Jarmo Pesola

Financial fragility, macroeconomic shocks and banks' loan losses: evidence from Europe

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The views expressed are those of the author and do not necessarily reflect the views of the Bank of Finland.

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Financial fragility, macroeconomic shocks and banks' loan losses: evidence from Europe

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Abstract

This paper tests the hypothesis that the more fragile a banking system is, the more likely it is to experience problems when an unexpected shock hits. The empirical framework where this test is conducted is a reduced form model, where macroeconomic factors explain banks' loan losses. The dependent variable is the ratio of net loan losses to lending in a panel comprising the banking sectors of nine sample countries. An econometric model is estimated on pooled annual data mostly covering the period from the early 1980s to 2002. There are three separate explanatory terms. Two of these include a surprise change both in incomes and real interest rates. Both form a separate cross-product term with lagged aggregate indebtedness. The lagged dependent variable is the third explanatory term possibly capturing the feedback effect from loan losses back to the real economy. The underlying macroeconomic account that this paper puts forward is that loan losses seem basically to be generated by strong adverse aggregate shocks under high exposure of banks to such shocks. The model has been used in connection with stress testing in the Bank of Finland.

Key words: financial fragility, unexpected macroeconomic shock, loan loss, stress test

JEL classification numbers: G21, E44

Rahoituksellinen haavoittuvuus, makrotalouden shokit ja pankkien luottotappiot
Estimointeja eräiden Euroopan maiden aineistolla

Suomen Pankin keskustelualoitteita 15/2007

Jarmo Pesola
Rahapolitiikka- ja tutkimusosasto

Tiivistelmä

Tässä tutkimuksessa testataan hypoteesia, jonka mukaan pankkijärjestelmä kokee odottamattoman sokin iskiessä ongelmia sitä todennäköisemmin, mitä haavoittuvampi se on. Testin empiirisenä kehikkona on redusoidun muodon malli, jossa makrotaloudellisilla muuttujilla selitetään pankkien luottotappioita. Selitettävänä muuttujana ovat yhdeksän maan pankkisektorin muodostaman paneelin nettoluottotappiot suhteessa antolainaukseen. Ekonometrinen malli on estimoitu tämän vuosittaisen paneeliaineiston avulla. Estimointivuodet käsittävät useimpien maiden tapauksessa 1980-luvun alkuvuosista alkavan ja kaikilla vuoden 2002 loppuun päättyvän ajanjakson. Mallissa on kolme erillistä selittävää muuttujaa. Kaksi niistä sisältää yllätysmuutoksen tuloissa ja reaalikoroissa. Molemmat näistä muuttujista muodostavat erillisen ristitermin viivästetyn velkaantuneisuuden kanssa. Kolmantena selittäjänä on käytetty viivästettyä selitettävää muuttujaa, jonka tarkoituksena on kuvata takaisinkytkentää luottotappioista reaalitalouteen. Makrotaloudellisena tulemana paperissa on, että luottotappiot näyttävät syntyvän voimakkaiden aggregaattitason sokkien vaikutuksesta, kun pankit ovat selkeästi altistuneet sokkivaikutuksille. Mallia on käytetty Suomen Pankissa stressitestauksen yhteydessä.

Avainsanat: rahoituksellinen haavoittuvuus, odottamaton makrotaloudellinen sokki, luottotappio, stressitesti

JEL-luokittelu: G21, E44

Contents

1 Introduction

Financial disturbances can be costly. In particular, systemic events in financial markets, such as banking crises, often affect the whole society in a deeply traumatising way. Consequently, it is important to anticipate the risks of such adverse development so as to try to prevent that kind of disaster and ensure the financial stability. For example, central banks and other financial market authorities have started to develop stress tests for analysing financial stability.[1]

This paper aims at revisiting empirical modelling of aggregate loan losses, using macroeconomic variables in particular for stress testing purposes. Loan losses are a central factor affecting banking sector stability and hence a natural subject of stress testing. Moreover, it is important to understand how macroeconomic developments affect aggregate loan losses in that banking sector resilience can be stress tested in the light of adverse macroeconomic scenarios.

The empirical model developed here builds on the following three novelties: 1) a panel of banking sector level loan loss data from ten European countries, 2) joint effect of aggregate indebtedness and macroeconomic shocks on loan losses and 3) use of macroeconomic forecasts for expectations in surprise variables. A surprise (an unexpected shock) is the difference between realized and expected outcome.

The annual aggregate banking sector loan loss data was provided for this study by the central banks of Belgium, Denmark, Finland, Germany, Greece, Iceland, Norway, Spain, Sweden and the United Kingdom. The estimated data cover the period from the early 1980s until 2002. In that period a relatively large number of banking crises has occurred in several of these countries, notably in Scandinavia.

A central idea to be tested in the model is that financial fragility, measured by aggregate indebtedness, affects banks' loan losses jointly with macroeconomic shocks. In particular, we assume that the combined effect on loan losses of fragility and a shock is multiplicative:

banks' loan losses = f(macroeconomic shock * financial fragility)

This makes the effect of a macroeconomic shock on loan losses non-linear: the effect of a shock is amplified if the prevailing fragility (indebtedness) is high.

The joint non-linear effect of shocks and fragility is aimed to capture the stylized fact of fat tails in the distribution of the aggregate number of defaults and hence loan losses. Moreover, it can be motivated by the Mertonian credit risk

[1] The joint IMF-World Bank financial sector assessment programmes (FSAP) have stressed the need for more quantitative tools for macro prudential analysis in monitoring, assessing and anticipating financial stability. Stress testing the financial system is one of these.

dynamics and the portfolio models of credit risk derived from that basis, such as the CreditMetrics. Drawing from such models, we can think of our macroeconomic shock variables as representing the common factors driving aggregate (portfolio) credit losses and of our fragility variable as representing the aggregate (average portfolio) credit quality.

A macroeconomic shock is constructed as a surprise relative to expectation where a published macroeconomic forecast represents the expected development. This, to our knowledge, is a new approach in the literature, as the most conventional way has been to model shocks as trend deviations or as mere changes.[2] These last mentioned simpler approaches have disadvantages because, eg, of the question of how should the correct trend be constructed.

Regarding the relevant macroeconomic shock variables, a sample of the most feasible macroeconomic explanatory factors for banking distress can be found among the IMF's macroprudential indicators. These are related to economic growth, balance of payments, inflation, interest and exchange rates, lending and asset price booms etc.[3] Data based on these indicators have been used in numerous financial crisis studies as explanatory variables, as can be seen in the survey by Demirgüc-Kunt and Detragiache (2005) or earlier in a comprehensive summary done at the IMF (2000).

According to the results, high customer indebtedness combined with adverse macroeconomic surprise shocks to income and real interest rates contributed to the increase in loan losses and distress in the banking sector. Loan losses also display strong autoregressive behaviour, which might indicate a feedback effect from loan losses back to the macroeconomic level in deep recessions. The non-linear model structure seems to fit particularly well to the extreme amounts of loan losses in crisis periods. The model seems fit better to the Nordic countries than to the rest of sample countries.

The structure of article is following. In section 2 data and the data sources are presented. In section 3 the model specification for econometric estimation is laid out, after which the estimation results are presented. In section 4, we briefly demonstrate how the estimated model can been used in connection with stress-testing the banking sector. We conclude with the results and their connections to the literature background.

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[2] For example, Bikker and Metzemakers (2004) and Valckx (2003) used GDP growth in their loan loss provision studies and Sorge and Virolainen (2005) deviation from GDP trend in a bankruptcy model.

[3] For example: Macroprudential Indicators of Financial System Soundness, IMF Occasional Paper 192, Washington DC 2000, pp. 4 and 15.

2 Data and variables in econometric analysis

2.1 Dependent variable: banks' net loan losses

The central banks of sample countries have provided the banks' loan loss data for this study. The sample of countries consists of Belgium, Denmark, Finland, Germany, Greece, Norway, Spain, Sweden and the UK.[4] The Figures 2.1 and 2.2 show percentage of banks' loan losses/outstanding lending (LT/L variable) in the sample countries (except for Germany[5]) from the 1980s and 1990s until 2004. Note that the length of time series varies country by country. The year of first observation is: Belgium 1994, Germany 1993 and the UK 1987. In all the other countries the observation period starts in 1982.

The received data is net loan losses. There are no separate observations about recoveries. The recoveries however affect the timing and size of observed loan losses and at the same time it might give extra cyclical dynamics to net loan losses.[6] On the banking sector level in a selected time period (eg a year), deducting the aggregate flow of recoveries from the aggregate flow of new loan losses (gross) gives the flow of net loan losses. It is however likely that a part of the recoveries observed this year are due to provisions in earlier years, which meanwhile has been posted as gross loan losses. This can even sometimes have an amplifying effect on net loan losses as compared to gross loan losses.

On the basis of loan loss time series (Figures 2.1 and 2.2) one can say that the adverse development was clear in the Nordic region in the 1990s even though Denmark avoided a banking crisis (as did also Iceland). The picture is more mixed in the rest of the European sample countries. Banks' loan losses in the UK and Spain show a clear peak in the early 1990s. The percentage of banks' loan losses/outstanding lending stock touched even a 'Nordic' level in Spain that time. However, the overall level of loan losses in the other countries in Figure 2.2 is much lower than in the Nordic countries.

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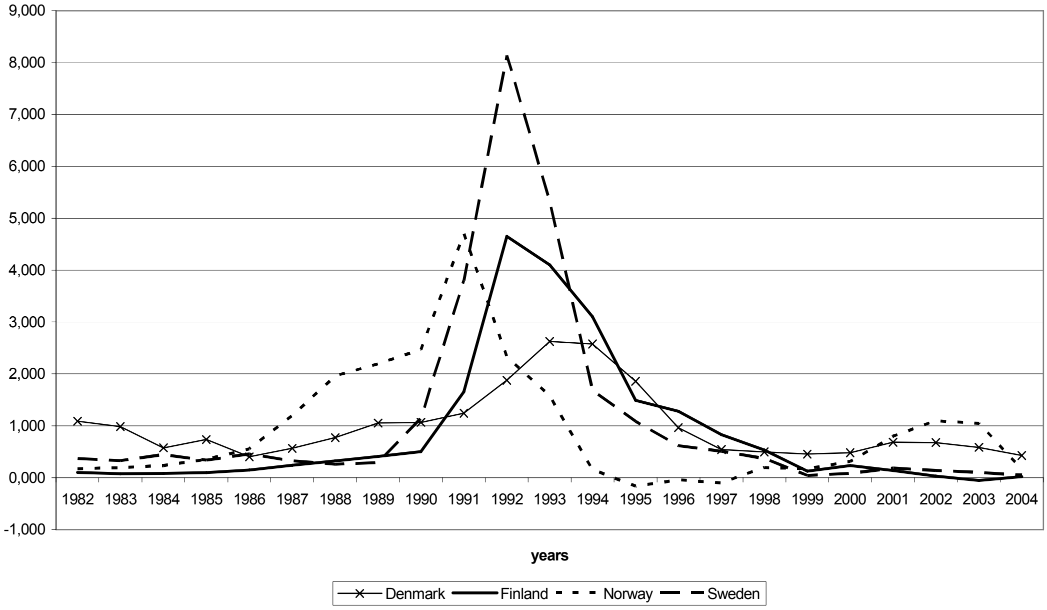
[4] Iceland has been dropped out of this study because of its exceptional small size as compared to the other sample countries.

[5] Germany is not shown for confideliaty reasons.

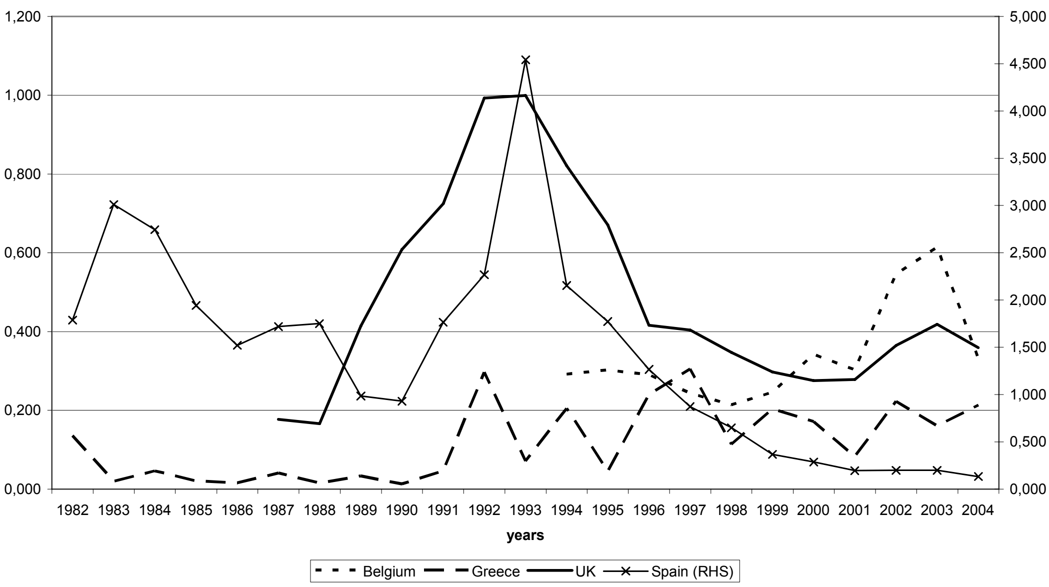
[6] As seen from the viewpoint of a single loan, the ultimate amount of loan loss depends on the market value of the loan's collateral. The timing of ultimate loss depends on the length of judicial process needed to close the case and to sell the collateralized asset. Both the resale value and selling time may vary along with the macroeconomic situation and outlook, in addition to the micro level specific factors. The usual case is that the recovery does not cover the whole value of the defaulted loan, but only a part of it. Hence, the creditor also often suffers at least some loss ultimately.

Figure 2.1 **Nordic countries: Banks' loan losses/lending, %**



Source: The central bank of the respective country and the IFS

Figure 2.2 **Rest of sample countries: Banks' loan losses/lending, %**



Source: The central bank of the respective country and the IFS (German data (1993–2003) is not shown for confidentiality reason)

2.2 Explanatory variables: financial fragility and macroeconomic shock variables

Financial fragility variable L/Y is presented, in its operationalized form, by aggregate indebtedness. Actually, the aggregate leverage, loans divided by assets, would be more relevant concept in this connection.[7] As there nevertheless is no appropriate aggregate wealth data available for all the sample countries, we use GDP value, Y, in the denominator. Debt L is banks' total outstanding lending stock.

Explanatory variables are graphically presented in the appendix. The country specific time series of indebtedness is shown in Figures A1.1 and A1.2. The source of the banks' outstanding domestic lending as well as of GDP value figures is the IMF's International Financial Statistics (IFS). Indebtedness variable includes both firms and households in our study.[8] In the Nordic countries' group (A1.1) the indebtedness seems to strongly increase prior to the increase in banks' loan losses, whereas it comes down quickly after. Denmark is an exception where the indebtedness seems to develop rather evenly throughout the period. Among the other sample countries the indebtedness increased rapidly in the UK prior to the increase in loan losses (A1.2). The level of indebtedness has stayed at higher level in the group of other countries than in the group of Nordic countries.

We have two macroeconomic shock variables: income surprise and change in expected real interest rate. Their country specific time series are presented in appendix-figures A1.3–A1.6. Let us first however see how the shock variables are designed.

Regarding the income shock variable, the plans of economic agents are based on the current state of affairs, the economic outlook and expectations. The expectations affect the agents' investment and borrowing plans and, thus, also future indebtedness. Macroeconomic shocks tend to cause deviations from these plans. Although economic agents may try to adjust their actions and plans accordingly, the effect of a shock can be seen in the number of bankruptcies, unemployment development and eventually in loan losses.

We start from the assumption that the basis for agents' income expectations is the outlook for GDP growth, which represents generally the expected change in the flow of income. We denote the expected annual growth of nominal GDP by y^e. Thus, $y^e = (Y^e – Y_{-1})/Y_{-1}$ and correspondingly realised GDP growth $y = (Y – Y_{-1})/Y_{-1}$.

[7] Non-financial private sector leverage is, according to the IMF, one of the crucial macroprudential indicators. Both the firm debt-equity ratios and household indebtedness are listed as important aggregated microprudential indicators (see the IMF, 2000, p. 4 and 7).

[8] To be exact, both variables, indebtedness and GDP, as well as also lending rate, include public sector and net export. Public sector could be treated here as an extension of household sector.

Instead of deriving theoretically the optimal function for expected GDP from an underlying theory, we use the OECD forecasts for the sample countries on percentage changes in GDP volume and GDP deflator, denoted by y_q^e and y_p^e respectively.[9] The underlying assumption is that the OECD forecasts commonly have a strong expectations generating effect.

We put the surprise variable together with two parts, a volume and a price part, along with the separate OECD forecasts of GDP volume and price change components. It is assumed that a positive shock or surprise in GDP volume, $y_q - y_q^e$, decreases the amount of loan losses and vice versa at any given level of fragility.

The effect of a GDP deflator surprise or error, $y_p - y_p^e$, can nevertheless be ambiguous ex ante. The direction of the effect depends on whether the change in GDP deflator or price component is due to demand pull or cost push. In the latter case the surprising increase in deflator tends to boost the amount of loan losses.

By adding together the GDP volume error part and deflator error part we get an error in income surprise variable YS

$$YS = y - y^e = (y_q + y_p) - (y_q^e + y_p^e) = (y_q - y_q^e) + (y_p - y_p^e)$$ [10]

Despite the ambiguity in the GDP deflator surprise part of income surprise variable, we assume that income surprises affect loan losses negatively at any given level of fragility.

The income surprise variables are shown in appendix-figures A1.3 and A1.4. The expectations error was particularly significant during the banking crisis years in Finland (A1.3). Also Norway and Sweden suffered from a clear negative surprise in those years (A1.3). The UK, Spain and Greece seem also to have suffered from a negative surprise before the rise in their banks' loan losses (A1.4).

Interest rate i is another crucial variable which directly affects the profitability of an investment project.[11] That effect is direct if the project is financed by borrowed money or, otherwise, the effect is indirect through the so called

[9] We use the June forecast in each year in OECD economic outlook as the forecast for the GDP next year. Or, if we put it as the variable is formulated in this study, the expected GDP growth this year is based on forecast made in June last year.

[10] Adding the volume and price components so as to get the value growth is an approximation. Correctly, there should also be a cross term $y_q\ y_p$ for getting the value change, like $y = y_q + y_p + y_q\ y_p$. Usually, however, the effect of cross term is very small in the developed economies, so an approximation $y = y_q + y_p$ can be used.

[11] Exchange rates and terms of trade are other relevant variables for formation of expectations that are mentioned in the literature. In particular, in the Nordic countries (small open economies) they should have a significant impact (see eg Pesola, 2001).

opportunity cost effect.[12] The difficulty regarding interest rates is that usually there are no regularly published predictions of that variable by the OECD or any other public body. However, assuming it behaves approximately like a random walk, we can simply use annual changes in nominal interest rate $i - i_{-1}$ to measure unexpected changes in them.[13] On these grounds, we assume that an increase in interest rates will tend to increase loan losses. Banks' lending rate is the empirical interest rate variable in this study.

The nominal interest rate tends to correlate with inflation like income variable. In order to avoid duplication in explanation it could be reasonable to use real interest rate $i - y_p$.[14] For the same reason we do not use the pure price surprise variable $y_p - y_p^e$, but the change in OECD GDP deflator forecast, $y_p^e - y_{p-1}^e$. That change in expected GDP deflator is subtracted from the expected change in nominal lending rate. That gives us our interest rate variable RE

$$RE = (i^e - i_{-1}^e) - (y_p^e - y_{p-1}^e) = (i_{-1} - i_{-2}) - (y_p^e - y_{p-1}^e)$$

By rearranging $RE = (i^e - y_p^e) - (i_{-1}^e - y_{p-1}^e)$ we can see that variable RE is a change in expected real lending rate. The nominal part of RE is a product of interest rate surprise from period t–1 according to the random walk assumption. There is also some evidence that a surprise in the price component from period t–1 contributes to a change in current period's price expectations (see Appendix 2, chapter 1.2).[15] Thus, the change in expected real lending rate RE can be stated to stand for errors in expectations or surprise in expectations, which should have a positive impact on loan losses.

The country specific time series of variable RE are shown in appendix-figures A1.5 and A1.6. An increasing change in RE (a negative surprise) seems to have coincided with increasing loan losses in Norway, Sweden, Finland and Greece.

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[12] Even though a project is not financed by loan capital, the alternative cost of interest rate (and its expectations) affects the selection of projection (ie whether to start the project at all or to invest the money on other placement). Hence, it affects indirect on the investment project. The effect is valid also in the cases where the project is only partly financed by borrowing. The interest rate also affects the calculated present value of the future cash flow and, hence, the expected profitability.

[13] In an augmented Dickey and Fuller one sided test the hypothesis assuming a unit root for interest rate series had to be rejected in two of nine sample countries. Hence, assumption of random walk could not be rejected in seven countries.

The static expectations for interest rates can also be motivated by a long earlier period of regulation, especially in the Nordic countries. The financial markets were strictly regulated in the Nordic countries until the 1980s, when a gradual liberalization started. Interest rates were very rigid during regulation and there is usually some inertia in changing the way in which expectations are formed (Pesola, 2001).

[14] Actually, the correct form of interest rate in real form r would be $r = i - y_p - ry_p$. The cross term ry_p is nevertheless usually very small in the developed economies, so an approximation $r = i - y_p$ is commonly used.

[15] Appendix 2 is available by request: jarmo.pesola@bof.fi.

3 Econometric analysis

We stated earlier that the realisation of banks' credit risks is caused by a joint effect of financial fragility and shocking errors in the expected macro economic development. Realized credit risks appear as loan losses to banks as firms go bankrupt and households become unable to repay their debts. We shall transform this idea into an equation in section 3.1 so as to be able to test it econometrically.

Summarising the test results, we can say that the estimated model seems to be econometrically plausible and supports the idea of joint effect of fragility and shock. Both of the surprise variables, income and interest rate in combination with indebtedness, appear to contribute to explaining observed variations in banks' loan losses in the sample countries. Out of sample tests also support this result.

3.1 Model specification

It is assumed that the expected cash flow and interest rate affect the investment plans of any actor in private sector (a firm or household). An investment project is affected by interest rate directly or indirectly through the opportunity cost effect.

A shock, which causes an outcome that deviates from the expected cash flow or interest rate, affects the borrower payback capacity. The payback capacity is affected also by the indebtedness (or fragility) of borrower. The shock and indebtedness affect jointly the payback capacity and may eventually cause a loan loss to the lender.

Our ultimate interest is however the loan losses on the aggregate or macro level. Aggregating over single firm and household incomes, loans and loan losses gives in principle the respective data on the aggregate level. However, the single actors can receive incomes and borrow from each other causing thus a multiple counting problem. In order to avoid that problem we use macro level proxies.[16] The banking sector's outstanding lending stock is used as a proxy for the sum of single loans because the main part of loans is emitted by banks. (The bank lending is a natural selection also because we are looking at banks' loan losses.)

Bear in mind that indebtedness indicator (fragility) covers the entire economy, including both the corporate and household sectors. Consequently, we assume implicitly that the same behavioural principles apply both to firms and households. Moreover, these two sectors are closely interconnected. Indebtedness and macroeconomic shocks affect both sectors in a similar manner, at least qualitatively. For instance, deteriorating outlook weakens households'

[16] In practice, it would be very hard to get such aggregated data reliably otherwise.

employment and wage income expectations and high indebtedness raises the probability of loan default.

The closest proxy for the flow of aggregate income is the value of GDP. As we are basically interested in changes in the income flow, we use the percentage change of GDP value. The unexpected changes in the income flow are the surprising shocks, which can cause loan losses. The design of that income surprise variable was described in section 2.2.

The earlier mentioned joint effect is got by putting the shock variable together with fragility (lagged by one year) as cross product term. Financial fragility, proxied by aggregate indebtedness, is a kind of magnifying factor. As fragility increases, the effect of a given surprising shock likely gets stronger giving a non-linear relationship between the shock or fragility variable and loan losses. This construction is supposed to capture particularly well the extreme crisis situations. We have two different macro level shock variables: income and interest rate variables, YS and RE (see section 2.2).

In sufficiently severe economic recessions, a vicious circle can emerge, in which bankruptcies and loan losses can further worsen the macro economic situation. This, in turn, contributes in generating new bankruptcies and so on until a banking crisis, in the worst case. A lagged dependent variable can thus capture this kind of feedback effect in such a vicious circle.[17]

Hence, before any further estimation experiments were made, a preliminary estimation without lagged dependent variable as a regressor was made ie we tried a static model structure. The residuals in that estimation displayed statistically significant positive autocorrelation. The autocorrelation in residuals looked particularly striking during the crisis years. Also, the total explanatory power of estimated equation was rather poor. These facts indicate that the variation in dependent variable has some dynamic persistence, which seems not to be captured with the other explanatory variables. Consequently, the dependent variable lagged by one year is included as an explanatory variable in the equation to be estimated.

Assuming that the shock variables are mutually independent,[18] we can specify the following equation for estimation, where the dependent variable is banks' loan losses divided by total lending[19]

[17] A theoretical basis for this kind of dynamic development is laid down by Kiyotaki and Moore (1997) and von Peter (2004).

[18] It looks a rather strong assumption, but in a sufficiently short time span we could assume that these are independent. As the variables include an expectation element, we can think that they are formed separately and need not be related with each other. Moreover, in the euro environment (this includes also non-euro countries in the sample) this might be rather relevant assumption from the viewpoint of a single country as the monetary policy is conducted by the ECB.

$$\frac{LT}{L} = c + b_1\left(\frac{LT}{L}\right)_{-1} + b_2 \cdot \frac{L_{-1}}{Y_{-1}} \cdot YS + b_3 \cdot \frac{L_{-1}}{Y_{-1}} \cdot RE + u$$

where

$\frac{LT}{L}$	=	net loan losses per banks' outstanding lending stock, %
YS	=	income surprise ($YS = y - y^e$, where y = actual nominal percentage growth of GDP, y^e = expected nominal percentage growth of GDP, based on the OECD forecast in June preceding year)
RE	=	change in real interest rate expectations (see section 2.2)
L/Y	=	indebtedness indicator: banks' domestic credit L divided by GDP in current prices (proxy for financial fragility)
c, b_1, b_2, b_3	=	coefficients ie the parameters to be estimated. Expected signs: $c > 0, b_1 > 0, b_2 < 0, b_3 > 0$
u	=	residual

A positive correlation is assumed between indebtedness and loan losses. As indebtedness is lagged by one year in the model, we assume that the lenders know borrowers' indebtedness when they agree on new loans. The confidence connected with that awareness is an essential part of the potential surprise effect, which can hit both the lender and borrower in next period.

As concluded in the previous section, the income surprise variable is assumed to affect loan losses negatively at any given level of fragility. Increase in interest rate variable is assumed as a negative surprise and it will thus tend to increase loan losses.[20] We also assume that income surprises and real rate surprises are not correlated.[21]

[19] Mind that we use realized loan loss data and not loan loss provisions. The difference between realized loan losses and the provisions is that, while a realized loan loss should be more or less a kind of real time event, the loan loss provision is an accounting concept. A loan loss provision is usually made when the likelihood of default passes some threshold. Loan loss realisation in gross terms (ie recoveries excluded) follows if and when the default takes place, although there can be some room for judgement in timing when the event is registered in accounting and, hence, included in statistics. There can however be a considerable time lag between gross and net (ie recoveries included) loan losses as there usually is some judicial process in between.

[20] The negative effect of interest rate increase comes, firstly. through the collateral value effect: assets' present value is depressed when interest rates rise. Secondly, the interest rate increase depresses simultaneously the borrower's payback capacity.

[21] Actually, the correlation between income surprise variable and real lending rate expectation change ranks between 0.58 in Belgium and 0.01 in Sweden in 1981–2004.

3.2 Main results

The panel of sample countries are estimated with pooled least squares estimation method (PLS) in the equation presented in section 3.1. In this paper only the main econometric results are presented. Regarding the more detailed analysis, the reader is advised to see the separate appendix 2, which is available by request from the author.

The estimation result for the period of 1983–2002 is presented in Table 3.1. The basic model in multiplicative form is presented in column a (model 1/a). That model is able to explain close to 70% of the observed variation in loan losses relative to total loans, which as such is satisfactory. The coefficients in model 1/a have expected signs and are all significant at conventional confidence levels (99%). A separate Wald-test was made for the restriction hypothesis that both of the cross terms' coefficients were simultaneously zero. The hypothesis was rejected in the test on 99 per cent significance level.

Modest positive autocorrelation remains in the residuals. Proper caution should, however, be exercised in interpreting the DW-statistic when a lagged dependent variable is on the right hand side of equation.[22] Therefore, a separate Wald test was run on the residuals. According to the results of Wald test the hypothesis of no first order autoregression in the residuals could not be rejected on 95 per cent significance level except for Sweden. Ie the lagged dependent variable did not totally remove the problem of positive autocorrelation from the Swedish part of the panel estimation results. (See Appendix 2 for more thorough and detailed results.)

The autocorrelation in loan losses raised the question whether there would be a feedback effect from loan losses to GDP. An experiment was done by using instrumental variable estimation technique so as to capture the possible feedback. The income surprise variable includes GDP variable as a part. Because of the potential endogeneity problem, OLS estimates can suffer from a simultaneity bias. Therefore, a two stage least square (TSLS) estimation procedure followed where in stage one estimated fitted values for the income surprise variable was used as an explanatory variable in stage two estimation (Appendix 2, chapter 9). The outcome was essentially no changes in the estimated parameter values. This result is consistent with the view that banking distress does not affect the real economy or it could reflect the idea that the lead-lag structure between credit losses and the real economy is relatively involved.[23]

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[22] DW-statistics tends to be biased when a lagged dependent variable is on the right hand side of the equation. See eg Brooks (2002) p. 164.

[23] This result is in line with the conclusion made in Lowe (2002, p. 13) based on several empirical studies. According to his conclusion, the evidence is largely inconclusive that reductions in bank lending caused by financial stress would affect the macroeconomy. On the other hand Dell'Arriccia et al (2005) found signs of feedback effect in their empirical study.

There can also be other underlying factors affecting the persistency of loan losses. It could be simply so that it is associated with the general cyclical dynamics. Moreover, it could reflect the legal process, whereby the completion of bankruptcies in the legal system can take several years.

In order to check the robustness of the multiplicative (non-linear, bi-linear) basic form of the cross term (surprise*fragility), a corresponding PLS was run in an additive (linear) form (Table 3.1, column b), model 1/b.

Comparison of these two results brings lot of similarities. There is no significant difference between the multiplicative (1/a) and additive models (1/b) according to F-statistic, though the adjusted R-squared statistic is slightly higher in the additive form. The signs of coefficients are correct, except for c coefficient in the additive model, and significant on the 99 per cent confidence level in both of the models.

It is worth to pay attention to the intersection coefficient c in the additive form (1/b). It is negative and significant on the 99 per cent confidence level in one-sided test. Rationally, the intersection coefficient should be positive. Even though there would be no surprising shocks, there always will be some positive loan losses not negative ones in the long run. Note, that also the country specific estimated fixed effects change markedly between the different estimated forms.

Next step was to try to find out in a combined model, 1/c (Table 3.1, column c), whether there would be differences between multiplicative and additional form coefficients. According to the estimation results, only the coefficients of lagged dependent variable (no 1) and the separate fragility variable (no 7) are significant on the 95 per cent level in the combined model.

A Wald-test for the explanatory power of the two different sorts of coefficients in the combined model 1/c was done. The test results (see separate appendix 2, section 2.1) point to that the additive form coefficients would give a significant explanation to loan losses whereas the multiplicative form would not in the combined model 1/c. Like in the additive model, the coefficient of constant term is significantly negative in the combined model.

According to the partial derivatives calculated for explanatory variables in the combined model (applying the average values of the variables over the estimation period), all of the explanatory variables contribute to the loan losses in an expected manner.

Many different econometric experiments point to that both the multiplicative and additive form seem to give a reasonable explanation of banks' loan losses, albeit the sign of the coefficient of constant term in the additive model is not plausible.

Table 3.1 **Estimation results: Basic model**

Dependent variable: Banks' loan losses/lending, LT/L
Sample: 1983–2002
Total pool (unbalanced) observations: 153
Method: Pooled Least Squares

	MULTIPLICATIVE MODEL (a)				ADDITIVE MODEL (b)				COMBINED MODEL (c)			
Variable	no.	Coefficient	t-Statistic	Probab.	no.	Coefficient	t-Statistic	Probab.	no.	Coefficient	t-Statistic	Probab.
C	1	0.2614	3.6950	0.0003	1	-1.6118	-3.0489	0.0027	1	-1.5433	-2.9097	0.0042
(LT/L)(-1)	2	0.7081	13.5421	0.0000	2	0.6753	13.0648	0.0000	2	0.6826	13.2212	0.0000
YS*(L/Y)(-1)	3	-0.1193	-4.6525	0.0000					3	-0.1210	-1.2843	0.2012
RE*(L/Y)(-1)	4	0.0861	2.7993	0.0058					4	-0.1635	-1.2005	0.2320
YS					3	-0.0784	-4.0919	0.0001	5	0.0114	0.1577	0.8749
RE					4	0.0810	3.1067	0.0023	6	0.2220	1.8539	0.0659
(L/Y)(-1)					5	2.2198	3.5749	0.0005	7	2.1186	3.3960	0.0009
Fixed Effects												
(Cross-C)												
Denmark		0.0588				0.7118				0.7052		
Finland		-0.0606				0.4355				0.3912		
Norway		0.0852				0.7430				0.6916		
SWEDEN		0.1773				0.5037				0.5077		
Belgium		-0.1817				-1.4156				-1.4217		
Germany		0.1654				-0.2409				-1.3281		
Spain		-0.1398				-0.3428				-0.1965		
Greece		-0.3293				-1.2812				-0.2882		
United Kingdom		-0.0752				-0.7956				-0.7647		
R-squared			0.6934				0.7172				0.7239	
Adjusted R-squared			0.6695				0.6930				0.6959	
S.E. of regression			0.6551				0.6314				0.6285	
Durbin-Watson stat			1.6583				1.6924				1.7061	
F-statistic			28.9960	0.0000			29.5922	0.0000			25.8420	0.0000

3.3 Robustness and model evaluation

3.3.1 Out-of-sample forecast

We look at the out-of-sample forecasting ability between the basic models in Table 3.1 (the multiplicative model 1/a and the additive model 1/b) for the years 2003 and 2004 (Germany 2003 only). The comparison has been done with the help of mean error (ME), mean square error (MSE) and mean absolute error statistics (MAE) in out-of-sample forecast (next page).

Adding over all the sample countries gives a general result that in all of the different error categories the multiplicative model gives more accurate forecasts than the additive one. The additive model is better only for Norway when we look at single country cases. Hence, it seems that the multiplicative model outperforms the additive one in the forecasting period.

Looking at the general results above, we must bear in mind that in mean error statistics relative big observations with opposite signs can outweigh each other and thus hide information. Further, in MSE a single outlier could have a disproportionate effect as there is only a limited amount (two years) of observations in the out-of-sample period. On the other hand, as the errors in our models usually are smaller than one, MSE statistics tend to be decreased as compared to the MAE statistics. That effect is opposite to the case where the general size of error happened to be bigger than one. Thus, the MAE statistics is probably the best analysing tool in this case. The further analysis is done with the help of MAE statistics.

A country specific percentage of MAE-statistics over out-of-sample period (2003–2004) has been calculated as a percentage of the estimation period average of dependent variable (LT/L). For the sake of comparability, a similar country by country percentage of MAE has also been presented for the estimation period years ending at 2002 in all countries. This scaling is done for controlling the potential country specific differences in the lending and loan loss data thus allowing us comparisons between countries. The simple rule for comparison is: the smaller the percentage of MAE, the better the model performs. We got the following results

Out-of-sample forecasting errors (2003–2004 average) in multiplicative (table 3.1/a) and additive (Table 3.1/b) models

		Denmark	Finland	Norway	Sweden	Belgium	Germany	Greece	Spain	UK	SUM
ME	Multiplicative 1/a	-0.32	-0.29	-0.41	-0.33	0.14	-0.05	0.11	0.27	0.11	-0.77
	Additive 1/b	-0.44	-0.34	0.00	-1.37	0.71	-1.24	0.71	-0.66	-0.65	-3.28
MSE	Multiplicative 1/a	0.10	0.14	0.21	0.28	0.03	0.00	0.02	0.22	0.01	1.01
	Additive 1/b	0.20	0.17	0.00	1.92	0.51	1.53	0.51	0.44	0.44	5.72
MAE	Multiplicative 1/a	0.32	0.29	0.41	0.41	0.14	0.05	0.11	0.39	0.11	2.23
	Additive 1/b	0.44	0.34	0.07	1.37	0.71	1.24	0.71	0.66	0.65	6.20

Out-of-sample forecasts in the multiplicative basic model (in Table 3.1/a)

MAE as a percentage of the average LT/L in the estimation period

	Denmark	Finland	Norway	Sweden	Belgium	Germany	Greece	Spain	UK
Est.period \ Years\	1983–2002	1983–2002	1983–2002	1983–2002	1994–2002	1993–2002	1983–2002	1983–2002	1987–2002
-2002	26.5 %	36.0 %	55.9 %	68.3 %	73.2 %	42.2 %	443.5 %	39.7 %	38.7 %
2003-2004	31.1 %	30.4 %	42.0 %	33.5 %	44.5 %	13.2 %[a]	100.1 %	24.8 %	21.8 %

[a] 2003 only.

It seems that the MAE criterion is better in the forecasting period than in the estimation period. Comparing the results with the respective results in the additive model gives at hand that, except for Norway, the multiplicative basic model outperforms the additive one (see Appendix 2).

In sum, it seems as if the multiplicative model works better than the additive model in the out-of-sample forecasts. The multiplicative model seems also to fit better in general in the estimation period. These facts point strongly to the impression that the non-linear model structure fits better to the extreme amounts of loan losses in crisis periods than the linear structure.

3.3.2 Testing the expectation hypothesis

As mentioned earlier the expected aggregate income and the price component of real rate are directly based on the published OECD macro forecast for respective countries. The income surprise variable is then defined as a difference between the annual actual outcome of percentage growth of GDP value and its forecasted respective growth rate published by the OECD in June preceding year. We have in the earlier examples seen that the surprise variable has worked well.

We try to find out here whether some widely used alternative expectation proxies would work even better. We compare in the framework of our multiplicative model our results with the result of using trend deviations instead of our income surprise variable. Perhaps the most usual trend deviation is a deviation from an ordinary linear OLS-trend.[24] Another alternative variable for income surprise variable was also taken into consideration. This variable, a difference between annual percentage change in GDP in current prices and its historical average, is by its construction closer to the income surprise variable than the trend deviation. Also here, it is a question of a deviation from the 'trend' of historical average of percentage growth.

A correlation analysis over the period 1983–2002 was run in order to see how close to each other these three shock variables are (for the detailed analysis, see appendix 2, chapter 5). The correlation of income surprise variable with the percentage deviation of GDP value index from its OLS-trend is only 0.04 while the correlation is correspondingly 0.81 with the difference between the percentage growth in GDP value and its average.

Both of these alternative expectation variables were estimated in the basic multiplicative form model 1/a by substituting the alternative variables for the income surprise variable. According to the test results, neither one of the cross terms including alternative income surprise variables are statistically significant

[24] That is used eg in Sorge-Virolainen (2005).

though their coefficient have correct signs.[25] Consequently, the assumption based on various static trend expectations does not work in this model. Hence, the expectations based on published macro economic forecasts in Table 3.1 give a better explanation to banks' loan losses than these alternatives.

3.3.3 The sample split in the Nordic countries and 'rest of Europe' countries

The Nordic countries (except for Denmark) are a group which suffered badly from banking crisis in the early 1990s. As a relatively homogeneous group regarding the economic and social as well as legislative structures the Nordic countries would be a natural sub-group. It is expected that the basic model would function particularly well for the Nordic countries.

Splitting our sample in two sub-samples does not reveal any essential differences in estimation results between those two groupings (Table 3.2). The total explanatory power is roughly the same in both of the groups. Also the coefficients of the estimated variables have all an expected sign. One striking difference between the group results is that the coefficient of interest rate variable is statistically clearly insignificant in the 'rest of Europe' countries (variable no 4 in 3.2/b). Consequently, the model fits marginally better in the Nordic countries than in the rest of the sample countries.

In addition, the method of seemingly unrelated regression (SUR) was applied in estimating the basic model in multiplicative form on pooled data for four Nordic countries in period 1983–2002 (see the separate appendix 2, chapter 4). The SUR estimation method should, with panel data, give more precise coefficients, as it takes into account possible contemporaneous correlation between the country specific regression error terms.[26] As a small, fairly homogeneous open area, the Nordic countries can be affected by some common outside factor that is not captured here. Furthermore, as close neighbouring countries, their trade and other economic ties make the contagion of events between the countries fast and easy. The SUR estimation can eg take such omitted factors into account in this particular case. The result of SUR-estimation did not materially differ from the PLS-result in 3.2/a.

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[25] The values of t-statistics are -0.857 and -1.638 respectively for the trend deviation and the difference from GDP percentage growth average (see appendix 2, chapter 5). Furthermore, an experiment was done by using a Hodrick-Prescott trend (lambda 6.25): the coefficient of corresponding cross term had wrong sign and was not significant (t-value: 0.193). Moreover an experiment was done by using a no-change expectation in the GDP growth percentage: correct sign but insignificant t-value (-1.094).

[26] See eg Greene (2000, p. 614–623).

Table 3.2 **Estimation results: Nordic vs 'rest of Europe' countries, multiplicative model**

Dependent variable: Banks' loan losses/lending, LT/L
Sample: 1983–2002
Method: Pooled Least Squares

	NORDIC COUNTRIES (a) Balanced observations: 80				'REST OF EUROPE' COUNTRIES (b) Unbalanced observations: 73			
Variable	no.	Coefficient	t-Statistic	Probabil.	no.	Coefficient	t-Statistic	Probabil.
C	1	0.3323	2.8161	0.0062	1	0.1931	2.7759	0.0072
(LTL/L)(-1)	2	0.7059	10.4424	0.0000	2	0.6727	6.9374	0.0000
YS*(L/Y)(-1)	3	-0.1513	-3.5051	0.0008	3	-0.0391	-1.9428	0.0564
RE*(L/Y)(-1)	4	0.3027	3.4125	0.0011	4	0.0200	1.1020	0.2745
Fixed Effects (Cross)								
Denmark		0.0125						
Finland		-0.1761						
Norway		0.0135						
Sweden		0.1501						
Belgium						-0.0915		
Germany						-0.1076		
Spain						0.2158		
Greece						-0.1220		
United Kingdom						-0.0055		
R-squared			0.7110				0.7311	
Adjusted R-squared			0.6873				0.7021	
S.E. of regression			0.7865				0.3431	
Durbin-Watson stat			1.7388				2.1239	
F-statistic			29.9374	0.0000			25.2457	0.0000

Figure 4.1 (in chapter 4) shows actual and fitted loan losses as well as out of sample forecasts for 2003 and 2004 plotted for Finland with the coefficients of estimated PLS model. Visually, the fit-curve looks particularly good during the banking crisis years. The relatively poor fit in 1992 is due to an exceptional amount of filed loan losses associated with the bank support offered by the Finnish Government that year.[27] In the 1980s and again early this decade the model tends to generate changes in loan losses that did not materialize. Those features could be explained by the fact that, on the other hand, loan losses in the 1980s remained modest under the then prevailing tighter financial market regulation. The regime change towards a more stable environment after the introduction of euro in 1999, on the other hand, has also contributed to the fall in loan losses. In addition, an increased cautiousness in the aftermath of banking crisis could still have affected the behaviour of both lenders and borrowers.

Out of sample forecast fits rather well (Figure 4.1). The forecast converges rapidly towards the prevailing very low level of loan losses in 2003–2005 supporting the result in section 3.3.1. Actually, loan losses in net terms were slightly negative in 2003 because recoveries exceeded gross loan losses. The amount of net loan losses in Finland was a bit over zero in 2004 and 2005.

Pooled regression imposes a common set of parameters on the explanatory variables throughout the panel. Separate country by country estimation would probably give a better overall fit for single countries. In order to assess whether the implied parameter restrictions in the PLS-estimation are valid an F-test on the validity of these restrictions was performed. According to the F-test results (Appendix 2, chapter 10), there seem to be rather generally an autoregressive element in loan losses. The results give also an impression that the cross term including income surprise variable has a common explanatory behaviour in the sample countries, in particular in the Nordic countries, even though the restriction on the parameter fails to be supported in a relatively narrow margin by the data in the case of all countries. Instead, the restriction on the parameter of the cross term including interest rate variable was not supported by the data over 1983–2002.

The reason for the test failure regarding interest rates is most likely related to the different role of country specific interest rate movements during the period of exchange rate tensions before the late 1990s. Interest rates have since moved more in unison along with adoption of the euro and the integration of financial market. Hence, the pooling restriction would probably better fit to the few last years than the earlier estimation period.

[27] See Pesola (2000) pages 16 and 17.

4 Estimated model in stress testing of the banking sector

The estimated loan loss model is relatively easy to use in banking sector stress testing because of its simple structure. We recall that the model needs both realized macroeconomic explanatory variables and their expectations, in order to get the needed surprise effect. This was demonstrated earlier in connection with out of sample forecasting example. In stress test we need in principle four separate sets of different macroeconomic explanatory variables: one set for basic forecasting, another set for a scenario and, for the both ones, their respective sets of expected values.

Let us look with the help of a practical example how the model can be used in stress testing. We construct for that purpose a simple macroeconomic scenario in Finland for years from 2003 to 2005. The realized development can in this case proxy the basic forecast.

The input variables needed for stress testing are loan losses, banks' outstanding domestic lending stock and its lending rate, percentage changes in GDP volume and deflator as well as the respective OECD forecasts, and the GDP at current prices. These variables, together with the results, are presented in table 4.1.

The scenario has been kept extremely simple for demonstration purposes. As compared to the basic forecast (~ realized development), the alternative GDP growth rate in current prices has been set zero. Along with that, the lending stock has been depressed in the scenario by the same percentage as GDP has been depressed as compared to the basic forecast. All other variables are same as in the basic forecast, the expectations among them.

The more or less plausible story behind the scenario would be an idiosyncratic shock hitting Finland. For instance, demand for ITC and forestry exports weaken suddenly leading to zero growth and inflation in Finland, but interest rates are intact due to integrated financial markets. Rigid expectations react slowly and are in practice unchanged throughout the scenario period.

Table 4.1 **Stress testing the financial markets: Banks' loan losses/lending in Finland, %**

Model 1/a

BASIC FORECAST

Year	LT/L real %	LT/L model %	L bill.euro	ΔYq %	ΔYq^f %	ΔYp %	ΔYp^f %	YV bill.euro	R %
2003	-0.05	0.29	95.0	1.88	3.4	0.71	2.0	143.4	2.99
2004	0.02	0.23	103.9	3.62	3.4	0.59	0.8	149.5	2.98
2005	0.01	0.23	110.8	1.60	2.8	1.92	1.3	154.8	2.94

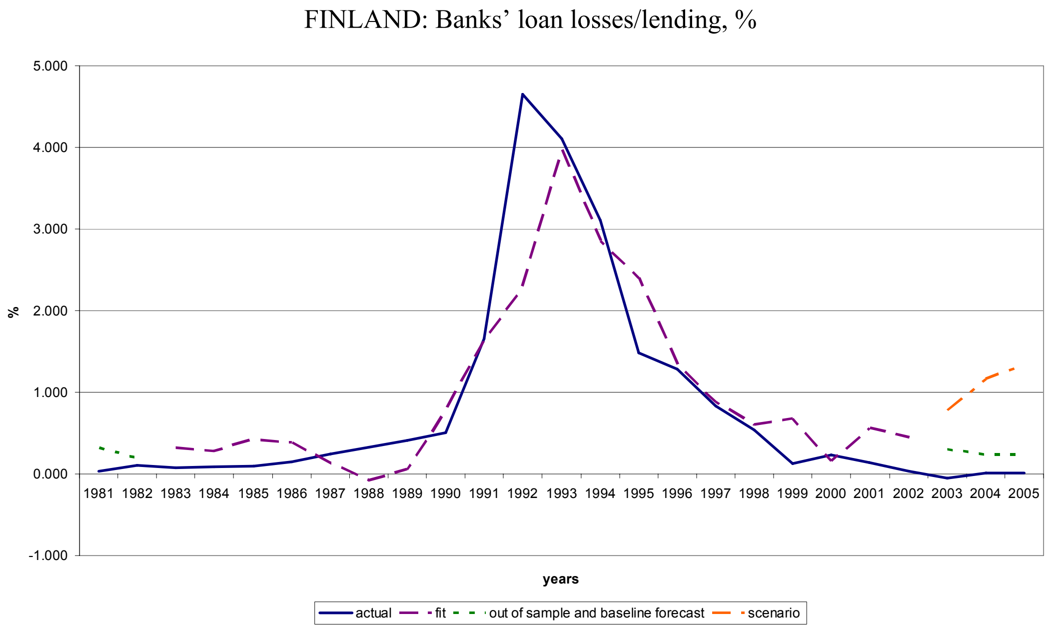
SCENARIO

Year	%	LT/L model %	L bill.euro	ΔYq %	ΔYq^f %	ΔYp %	ΔYp^f %	YV bill.euro	R %
2003		0.78	92.6	0	3.4	0	2.0	139.8	2.99
2004		1.16	97.2	0	3.4	0	0.8	139.8	2.98
2005		1.33	100.1	0	2.8	0	1.3	139.8	2.94

LT = net loan losses
L = banks' outstanding lending stock
ΔYq = percentage change of GDP volume
ΔYq^f = percentage change of GDP volume forecasted by the OECD in June preceding year
ΔYp = percentage change of GDP deflator
ΔYp^f = percentage change of GDP deflator forecasted by the OECD in June preceding year
YV = GDP value
R = lending rate

This scenario produces clearly increased loan losses (Table 4.1 and Figure 4.1) as compared to the baseline forecast. The experiment demonstrates that a rather small change in macroeconomic variables can generate a markedly different development in banks' loan losses. The extremely rigid expectations might not be realistic. It is without doubt probably that the expectations have time to react during that long scenario. This question nevertheless is beyond the scope of this paper. An additional change in interest rates would, in turn, provide in combination a wider shock than only that idiosyncratic one which was assumed to hit Finland alone.

Figure 4.1 **Finland: Banks' loan losses/lending, %**
forecast 2003–2005 (model 1/a)



5 Conclusion

The main result is feasible: macroeconomic shocks jointly with financial fragility generate loan losses in banking sector. The estimated model is parsimonious and rather robust over different country samples. The non-linear model structure seems to fit better to the extreme amounts of loan losses in crisis periods than the linear structure, which was also tested. Consequently, the model structure fits better to the Nordic countries, which badly suffered from banking crises, than to the rest of sample countries.

There are several novelties in the model. First, we use a unique data for dependent variable, which is delivered by request for this study. The central banks in the sample countries have provided aggregate net loan loss data concerning their banking sector. Second, indicators of actual expectation errors have been used as macro economic shock or surprise variables. They have been constructed by deducting the forecasted (by the OECD) from the actual development. Third, a non-linear relationship between financial fragility and macroeconomic shocks is applied in the model in the form of cross product terms of these variables.

Even though the estimated model is a proper tool in stress testing banking sector, the results contribute the macroprudential analysis directly too. We can see how important it is to monitor different fragility related variables.

Furthermore, a recommendation to regulation is that it is important to try to strengthen the robustness of financial markets so as to better absorb the shocks. Also the economic policy makers are advised to avoid generating unnecessary shocks with policy initiatives.

As regards our model's position in the literature, using the classification of Sorge-Virolainen (2005) in their survey of stress tests for financial stability analysis, the model in this paper belongs to the class of reduced form model cross-country panel regressions. In Chan-Lau's (2006) classification it is a macroeconometric based econometric model with exogenous economic factors. Those models typically explain banking crises or some indicator of banking distress, like non-performing loans or loan loss provisions, with a few macroeconomic variables. For example, Bikker-Metzemakers (2004) and Valckx (2003) used, among other things, GDP, interest rates and lending data in their loan loss provision studies and Sorge-Virolainen (2005) same explanatory variables in a bankruptcy model. To the similar model group can also the models estimated by van den End – Hoeberichts – Tabbae (2006) and the multivariate logit approach models by Demirgüc-Kunt and Detragiache (2005) be included.

The joint non-linear effect of shocks and fragility, which capture the stylized fact of fat tails in the distribution of the aggregate number of defaults and hence loan losses, can be motivated by the Mertonian (1974) credit risk dynamics and the portfolio models of credit risk derived from that basis. Drawing from such models, we can think of our macroeconomic shock variables as representing the common factors driving aggregate (portfolio) credit losses and of our fragility variable as representing the aggregate (average portfolio) credit quality.

Furthermore, the specification of model variables fits well in the non-linear model structure as one of the crucial mechanisms behind fat tails might be a vicious circle generated by the debt deflation phenomenon, which was originally presented by Fisher (1933). The asset value of debtor is reflected in expected cash flow income, which is used as a part of the income surprise variable. The idea of debt deflation is included in the studies of Kocherlakota (2000), Allen and Gale (2004) and von Peter (2004) in various ways.

The possible reverse impact from banking sector distress back to the rest of economy, which Bernanke (1983) and others, like Dell'Ariccia et al (2005), have studied, is treated only indirectly in this study. That feedback effect was reflected as certain inertia in the development of loan losses, which was captured by the lagged dependent variable in the right hand side of the model.

Although the model is closed economy model it contains many elements of open economy, which give right to apply it in the small open economies like the Nordic and some other countries in our sample. First of all, the income shock often comes from exports. Also interest rate and asset prices are more and more international phenomena along with liberalised capital movements. The Economic and Monetary Union (EMU) and the introduction of euro have removed the exchange rate uncertainty between the euro area countries, which earlier easily increased tensions also in interest rates. The EMU has thus contributed to the financial stability of its member countries and also indirectly to the other European non-member countries. While the EMU has changed the whole euro area towards a closed economy system, it has at the same time contributed to the opening of the economies in its member countries.

Last, we must not forget that crises differ eg due to the phenomenon of endogenous parameter instability (Sorge-Virolainen, 2005, p. 27). The in this study estimated model has only captured the historical average in a certain sample of countries. We must bear in mind that preventing potential future crises is a much wider task than to be tackled only with the help of models, though they are important tools among all the others.

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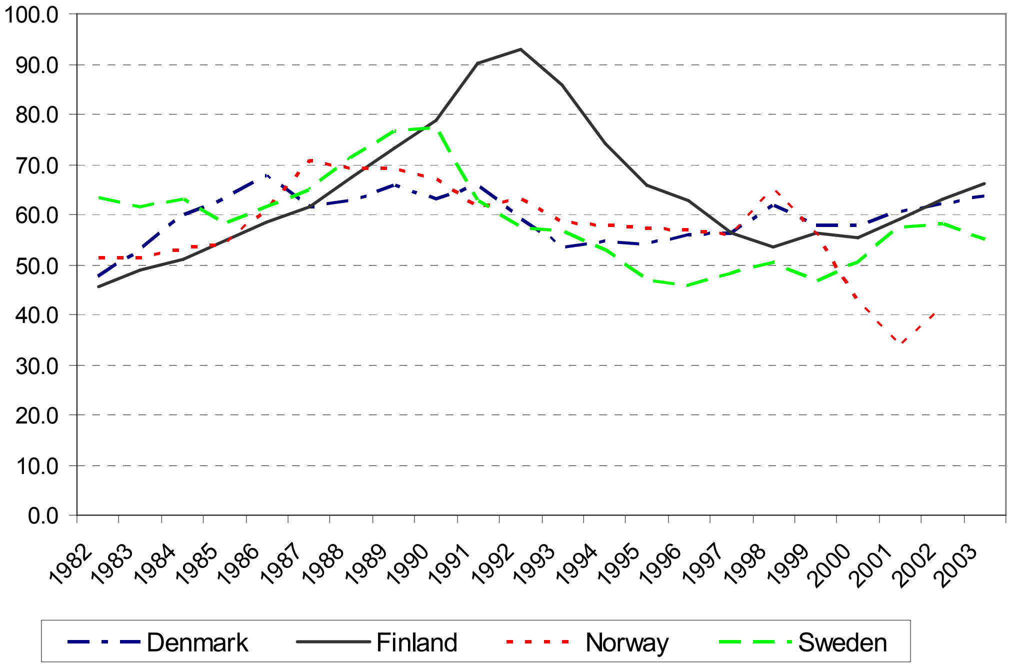
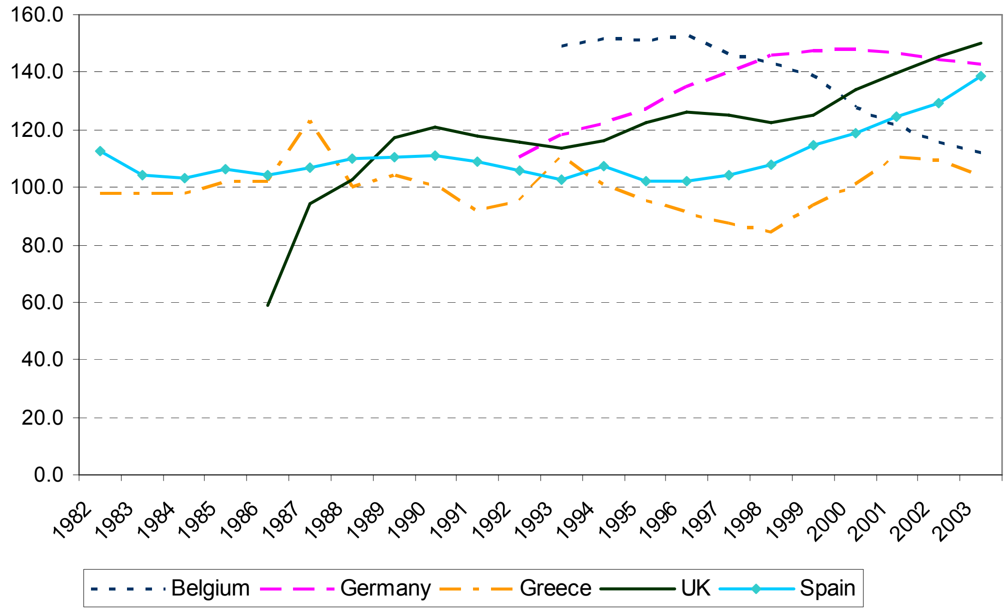
Appendix 1

Figure A1.1 **Nordic countries: Banks' outstanding lending/GDP, %**



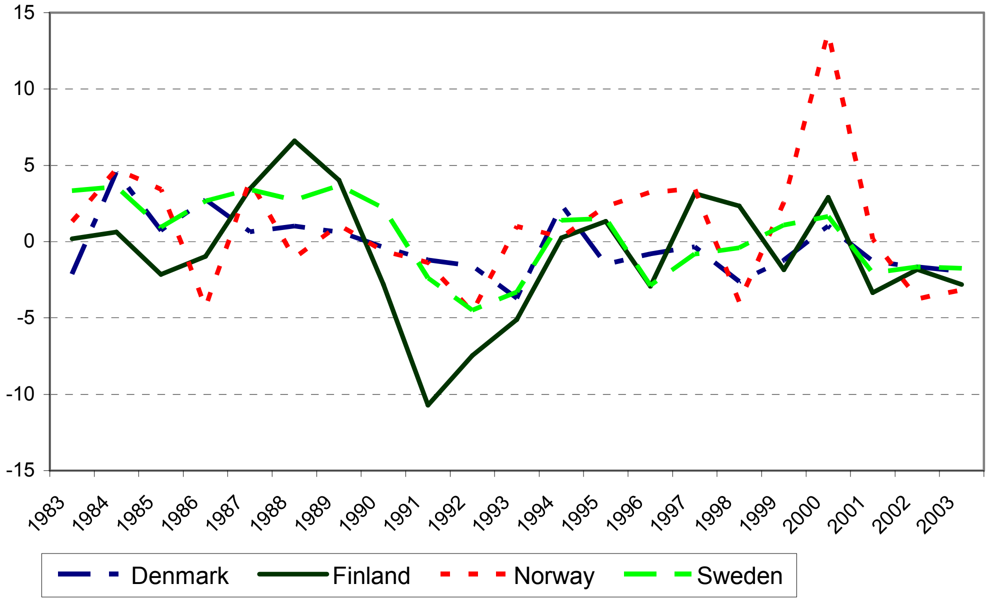
Source: IFS, Riksbank Sweden.

Figure A1.2 **Rest of sample countries: Banks' outstanding lending/GDP, %**



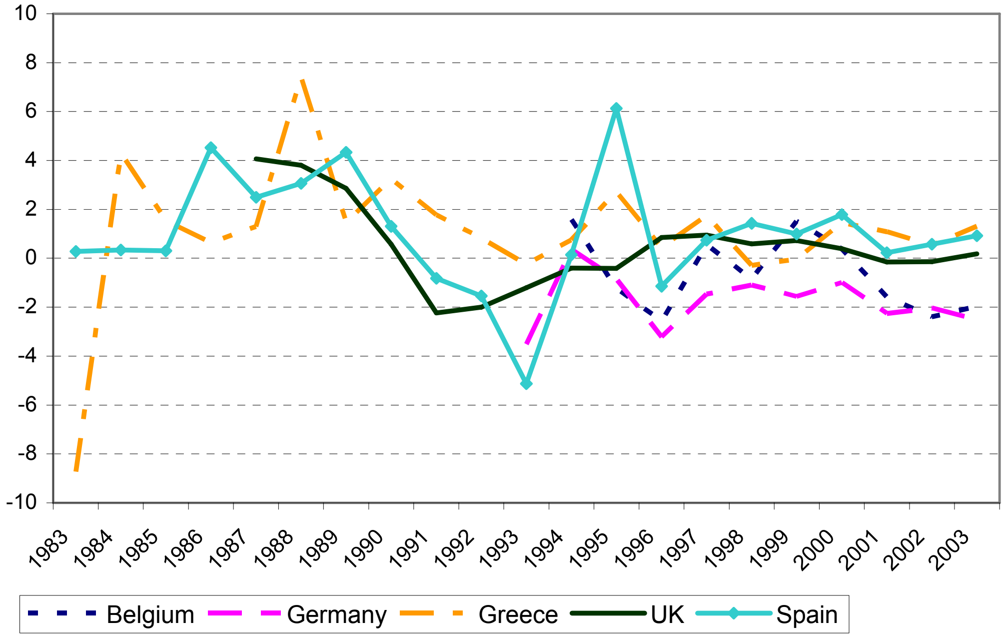
Source: IFS.

Figure A1.3 **Nordic countries: Income surprise (percentage change in GDPv minus OECD forecast (from previous year) for the percentage change in GDPv), %-p**



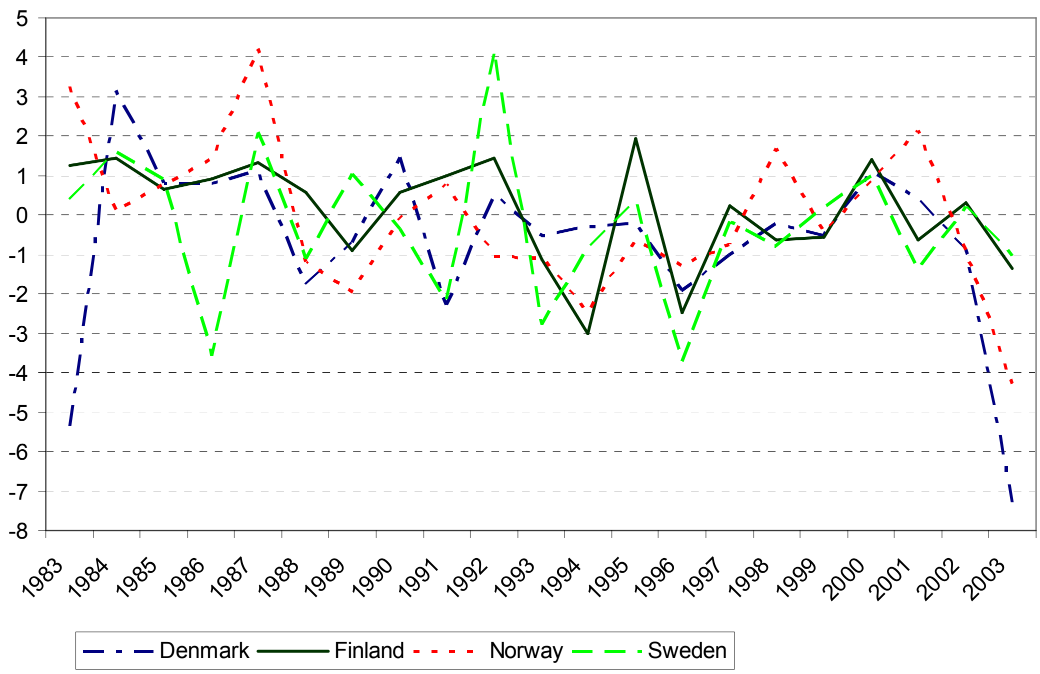
Source: IFS and OECD.

Figure A1.4 **Rest of sample countries: Income surprise (percentage change in GDPv minus OECD forecast (from the previous year) for the percentage change in GDPv), %-p**



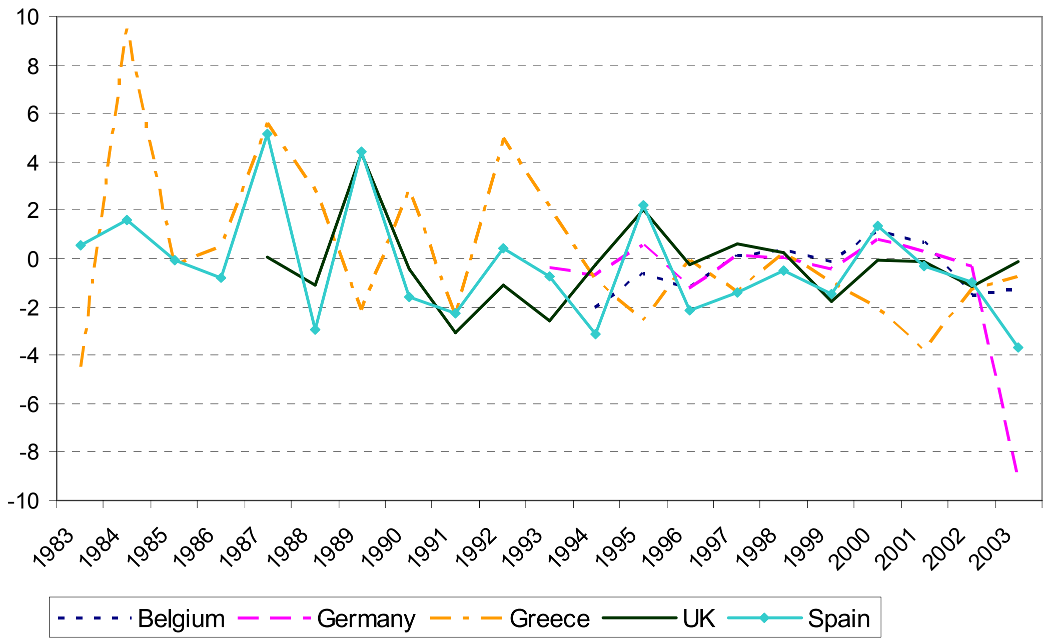
Source: IFS and OECD.

Figure A1.5 **Nordic countries: Change in banks' real lending rate, %-p**



Source: IFS and OECD

Figure A1.6 **Rest of sample countries: Change in banks' real lending rate, %-p**



Source: IFS and OECD

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