) of our sample up to time t . It is replaced with a more recent calculation when the sample is extended.

4. Forecasting stress in the Swiss banking sector

This section presents how we have chosen the best model to forecast stress. The main results include the estimation output, the forecasts and a discussion on the robustness. The limitations of our method and possible improvements are then given in the last part of this section.

We base our forecast of stress on a regression of our stress index on the standardised gaps described in the previous section. We focus on one-year-ahead forecasts (one period in the stress index series). Hence, at time t , the model gives a forecast for $t+1$. We estimate a model which regresses the stress

index (y_t) on the k observed standardised past gaps ($x_{k,t-z_k}$). Only one lag (z_k) per gap is used in the model.

$$y_t = \beta_1 x_{1,t-z_1} + \beta_2 x_{2,t-z_2} + \dots + \beta_k x_{k,t-z_k} + \varepsilon_t$$

4.1 How to find the best model

To pick the best model among all possible combinations of variables and lags, we use two types of criteria. First, the model has to fulfil the following plausibility criteria: (1) the regression coefficients must be significant at a 10% level and have the right theoretical sign; (2) no lag greater than four years should appear in the model;⁹ and (3) the model must contain at least three explanatory variables. Second, we use the following four efficiency criteria to distinguish the best model among all those that fulfil the plausibility criteria: (1) the R -squared; (2) the number of correct forecasts for the direction of the stress index variation; (3) the root mean squared error (RMSE) for an out-of-sample forecast on the last seven years; and (4) the number of correct out-of-sample forecasts for the stress index variation in the last seven years.

4.2 Main results

Estimation output

According to the criteria mentioned above, one final model has emerged. This model has the best R -squared, it has the best RMSE, it does not make any error in forecasting the direction of the stress index variation in-sample, and it has the second best performance in the out-of-sample forecast of the stress index variation. The results are presented in Table 1.

Table 1
Determinants of the stress index

Variable	Coefficient	Standard error
GDP gap (-1)	-1.761*	0.738
GDP Europe gap (-3)	-1.297*	0.386
Share price index gap (-4)	1.452**	0.233
Housing price index gap (-3)	2.132**	0.468
Credit ratio gap (-2)	2.185**	0.617
Investment ratio gap (0)	0.893*	0.305
Constant	-0.897**	0.229
Number of observations		16
R -squared		0.89
Errors in-sample		0
Root mean squared error (RMSE)		0.67
Errors out-of-sample		1

* Significant at the 5% level. ** Significant at the 1% level.

As shown in Table 1, the coefficients are significant at the 5% level. The R -squared with 0.89 is relatively high. The GDP gap and the GDP Europe gap - reflecting the general economic environment - each have a negative coefficient, which can be interpreted as a recession. The other variables, the

⁹ We considered a link between stress and six-year-old gaps to be theoretically implausible.

macroeconomic imbalances, have positive coefficients. The lags of the explaining variables (in brackets after the variables) are between 0 for the investment ratio gap and -4 for the share price index gap. Remember that at time t the stress index for the subsequent period $t+1$ is estimated. The lag of one year for Swiss GDP is relatively short and it shows that the economy enters a recession only shortly before the stress in the banking sector rises. The lag of GDP Europe with -3 is longer than the lag of Swiss GDP, indicating that the impact of the European business cycle takes longer to materialise in terms of stress.

Although the lag of -4 for the equity price index gap seems to be surprisingly long, it is consistent with the findings of Borio and Lowe (2002a). They note that the equity price gap indicates banking crises better if a lag of -5 years is used.¹⁰ To our knowledge, many studies on macro EWS models consider a maximum time window of two years before a banking crisis. As we allow for longer lags to predict the stress in the banking sector, it is somewhat difficult to compare our results with those that use shorter time windows.¹¹

The main results of our model can be summarised as follows: (1) we find that macroeconomic imbalances and the economic environment have an influence on future stress in the Swiss banking sector; (2) the gaps and the concept of the macroeconomic imbalances seem to be a useful method to detect early warning signals for stress. If we estimate our model with variables in levels or in differences, the explanatory power of the model drops; (3) the macroeconomic imbalances generally build up years before the stress rises in the banking sector; and (4) in our model, the lags for the macroeconomic imbalances are between one and five years. For the share price, the credit ratio and the housing price, the lags are longer than two years (the time horizon frequently used in other macro EWS models).¹²

Forecasts

Graph 5 shows the actual stress index value (bars), the in-sample forecasts for 1987 to 2003 given by our model (line) and its out-of-sample forecasts for 1996 to 2003 (dotted line). Our model predicts the major stress periods (beginning of the 1990s and 2001-02). It forecasts the tranquil periods at the end of 1980s and the end of the 1990s. On the other hand, it fails to foresee the stress episode in 1998. The model gives the right direction in every case for the in-sample forecast and makes one error for the out-of-sample one. The model predicts an amelioration of the Swiss banking sector's condition for 2003.

Robustness of the model

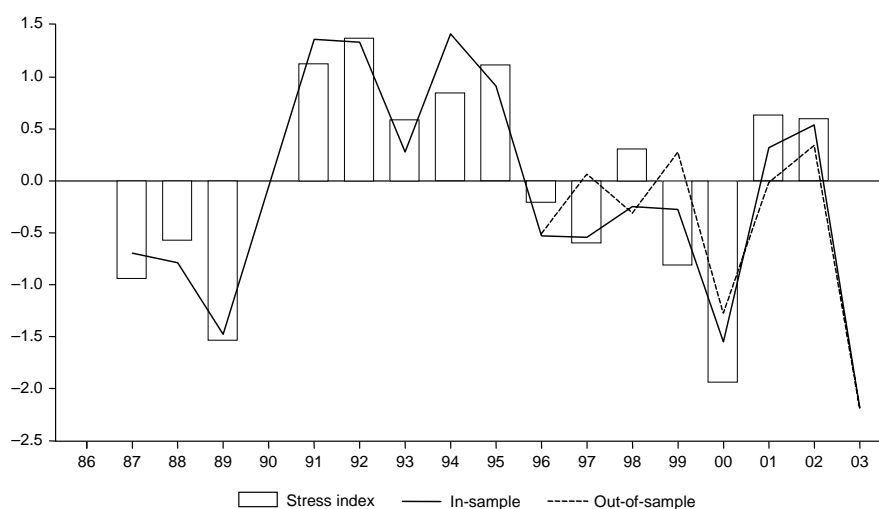
To assess the robustness of our model, we compare it with other specifications that successfully met our plausibility criteria. Three variables appear almost constantly in all these models: the equity price index, with a five-year lag; housing prices, with a four-year lag; and finally, but slightly less frequently, the credit ratio, with a lag of two or three years. The three other variables are not always significant and they do not always come out with the same lag. Their significance and their lags depend on how they are combined together.

¹⁰ Borio and Lowe (2002a) predict future banking crises with a horizon of up to three years. The equity price gap in their model has a lag of -2 , so the "total" lag of the share price variable corresponds to -5 years.

¹¹ A summary of the results of macro EWS models and the time horizons that were used can be found in Eichengreen (2002).

¹² We also tried to include more international indicators (the Swiss franc/euro exchange rate and the MSCI global stock index) and their gaps respectively in our estimations; however, they were not significant. In a different approach, we calculated an index for the total macroeconomic imbalances by summing up the standardised gaps. The stress index was then regressed on the imbalances index. Again this did not produce satisfactory results. Finally, we took real variables instead of nominal and re-estimated our model. This deteriorates the results of our model. The reason for that might be that banks write contracts based on nominal terms rather than on real terms. Changes in the γ , the smoothing parameter of the HPF, merely alter the results as long as γ is larger than 500 for the share price index (SP) and for the housing price index (HP). The smoothing parameter reflects the average size of the gap between the actual variable and its long-term value (Hodrick and Prescott (1997)). Assuming a higher smoothing parameter for the equity price index indeed makes sense because this variable seems to deviate more from its long-term trend than other variables.

Graph 5
Stress index forecasts



The last finding is a typical symptom of multicollinearity between explanatory variables. Multicollinearity has two important consequences for us: (1) it could artificially push the R -squared upwards, which can induce us to select the wrong model; and (2) it might bias the value of regression coefficients, which is used as a plausibility criterion. To check if multicollinearity is a problem in our case, we computed the BKW statistic (Belsley et al (1980)) for the different models. The higher this statistic is, the more harmful the multicollinearity for the biases mentioned above. According to Belsley et al (1980), a value greater than 30 can be considered critical. All our selected models have a statistic included in a range going from two to 21, with a value of 17.0 for our final model. According to this criterion, the consequences of multicollinearity are likely to be small in our case.

Note that multicollinearity does not affect the forecast accuracy of a model, as long as the linear relation between the explanatory variables observed in the past remains identical in the future. Therefore, even if the model's coefficients are not fit for explaining the causes of stress, the forecasts are still usable. Unfortunately, due to the shortness of our stress series, we are not able to draw any conclusion on the stability of this linear relation.

Robustness of the forecasts

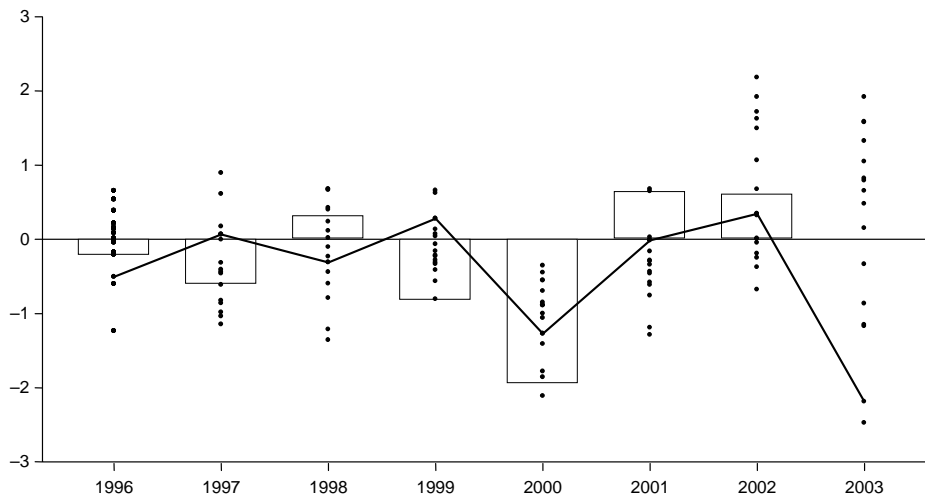
A crucial question, especially for policymakers, is: how robust are the forecasts? In other terms, how do changes in our basic specification affect the predictions? To check the forecast robustness, we compared the out-of-sample forecasts of the 16 models that fulfil the plausibility criteria. By looking at the dispersion of the forecasts, we obtain an idea of the degree of similarity between the models.

Graph 6 shows the actual value of the stress index and the out-of-sample forecast for each model (symbolised by dots). The solid line represents the forecasts of our basis model. For each model, the mean of the forecasts is not significantly different from zero, which implies that none of them systematically over- or underestimates the stress level.

One can split the results into two periods. Between 1996 and 2001, the dispersion of the forecasts is relatively constant. The standard deviation of the forecasts' distribution varies between 0.39 and 0.64, with an average of 0.54. The variance equality hypothesis between these years cannot be rejected. The dispersion is much higher in 2002 and 2003, with a standard deviation of 0.92 and 1.35 respectively. The variance equality hypothesis is clearly rejected when these two years are taken into account.

Two main conclusions can be drawn from these results: (1) globally, there is great uncertainty about the forecasts, since different models give very disparate predictions; and (2) this uncertainty seems particularly important for 2003. Indeed, the dispersion of the out-of-sample forecasts for this year is clearly greater than in the previous years.

Graph 6

Dispersion of the out-of-sample forecasts**4.3 Limitations of the method and possible improvements**

The main problem of our forecast is that our stress index series is too short. Due to the frequency and the availability of the variables included in the index, we have only 17 observations for the banking sector's stress. This is not sufficient to obtain a robust estimation of our model. One way to increase the number of observations would be to drop the variables that have a low frequency or those that have been available for only a few years. The disadvantage of a reduced index is that it might be less accurate in measuring the stress (see Section 2.7). To avoid discarding some variables, it is also possible to artificially increase the frequency by simulating the evolution of a variable between two observable points. With this technique, it is possible to exploit all the information contained in the high-frequency variables without abandoning the low-frequency variables. Finally, another possibility to obtain more stress observations is to use a cross-country analysis. Unfortunately, in this case, some variables might not be available for every country, eg the Swiss Federal Banking Commission's list of banks under special scrutiny. Furthermore, a model based on a cross-country analysis would not reflect the particularities of the Swiss banking sector.

Another problem with our method lies in the estimation of trends. The HPF recognises changes in the direction of the trend only with some delay, which means that the estimated trends are less reliable at the end of each observation period. In addition, the HPF is a mechanical trend and only one possible way to identify the fundamental value of a variable. The HPF might not be the best way to do this, especially for variables such as asset prices.

Although the macroeconomic imbalances and the weak economic environment can explain a substantial part of the banks' stress, they are not the sole factors behind systemic banking sector problems. Other factors, such as deregulation or restructuring due to overbanking, could also play a role regarding banking sector stress. But they are not included in our model.

Our method also supposes a linear relation between the stress and the gaps. If this was not the case in reality, our model would rely on a spurious link between the variables and the quality of the predictions would be altered. As underlined by Eichengreen (2002), banking crises are complex phenomena which certainly involve non-linear interactions. This might explain the lack of robustness in our forecasts.

Finally, the fundamental problem of our method is that a great amount of uncertainty intrinsically exists over both the measure of the explained variable (the stress index) and the relation between the explained and the explanatory variables. In a way, it is like solving one equation with two unknowns (the stress and the model). Our solution to this problem is to implicitly assume that we had a perfect measure of the stress level and thus reduce the number of unknown variables to one (the model). Unfortunately, this is not the case, and if large discrepancies between our index and the "true" banking sector stress exist, our estimated model and forecasts could be biased.

5. Conclusion

The aims of this paper have been: (1) to develop a measure that summarises the banking sector's condition in an industrialised country such as Switzerland; and (2) to provide a framework that could help policymakers to predict the development of the banking sector's condition.

Our stress index estimates the banking sector's condition on a continuous scale ranging from tranquil periods to severe crisis. It distinguishes itself from the traditional binary indicators found in the literature because it describes a continuous range of states rather than just differentiating crises from tranquil periods. This characteristic makes it particularly appropriate for depicting banking sectors which rarely (or never) experience severe crises. To our knowledge, it is the first time that a stress index focusing on the banking sector has been constructed.

Our stress index is an aggregation of several variables, each of them being a potential symptom of banking crises. Our assumption is that the more intense these symptoms are, the higher the stress. We combine different types of variables: market prices, balance sheet data, non-public information and other structural data. The estimated index fits well the experts' evaluation of the Swiss banking sector's history and it identifies all major stressful periods. We find that the value of the index differs substantially when only one type of information (market prices or balance sheet data) is used and that, in this case, it fails to detect the entire sequence of stress episodes. This confirms the fact, widely acknowledged in the literature, that banking crises can show up in different ways. A concrete implication is that, in order to detect the different forms that a banking crisis can take, a stress index should be constructed on several variables and incorporate different types of information.

After estimating the stress index, we try to forecast it by using macroeconomic imbalances. We identify the imbalances by computing the gap between a variable and its trend. The advantage of this method is that it exhibits the accumulation of yearly imbalances rather than focusing on the variable for one year only. We then regress the banking sector's stress index on the gaps and use the estimation equation to forecast the stress index.

Our main finding is that a model incorporating Swiss and European GDP, credit and investment ratios to national GDP, the stock price index and housing prices is able to explain a large part of the Swiss banking sector's stress level. This indicates that a significant link exists between the (macro)economic environment and the banking sector's condition. Furthermore, we find that the gaps precede the evolution of the stress and that they can be used by policymakers to forecast the stress level. We observe that the lag between the gaps and the stress index could go from one up to five years (eg share price index). This confirms the result in Borio and Lowe (2002a) and, more generally, suggests that long lags are useful for early warning systems. Previous studies usually focused on shorter lags, generally of one or two years. From a technical point of view, we also observed that using gaps, instead of variables in level or in difference, significantly improved the quality of the results. Finally, we tested the robustness of our specification and our forecasts. We find that the coefficient's significance varies with combinations of the different variables, which is a typical symptom of multicollinearity. We also observe that the forecasts are clearly dependent on the model's specification and that they are dispersed around the actual value, which makes accurate predictions difficult.

The main drawback of our model is that it relies on a small number of observations for the stress index. We think that the biggest improvement to this study would be to apply this method to a larger sample. Including more observations would probably decrease the uncertainty about the coefficients' significance and improve the robustness of the forecasts. Three options are available to enlarge our data set. First, one can compute the stress index with high-frequency variables only. Second, one could extend the study to other countries. For both options, some variables would have to be dropped from the stress index's estimation (the variables with low frequency or those that are not available for countries other than Switzerland). It is possible to construct a valuable measure of the stress with fewer variables, but, as the results of this paper show, it is important to include as much information as possible in the index to identify the multiple patterns that a banking crisis can follow. The third option is to artificially increase the frequency of some variables by estimating the values that are not directly available. This would allow incorporating the information on high-frequency variables without discarding the low-frequency ones.

Another significant improvement would be to choose a more sophisticated measurement of the gaps. As mentioned in the main text, our method tends to identify imbalances with some delay. The use of an empirical macroeconomic model to compute long-term equilibrium trends would probably refine our estimation of macroeconomic imbalances and detect them earlier than the actual method does. However, we believe that the most significant improvements could be made by increasing the number of stress index observations used in our estimation.

Appendix: Data sources

Stress variables

Swiss banks' share price index: SWITZ DS Banks (Thomson Financial Datastream) 1984-2002, weekly data. The largest 12-month price fall observed each year is computed (CMAX index).

Swiss banks' bond yield spread: spread between the banks' bond yield index and the Confederation bond yield index (1984-2000), spread between banks' and Confederation three-year bond yield (2001-02). Weekly data (Swiss National Bank). The annual average is computed.

Total amount of interbank deposits: total amount of interbank deposits, monthly data (Swiss National Bank) 1980-2002. The largest 12-month fall in deposits observed each year is computed (CMAX index).

Banking sector's rate of profitability: ratio of Swiss banks' aggregated profit to their total assets, yearly data (Swiss National Bank) 1982-2002.

Banks' total capital variation: difference in Swiss banks' aggregate capital from one year to the other, in per cent, yearly data (Swiss National Bank) 1987-2002.

Banking sector's provision rate: ratio of aggregated new provisions (and amortisation) to aggregated total assets, yearly data (Swiss National Bank) 1987-2002.

Total assets of banks under special scrutiny: aggregate total assets of the banks under the scrutiny of the Swiss Federal Banking Commission, yearly data (Swiss Federal Banking Commission and Swiss National Bank) 1987-2002.

Variation in bank branch numbers: difference in the number of bank branches from one year to the other, yearly data (Swiss National Bank) 1987-2002.

Macroeconomic variables

Share price index (for Switzerland): SWITZ DS Market (Thomson Financial Datastream) 1970-2002, quarterly data that have been converted into annual data by taking the average of the quarters for each year.

Housing price index (for Switzerland): constructed by taking the mean of the growth rates of the following subindices (Wüest & Partner): office floorspace, apartments, houses, industrial space, new and old rented flats, 1970-2002, quarterly data that have been converted into annual data by taking the average of the quarterly growth rates for each year.

Credits (for Switzerland): claims on the private sector, *International Financial Statistics* (IMF), 1970-2002, quarterly data that have been converted into annual data by taking the mean of the quarters for each year.

Investments (for Switzerland): gross fixed capital formation, *International Financial Statistics* (IMF), 1970-80, and gross domestic investment (State Secretariat for Economic Affairs), 1980-2002, quarterly data that have been converted into annual data by taking the sum of the quarters for each year.

Gross domestic product (Switzerland): Swiss GDP, current prices (Swiss Federal Statistical Office) 1970-2002, annual data.

Gross domestic product (Europe): euro area GDP, current prices, *OECD Main Economic Indicators*, 1970-2002, annual data.

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