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Macro stress testing with a macroeconomic credit risk model for Finland

Suomen Pankin keskustelualoitteita
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Abstract

In the discussion paper, we employ data on industry-specific corporate sector bankruptcies over the time period from 1986 to 2003 and estimate a macroeconomic credit risk model for the Finnish corporate sector. The sample period includes a severe recession with significantly higher-than-average default rates in the early 1990s. The results suggest a significant relationship between corporate sector default rates and key macroeconomic factors including GDP, interest rates and corporate indebtedness. The estimated model is employed to analyse corporate credit risks conditional on current macroeconomic conditions. Furthermore, the paper presents some examples of applying the model to macro stress testing, ie analysing the effects of various adverse macroeconomic events on the banks' credit risks stemming from the corporate sector. The results of the stress tests suggest that Finnish corporate sector credit risks are fairly limited in the current macroeconomic environment.

Key words: banking, credit risk, stress tests

JEL classification numbers: C15, G21, G28, G33

Pankkisektorin stressitestaus Suomea koskevan makrotaloudellisen luottoriskimallin avulla

Suomen Pankin keskustelualoitteita 18/2004

Kimmo Virolainen
Tutkimusosasto

Tiivistelmä

Tässä keskustelualoitteessa analysoidaan Suomen yrityssektorin luottoriskejä makrotaloudellisen luottoriskimallin avulla. Tutkimus perustuu toimialakohtaiseen konkurssiaineistoon ajanjaksolta 1986–2003. Ajanjakso sisältää Suomen talouden syvän laman sekä siihen liittyneet keskimääräistä korkeammat yrityssektorin konkurssiasteet 1990-luvun alussa. Empiiriset tulokset tukevat yrityssektorin konkurssiasteiden sekä keskeisten makrotaloudellisten muuttujien – BKT, korot ja yrityssektorin velkaisuus – merkittävää riippuvuussuhdetta. Tutkimuksessa arvioidaan estimoidun luottoriskimallin avulla yrityssektorin luottoriskejä nykyisessä makrotaloudellisessa tilanteessa. Lisäksi tutkimuksessa esitellään esimerkinomaisesti mallin hyödyntämistä pankkisektorin stressitesteissä, so. arvioitaessa erilaisten negatiivisten makrotaloudellisten kehitysten vaikutuksia pankkien yrityssektorista koituviin luottoriskeihin. Tulokset osoittavat Suomen yrityssektorin luottoriskien olevan suhteellisen pieniä nykyisessä makrotaloudellisessa ympäristössä.

Avainsanat: pankkisektori, luottoriski, stressitestit

JEL-luokittelu: C15, G21, G28, G33

Contents

1 Introduction

Stress testing has become an important tool in financial institutions' risk management. In a BIS report (2000), stress testing is defined as "a generic term describing various techniques used by financial institutions to gauge their potential vulnerability to exceptional but plausible events". Stress tests are generally used to complement financial institutions' internal models, such as value-at-risk (VaR) models. Standard VaR models have been found to be of limited use in measuring financial institutions' exposures to extreme market events, ie events that occur too rarely to be captured by statistical models, which are normally based on relatively short periods of historical data. The ongoing Basel II process also stresses the importance of carrying out stress tests to augment shortcomings in banks' internal models.

In addition to applying stress tests to the portfolios of individual institutions at the micro level, stress testing plays an important role in the macro-prudential analysis of public authorities. The role of macro-prudential, or financial stability, analysis has gained in importance in recent years, both among central banks, regulatory authorities and international agencies. In addition to regular surveillance of a set of macro-prudential indicators, there is a need to develop more quantitative tools for financial stability analysis. In this respect, the joint IMF and World Bank financial sector assessment programmes (FSAPs) have in many cases played a catalytic role.

"Aggregate" and "macro" stress tests are a key part of these quantitative tools. Aggregate stress testing is synonymous with a system-wide analysis. An aggregate stress test can be defined as a measure of the risk exposure of a group of financial institutions to a specified stress scenario. Aggregate stress testing has different objectives from those of stress testing individual portfolios (Blaschke et al 2001). The main objective of an aggregate stress test is to help public authorities identify structural vulnerabilities and overall risk exposures in a financial system that could lead to systemic problems. An example is a situation in which all financial institutions of a certain country have a large exposure to a single risk source (a segment or a sector of an economy). From the perspective of any individual institution, and without knowledge of the exposures of other institutions, this exposure might appear to pose no specific cause for concern. However, from the aggregate perspective, the large overall exposure of a financial system to a single risk source deserves special attention. In case of a sudden change in market sentiment, for example, it could well turn out that all institutions attempt to reduce their exposures simultaneously, thus adversely affecting market liquidity.

Another role for aggregate stress tests is that they can serve as tools for cross-checking results obtained with financial institutions' internal models, which may use different approaches and may be based on different sources of information. Currently, this is particularly relevant for credit risk models, whose development is an ongoing process within the financial community.

Macro stress testing refers to methods that analyse the impact of adverse developments in macroeconomic conditions on the risks of either an individual financial institution or a group of financial institutions. Macro stress testing may involve second-round, or feedback, effects, but their modelling poses additional challenges.

In this study, we focus on developing a framework for aggregate level macro stress testing banks' credit risks stemming from the corporate sector. Credit risk – the risk of changes in credit portfolio value associated with unexpected changes in credit quality ("mark-to-market" approach) or, alternatively, the risk of unexpected losses stemming from counterpart defaults ("default mode" approach) – is still typically the most important risk in banking in the vast majority of countries. Credit losses were the main source of problems during the severe banking crisis in the early 1990s in Finland.

Even though the relationship between credit risks and macroeconomic developments appears intuitively clear, and there is a lot of empirical evidence supporting this relationship (see Allen & Saunders (2003) for a recent survey), surprisingly few credit risk models have an explicit link between default probabilities and identifiable macroeconomic factors.[1] In ratings-based models, cyclical factors are typically taken into account by applying different ratings transition matrices for "expansion", "normal" and "recession" periods, or by adjusting ratings transition matrices using a "credit cycle index". In some models this index is actually modelled as a function of various macro factors, which makes them attractive from a macro-prudential perspective. In Merton-based market indicator models cyclical effects are captured primarily by asset value (stock price) fluctuations and, to some extent, by systematic factors affecting default correlations. In reduced form intensity-based models the mean default rate may also be modelled as a function of macro factors and thus capture cyclical effects. However, credit spread data that are required for these models are not widely available, and they appear to be rather noisy.

In this study, we model and estimate a macroeconomic credit risk model that links explicitly a set of macroeconomic factors and corporate sector default rates using Finnish data over the time period from 1986 to 2003. The sample period is unique in the sense that it includes the most severe recession in the industrialised countries since the Great Depression with significantly higher than average

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[1] Empirical evidence indicates that macroeconomic conditions are likely to impact all components of credit losses, ie the probability of default (PD), the loss given default (LGD) and the exposure at default (EAD). In this study, we concentrate on the relationship between macroeconomic developments and PD.

corporate default rates and very large loan losses for the Finnish banks in the early 1990s.[2] Another distinctive feature of this study is that we model and estimate industry-specific default rates, which yields more accurate loan loss estimates than models based on aggregate corporate sector default rates only. Finally, we employ the model to analyse the impact of adverse developments in macroeconomic factors on the current corporate credit portfolios of the Finnish banks at the aggregate level.

2 Related studies

This study is related to a growing body of literature that analyses the macroeconomic determinants of banks' credit risks. As data on banks' loan loss provisions (LLPs) and non-performing loans (NPLs) are relatively readily available, most existing studies examine the link between banks' loan losses, or non-performing loans, and macroeconomic factors. This approach yields very useful insights, but it may miss important changes in the relationships in the case of structural developments (eq changes in the distribution of bank credits across different types of debtors). Another, more data-intensive approach is to examine the impact of macro factors on the corporate and/or household sector default risk and map these developments into banks' loan losses using various techniques.

Previous studies analysing the macroeconomic determinants of banks' loan losses or non-performing loans include Pesola (2001) for the Nordic countries, Kalirai and Scheicher (2002) for Austria, and Delgado and Saurina (2004) for Spain. Typically, these studies find that loan loss provisions are negatively related to GDP growth and positively related to interest rates. The impact of corporate indebtedness turns out to be more ambiguous, albeit some studies find a significant positive effect. Some of these studies also apply the estimated models to stress test the robustness of the banking sector.

A few studies attempt to draw conclusions about banks' credit risks stemming from the corporate sector by modelling the relationship between the aggregate corporate sector default rate and macroeconomic factors. Vlieghe (2001) estimates a model for the aggregate corporate default rate in the UK and finds that the GDP, the corporate indebtedness, the real interest rate and real wages are the significant long-run determinants. Benito, Whitley and Young (2001) use the empirical model of Vlieghe (2001) to map macro-econometric model forecasts of corporate balance sheet developments into a forecast of corporate failure. Corporate sector

[2] Banks' loan losses were large enough to give rise to a banking crisis, which required the intervention of public authorities as well as public funds to be resolved. For further details about the Finnish banking crisis, see eg Nyberg and Vihriälä (1994).

loan risk in the UK is then examined by calculating a "debt at risk"[3] measure and analysing its development under various risk scenarios with the help of the macro model. Boss (2002) models and estimates a macroeconomic credit risk model for the aggregate corporate default rate to analyse stress scenarios for the Austrian banking sector. His findings suggest that industrial production, inflation, the stock index, the nominal short-term interest rate, and the oil price are the most important determinants of corporate default rates.[4] Boss also carries out various crisis scenario simulations with the estimated models.

Bunn and Redwood (2003) examine the determinants of failure among individual UK companies with a probit model to assess risks arising from the UK corporate sector. In addition to firm-specific factors like profitability and financial ratios, their explanatory variables also include macroeconomic conditions (proxied by the GDP growth rate). GDP growth proves to have a negative effect on the failure rate even after controlling for the firm-level characteristics. They find that the measure which uses firm-level information performs better in predicting actual debt at risk (ex post sum of all debt of failed firms) than a simple estimate that involves multiplying the average probability of failure by the total debt stock. Tudela and Young (2003) analyse the performance of a "hybrid model" by adding Merton-based default probability measures into a company account data based probit model for individual firm failures. They find that the implementation of the Merton approach clearly outperforms a model based solely on company account data. Interestingly, they also find that even after controlling for a Merton type default probability measure and company account variables, GDP has a significant effect on firm default. Pain and Vesala (2004) employ a dynamic factor model to analyse the determinants of firm default risk, as measured by the Merton-based Moody's KMV EDFs, using a large panel of quoted EU area companies. Although the factor analytic approach does not allow them to identify the explanatory factors, Pain and Vesala conclude that EU-wide, country and industrial sector effects seem to play only a minor role in explaining movements in corporate default risk.

[3] Defined as the sum of all loans outstanding weighted by the probability that each borrower will default within a particular period, but not including any estimate of loss-given-default. Benito, Whitley and Young also include household sector loans in their analysis.

[4] Boss actually estimates slightly different model specifications for different stress testing purposes. These macro factors are included in his "General business cycle model". In other model specifications industrial production is replaced either by corporate investments, household disposable income or exports.

3 A macroeconomic credit risk model

One of the few credit risk models that explicitly links macroeconomic factors and corporate sector default rates was developed by Wilson (1997a, 1997b).[5] The model has been applied to Austrian data at the aggregate corporate sector level by Boss (2002). The idea is to model the relationship between default rates and macroeconomic factors, and when a model is fitted, to simulate the evolution of default rates over time by generating macroeconomic shocks to the system. These simulated future default rates, in turn, make it possible to obtain estimates of expected and unexpected losses for a defined credit portfolio, conditional on the current macroeconomic conditions.

In order to be able to calculate meaningful empirical default rates, observations need to be aggregated into large enough groups. We apply Wilson's model to analyse industry-specific default rates. In principle, Wilson's model can be applied in a mark-to-market framework by linking the whole matrix of (industry or segment-specific) rating transition probabilities and macroeconomic factors, although in a rather ad hoc way. In this paper, due to data limitations, we apply the model in a default mode framework only.

First, the average default rate for industry j is modelled by the logistic functional form[6] as

$$p_{j,t} = \frac{1}{1+\exp(y_{j,t})} \tag{3.1}$$

where $p_{j,t}$ is the default rate in industry j at time t, and $y_{j,t}$ is the industry-specific macroeconomic index, whose parameters must be estimated. In this study, we adopt Wilson's original formulation and model the macroeconomic index in such a way that a higher value for $y_{j,t}$ implies a better state of the economy with a lower default rate $p_{j,t}$, and vice versa. The logistic functional form is convenient in that $y_{j,t}$ is given by the logit transformation

$$L(p_{j,t}) = \ln\left(\frac{1-p_{j,t}}{p_{j,t}}\right) = y_{j,t}$$

The logit transformed default rate (the industry-specific macroeconomic index) is assumed to be determined by a number of exogenous macroeconomic factors, ie

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[5] The model was initially developed for McKinsey and Co. and was known as *Credit Portfolio View*.

[6] The logistic functional form is widely used in modelling bankruptcies to ensure that default rate estimates fall in the range [0,1].

$$y_{j,t} = \beta_{j,0} + \beta_{j,1}x_{1,t} + \beta_{j,2}x_{2,t} + \ldots + \beta_{j,n}x_{n,t} + \upsilon_{j,t} \tag{3.2}$$

where β_j is a set of regression coefficients to be estimated for the jth industry, $x_{i,t}$ ($i = 1, 2, \ldots, n$) is the set of explanatory macroeconomic factors (eg GDP, interest rates etc.), and $\upsilon_{j,t}$ is a random error assumed to be independent and identically normally distributed. The equations (3.1) and (3.2) can be seen as a multifactor model for determining industry-specific average default rates. The systematic risk component is captured by the macroeconomic variables $x_{i,t}$ with an industry-specific surprise captured by the error term $\upsilon_{j,t}$. Individual functions can be estimated for each industry allowing the explanatory macroeconomic variables to differ between industries.

The second step is to model and estimate the development of the individual macroeconomic time series describing the health of the economy. In this study, as in Wilson (1997a) and Boss (2002), a set of univariate autoregressive equations of order 2 (AR(2)) are used for this purpose, ie

$$x_{i,t} = k_{i,0} + k_{i,1}x_{i,t-1} + k_{i,2}x_{i,t-2} + \varepsilon_{i,t} \tag{3.3}$$

where k_i is a set of regression coefficients to be estimated for the ith macroeconomic factor, and $\varepsilon_{i,t}$ is a random error assumed to be independent and identically normally distributed.

Equations (3.1)-(3.3) together define a system of equations governing the joint evolution of the industry-specific default rates and associated macroeconomic factors with a $(j + i) \times 1$ vector of error terms, or innovations, E, and a $(j + i) \times (j + i)$ variance-covariance matrix of errors, Σ, defined by

$$E = \begin{pmatrix} \upsilon \\ \varepsilon \end{pmatrix} \sim N(0, \Sigma) \quad , \quad \Sigma = \begin{bmatrix} \Sigma_{\upsilon} & \Sigma_{\upsilon,\varepsilon} \\ \Sigma_{\varepsilon,\upsilon} & \Sigma_{\varepsilon} \end{bmatrix}$$

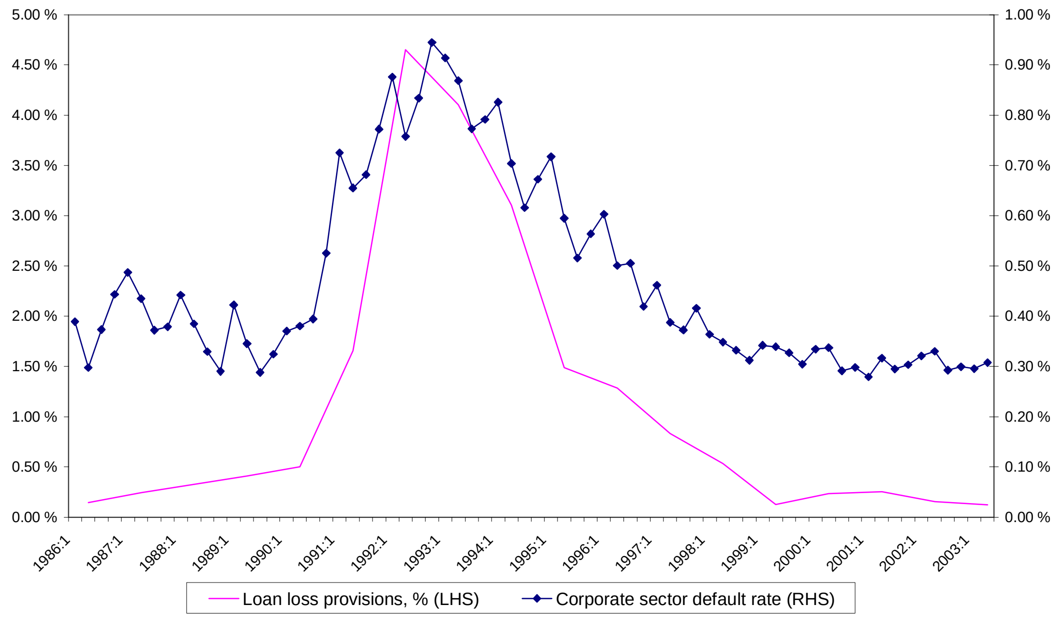
The final step is to utilise the parameter estimates and the error terms together with the system of equations to simulate future paths of joint default rates across all industries over some desired time horizon. By assuming that conditional on the state of the economy – as described by the macroeconomic factors included in the model – defaults are independent, it is then possible to determine credit loss distributions for portfolios of interest with Monte Carlo methods. Moreover, it is also possible to analyse various macroeconomic stress scenarios with the model.

4 Empirical model

We employ quarterly data on corporate sector defaults by main industries and on key macroeconomic factors over the time period from 1986:1 to 2003:2. "Default" is defined to take place when a bankruptcy proceeding is instituted against an enterprise for the first time.[7] This can be instituted either by the enterprise itself or by one of its creditors. Default rates are obtained by dividing the number of bankruptcy proceedings instituted by the number of active companies during the time period in question. Default data are available for the following six main industries: (1) agriculture (AGR), (2) manufacturing (MAN), (3) construction (CON), (4) trade, hotels and restaurants (TRD), (5) transport and communication (TRNS), and (6) other industries (OTH). A detailed description of the data is presented in appendix 1.

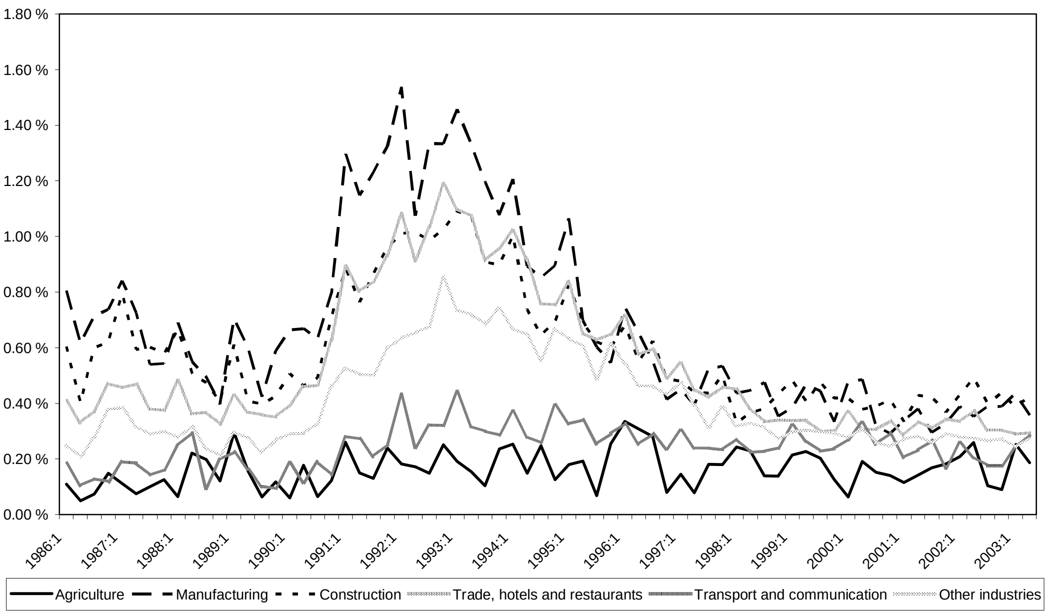
Figure 4.1 displays the development of the overall corporate sector default rate and the Finnish banks' loan loss provisions in the time period 1986:1–2003:2. Figure 4.2 displays default rates by the six main industries over the sample period.

Figure 4.1 **Corporate sector default rate (quarterly) and banks' loan loss provisioning (annual, percentage of loan stock)**



[7] This is a more stringent definition of default than that normally applied in the case of bonds.

Figure 4.2 **Quarterly default rates in the Finnish corporate sector by industry**



The relationship between corporate sector default rates and banks' loan losses is obvious from figure 4.1. The overall quarterly corporate default rate more than doubled from the level of 0.4% to almost 1% during the severe recession in the early 1990s in Finland. The peak was reached in 1992-1993, after which the default rate has declined back to the level it was at the start of the sample period in the late 1980s. In the worst year, in 1992, banks' loan loss provisions amounted to 4.7% of their loan stock. Moreover, the cumulative loan losses of the banks over the crisis period 1991-1995 amounted to 15% of their lending. At the end of the sample period, the Finnish banks' loan loss provisions have been at a very low level, averaging only 0.2% of lending annually.

Although the industry-specific default rates seem to converge towards the end of the sample period, an examination of figure 4.2 reveals significant differences in their development. In particular, four industries (MAN, CON, TRD and OTH) experienced a significant hike in default rates in the recession years while the default rates in AGR and TRNS developed more smoothly. In most industrialised countries – including Finland – business environment in agriculture differs from other industries, which is reflected in the development of the default rates in agriculture. There is a slight increase in the default rate of the transport and communication industry in the early 1990s, but the reaction is not particularly strong. MAN, CON and TRD appear to be the most affected in the recession years.

In previous studies on the determinants of corporate default rates, the set of explanatory variables typically involves measures of profitability (or its determinants), indebtedness and interest rates. Theoretical justifications for these variables are presented eg in Vlieghe (2001). In addition, a number of other possible determinants of corporate default rates can be identified. Boss (2002) examines the explanatory power of a large number of macroeconomic variables falling into the following categories: cyclical indicators, price stability indicators, household indicators, corporate indicators, financial market indicators and external variables. He chooses the explanatory variables for his preferred multifactor model on the basis of a series of univariate regressions.

In this study, in choosing the macroeconomic factors that are assumed to drive the development of average industry-specific default rates, we aim at a parsimonious model with a limited number of key factors that would be useful from a macro stress testing point of view. Initially, we use only three key macroeconomic factors: the GDP, the interest rate and the corporate indebtedness. Later on we examine the additional explanatory power of a set of other macro factors.

Even though we estimate the determinants of industry-specific default rates we use the aggregate real GDP as a proxy for profits/demand for each industry. We examine two different specifications for the GDP variable: annual GDP growth rate and the deviation of GDP from trend. For the interest rate variable, we use the 12-month money market interest rate.[8] The majority of loans taken by the Finnish corporations are variable-rate and linked to short-term market interest rates. We examine the explanatory power of both the nominal and the (ex post) real interest rate.[9] For corporate sector indebtedness, we use industry-specific variables, which are measured by the gross debt of an industry (excluding intra-corporate sector credits) divided by the value added of that industry. Finally, a dummy variable is included to examine whether a change in the bankruptcy law in 1993 had an impact on corporate sector default rates.[10] The variable takes the value of 1 from 1993Q1 onwards. Detailed descriptions of the variable definitions are presented in appendix 1.

As a higher value for the macroeconomic index implies a better state of the economy with lower corporate default rates, we expect the GDP to be positively related with the industry-specific macroeconomic indices, and the interest rate and the corporate indebtedness to be negatively related with them. We estimate the

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[8] Helsinki interbank offered rate (Helibor) up till end-1998, and Euribor from 1999 onwards.

[9] The ex post real interest rate is calculated as $[(1 + i_t)/(1 + \pi_{t+1})] - 1$. Inflation rate is based on the GDP deflator.

[10] The law was changed to facilitate restructuring instead of formal bankruptcy proceedings and so it may have reduced the number of bankruptcies (ie a positive effect on the macroeconomic index). The change in the law was effected in February 1993.

macroeconomic index (ie logit transformed default rate) equations for the six industries as static models with the seemingly unrelated regression (SUR) method.

The results for our preferred equations, with dummy interaction variables for structural changes included, are presented in table 4.1. Both the GDP variable and the industry-specific measures of corporate indebtedness have the expected sign and are statistically significant in all equations. For agriculture, the explanatory power of the model is modest, however. In our preferred specification, we use the "deviations from trend" measure of the GDP, which turned out to be significantly better than using the GDP growth rate. It appears that the annual GDP growth rate is not able to capture the full adverse effect in cases of large negative deviations in the GDP.[11]

Table 4.1 **SUR estimates for the static model; sample period 1986Q1-2003Q2, no. of observations 70**

	y_{AGR}	y_{MAN}	y_{CON}	y_{TRD}	y_{TRNS}	y_{OTH}
Constant	7.747	5.997	5.670	6.566	6.300	6.245
	(17.5)	(73.9)	(118.3)	(50.7)	(32.7)	(82.5)
D_{9303}				-0.736		
				(-5.29)		
GDP	2.743	4.427	2.125	3.554	1.529	5.004
	(3.27)	(12.1)	(4.20)	(9.29)	(2.53)	(13.9)
$D_{9303}\times$GDP				1.531		1.309
				(2.91)		(2.91)
R		-3.027	-1.748		10.07	-3.072
		(-2.69)	(-2.49)		(3.59)	(-8.71)
$D_{9303}\times$R					-12.81	
					(-2.58)	
$DEBT_j$	-0.895	-0.665	-0.513	-1.041	-2.521	-0.874
	(-2.83)	(-4.58)	(-4.82)	(-11.3)	(-4.22)	(-6.80)
$D_{9303}\times DEBT_j$				0.5548	2.004	
				(4.61)	(2.30)	
Adj. R^2	0.132	0.864	0.828	0.929	0.559	0.898
SEE	0.429	0.169	0.140	0.114	0.233	0.123
DW	1.878	1.676	1.697	1.832	2.306	1.606

Note: DEBTj variable is industry-specific.
t-statistics in parentheses.

The dummy variable was initially included only as a constant to capture a possible shift in the level of corporate default rates from 1993Q1 onwards. However, this yielded poor results with a statistically significant coefficient only for TRD, but with the wrong sign. It thus appears that the change in legislation in 1993 did not induce significant reductions in the corporate sector default rates. The initial

[11] A similar result is obtained with Swedish data in Jacobson and Lindé (2000).

regressions without structural dummy interaction variables (reported in appendix 2) yielded mixed results for the interest rate effect. In particular, the results suggested a perverse and significant interest rate effect for TRNS, and no significant interest rate effect at all for AGR and TRD.

In light of the mixed results for the interest rate effect in the initial regressions, we decided to analyse whether there might have been structural changes in the relationships. The Finnish economy has undergone major changes over the sample period, so it is not unreasonable to assume that the relationships may have changed over time. Hence, we let the 1993–2003 dummy interact with all of the explanatory variables in all equations.[12] Table 4.1 reports the results with all statistically significant dummy interaction variables included. Except for TRD and TRNS, the relationships appear to be fairly robust over the sample period. The perverse positive interest rate effect in TRNS turns out to change sign in the latter part of the sample period, thus conforming better to the hypothesised relationship.

As regards the interest rate variable, the ex post real interest rate turned out to be statistically insignificant, so we use the nominal interest rate in our preferred equations.[13] A possible explanation for the poor performance of the interest rate variable is that the short term interest rate measure may not be the most relevant for the early part of the sample period. Banks' lending rates were either fixed or linked to the relatively stable base rate in the early 1980s, and it was not until after the gradual deregulation of the financial markets in the mid-1980s that firms started to obtain loans with market interest rate linkages. There may have been differences between the industries in adopting these new financing instruments. Moreover, as a result of the deregulation, firms borrowed from the banks significant amounts in foreign currency due to the favourable interest rate compared with loans denominated in domestic currency. In 1991–1992, the Finnish markka depreciated strongly, thus exacerbating significantly corporate sector debt burden in an already difficult situation. This effect should be captured by the indebtedness variable in the model, but the large share of foreign currency denominated debt is likely to weaken the explanatory power of the domestic interest rate. Furthermore, the "structural break" point in 1993 coincides with the regime shift from a high inflation to a low inflation environment in Finland. Therefore, the nominal interest rate may simply reflect the effects of inflation in the 1980s.

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[12] As the timing of the possible structural changes is unclear, we also analysed slightly different specifications with dummy variables taking the value of 1 from 1992Q1 onwards or from 1994Q1 onwards, respectively. The 1992–2003 dummy yielded by and large the same results as the 1993–2003 dummy, whereas the results with the 1994–2003 dummy were noticeably weaker.

[13] The ex post real interest rate measure is highly volatile in the sample period, possibly reflecting uncertainties related to a significant regime change from a high inflation environment to a low inflation environment in the early 1990s.

Having estimated the parsimonious model specification, we also checked the explanatory power of a set of additional regressors. These included the inflation rate (both consumer and producer prices, respectively), the growth rate of real wages, the oil price, property prices, the long-run interest rate, and unemployment rate. In general, none of the additional explanatory variables turned out to be systematically significant in all equations. Unemployment rate appeared to have the best additional explanatory power with significant coefficients in three equations, but strong collinearity with the GDP variable makes its inclusion in the model problematic. The inflation rate (CPI) turned out to be significant in one equation only. All other additional variables were insignificant in all equations.

The SUR model diagnostics suggest that the static model is fairly well specified and fits the data rather well. In particular, the Durbin-Watson statistics imply that residual autocorrelation is not a major problem. However, as there may be problems in using static models with potentially non-stationary variables[14], we checked the robustness of the static model results with a more general dynamic specification.[15] The results were supportive of the use of the static SUR model.

5 Default rate and loss distribution simulation

With the estimated parameters[16] and the system of equations (3.1)–(3.3), we can simulate future values of joint industry-specific default rates with a Monte Carlo method. By assuming that default dependence is entirely due to common sensitivity to the macroeconomic factors, the simulation over some time horizon T is carried out in the following way. First, the Cholesky decomposition of the variance-covariance matrix of the error terms Σ is defined as A, so that $\Sigma = AA'$. Second, for each step of the simulation a $(j + i) \times 1$ vector of standard normal (pseudo) random variables $Z_{t+s} \sim N(0,1)$ is drawn. This is transformed into a vector of correlated innovations in the macroeconomic factors and the industry-

[14] See eg Banerjee et al (1993) for the econometric analysis of non-stationary data.

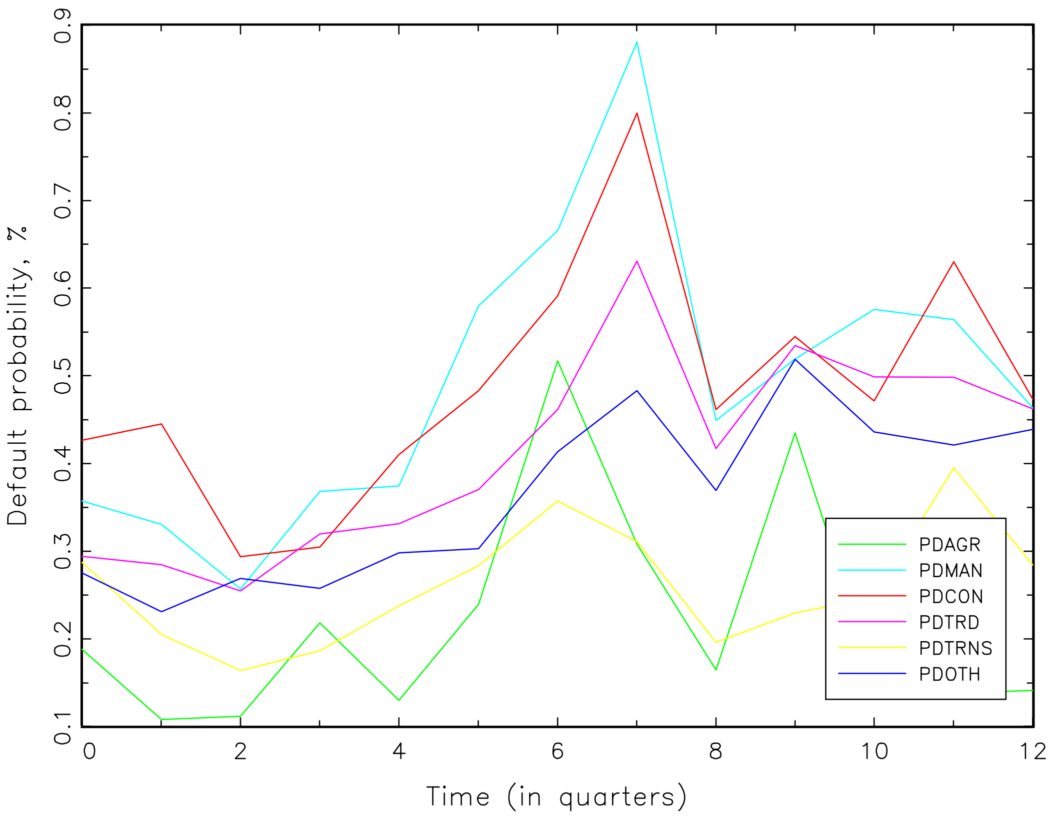
[15] Unit root tests (augmented Dickey-Fuller and Phillips-Perron) of the dependent and explanatory variables suggest that, with the exception of y_{AGR}, and potentially also y_{TRNS}, all variables are I(1). We estimated dynamic general autoregressive distributed lag models for all logit transformed default rates with the dependent variable in first differences and with both short-run dynamics and long-run variables as regressors. We initially used four lags in each differenced variable, and proceeded by step-wise reduction of insignificant variables. The resulting parsimonious equations included the same significant long-run variables as our static models. Moreover, the implied long-run coefficients of these dynamic models were, with only two exceptions, insignificantly different from those obtained with the static SUR model. A full error-correction specification of the equations would make it necessary to adopt a different approach to the default rate and loss distribution simulations, and is left for future work.

[16] SUR parameter estimates valid for the latter period 1993Q1–2003Q2 are used in the simulations.

specific (logit transformed) default rates by $E_{t+s} = A'Z_{t+s}$. Using the simulated realisations of the error terms and some initial values for the macroeconomic factors, the corresponding simulated values for $x_{i,t+s}$ and, subsequently, for $y_{j,t+s}$ and $p_{j,t+s}$ can then be derived using the system of equations (3.1)-(3.3). The procedure is iterated until the desired time horizon and the desired number of simulated paths of default probabilities is reached. The simulation takes into account correlations between the macroeconomic factors as well as any industry-specific shocks.

An example of a set of simulated paths of industry-specific default rates over a three-year (ie 12 quarters) horizon is presented in figure 5.1. It shows that the simulated time series of default rates for the different industries are positively correlated. This is due to their common sensitivities to innovations in the macroeconomic factors.

Figure 5.1 **Set of simulated industry-specific default rates**



The simulated paths of future default rates can then be used to determine loss distributions for specific credit portfolios with the additional information on credit exposures and debtors' industry. Conditional on the macroeconomic factors, the defaults of individual debtors can be considered independent events, and assuming further that the recovery rate is fixed, loss distributions can be determined under the assumption of binomially distributed defaults. The fixed loss given default (LGD) parameter is assumed to equal 0.5 throughout the simulations.[17] The simulated loss distributions and the corresponding estimates of both expected and unexpected losses are conditional on the assumed macroeconomic environment (as determined by the starting values for the macroeconomic factors).

In principle, it would be possible to simulate credit loss distributions with only aggregate level information on the industry breakdown of a credit portfolio of interest. However, this would require additional assumptions about the distribution of individual credit exposures across industries in the portfolio.

In this study, we define a credit portfolio that is representative of the Finnish banks' lending to the corporate sector. We utilise a comprehensive database containing financial statement information on a total number of 58 229 Finnish companies for this purpose.[18] We define "the Finnish corporate credit portfolio" as consisting of all firms with loans from "monetary financial institutions"[19] (MFIs). This yields a credit portfolio consisting of 28 971 firms. For computational reasons, the number of firms in the credit portfolio is finally limited to 3 000 in terms of the largest amount of MFI loans.[20] Moreover, due to limits on banks' large exposures, we define a 3% limit on any individual exposure in the portfolio, as eg in Jacobson, Lindé and Roszbach (2003).

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[17] No data on the Finnish banks' actual recovery rates from corporate credit defaults are publicly available. Appendix 3 presents data on total assets and total liabilities of bankrupt companies in Finland. Overall, these data appear to lend support for the "rule-of-thumb" assumption of LGD=0.5. Anecdotal evidence suggests that the assets of bankrupt companies are somewhat overvalued in these data, which decreases the actual recovery rates of creditors. On the other hand, banks usually have a high priority among the bankrupt companies' creditors, which increases the recovery rates of banks.

[18] Data are supplied by Suomen Asiakastieto Oy, which is a private credit information company jointly owned by the Finnish banks and other credit institutions. The data include information on each individual firm's credit rating (with seven grades), industrial classification and loans taken from MFIs. The data pertain mostly to year-end 2002, and for some companies to year-end 2003.

[19] In Finland, MFIs comprise deposit banks, other credit institutions, money market funds and the Bank of Finland. Of these, the role in corporate lending is non-existent for the Bank of Finland, and very limited for money market funds.

[20] This sub-sample accounts for 93.8% of all MFI loans outstanding in the total sample. In comparison to the aggregate statistics on banks' lending to different industries, the industry distribution of our credit portfolio is biased in having too few agricultural firms and having too many firms in "other industries". With our current data source, the first bias is unavoidable and due to the small size of the average agricultural firm. The second bias is due to the industrial classification system that assigns all holding companies (some with significant amounts of MFI loans) in the OTH category. We checked the impact of this second bias on the simulation results by deleting all holding companies from the sample and defining a new credit portfolio of 3 000 firms with the largest amount of MFI loans. The impact turned out to be relatively small.

Figures 5.2 and 5.3 present simulated loss distributions for the defined credit portfolio over a one-year and a three-year time horizon, respectively (conditional on the macroeconomic environment in Finland at 2003Q2).[21] Expected and unexpected losses (for the 99th and 99.9th percentiles) for these loss distributions are reported in table 5.1.[22] A one-year horizon is typically used in standard credit-VaR calculations. However, a longer time horizon of three years may be warranted by taking into account the fact that it is time-consuming both to unwind the credit exposures based on non-tradable bank loans and to raise new capital to cover up any shortfalls due to unexpectedly large credit losses.

Table 5.1 **Expected and unexpected losses of the Finnish corporate credit portfolio in the baseline simulation as of 2003Q2, in percent of total credit exposure**

	1-year horizon	3-year horizon
Expected loss	0.60%	1.82%
Unexpected loss (VaR 99%)	1.81%	2.94%
Unexpected loss (VaR 99.9%)	2.89%	4.17%

[21] Loss distributions are based on 50 000 simulations throughout the study.

[22] Unexpected losses are defined as the difference between the losses pertaining to the chosen percentile and the expected losses.

Figure 5.2 **Simulated baseline loss distribution of the Finnish corporate credit portfolio in 2003Q2, 1-year horizon**

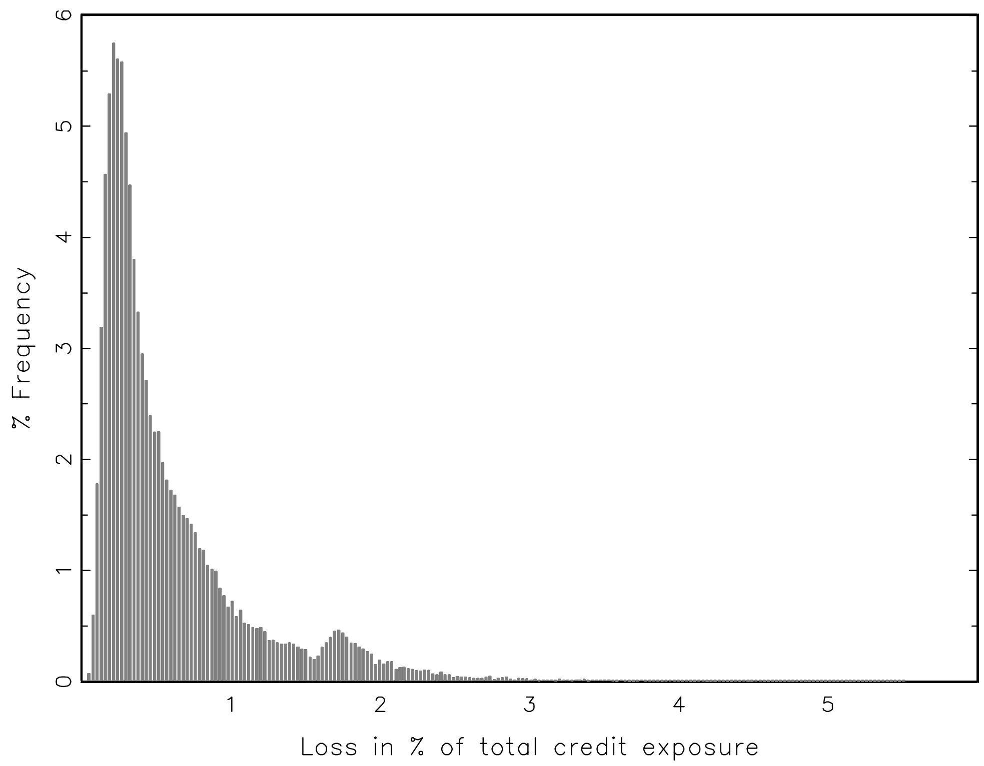
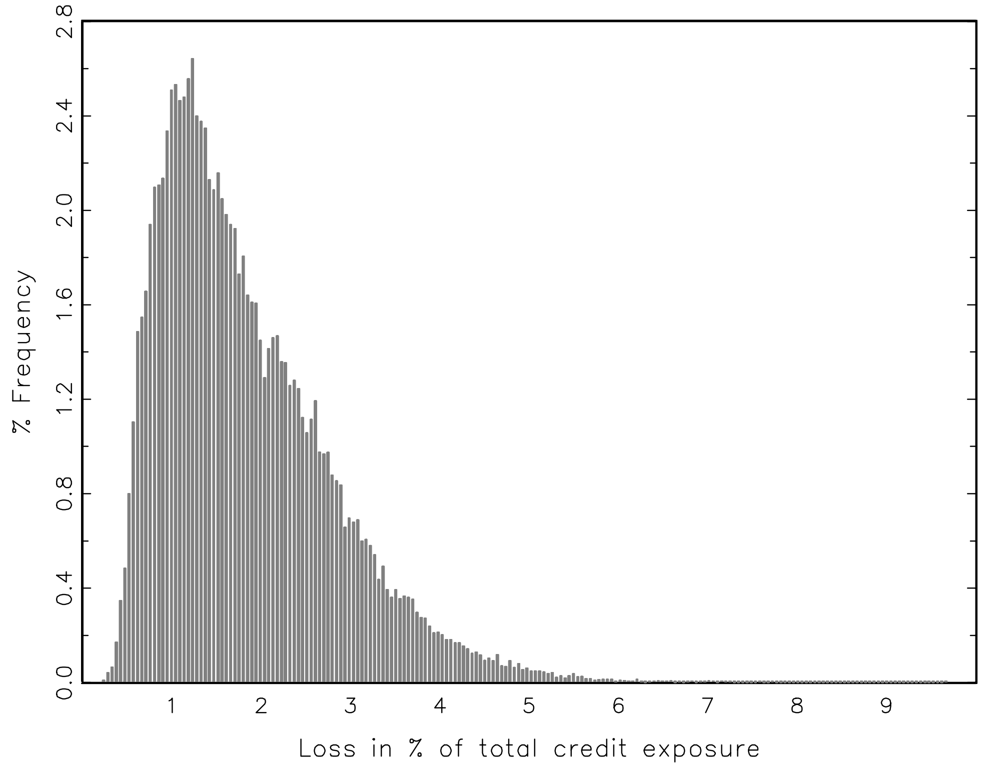


Figure 5.3 **Simulated baseline loss distribution of the Finnish corporate credit portfolio in 2003Q2, 3-year horizon**



As expected, the resulting loss distributions are skewed to the right, due both to the positive default correlation through joint sensitivity to the macro factors, and to the existence of large credit exposures in the portfolio. Conditional on the macroeconomic environment in Finland in 2003Q2, the expected losses of the Finnish corporate credit portfolio equal 0.60% of the total corporate credit exposure over a one-year horizon, and 1.82% over a three-year horizon.

In comparison with the Finnish banks' actual loan loss provisions (LLPs) in recent years (annual average of 0.18% of the lending stock in 1999-2003), these loss estimates appear to be significantly larger. However, the low level of banks' actual LLPs is largely explained by the fact that households play a dominant role in Finnish banks' lending. In 2003, the share of corporate lending amounted only to approximately 35% of banks' total lending to the public, ie to the household and corporate sectors. Exact information on the distribution of banks' loan losses between the corporate and the household sector is not publicly available but, according to Statistics Finland, the average proportion of household sector loan losses of banks' total loan losses is approximately 25%. Hence, the loan loss provisions on banks' corporate lending can be estimated to amount on average to 0.38% of the corporate credit exposure in 1999–2003.

Another comparison can be obtained from an analysis of expected corporate loan losses based on information about credit ratings and historical default rates per rating class. We also performed Monte Carlo simulations – with the same "Finnish corporate credit portfolio" of 3 000 firms as employed in the simulations of our macroeconomic credit risk model – based on the Suomen Asiakastieto Oy ratings-implied default probabilities and an assumption of a constant default correlation of 20% across all debtors. LGD was assumed to equal 0.5 also in these simulations. The resulting 1-year (3-year) expected losses and VaR 99%/99.9% measures were 0.17% (0.49%) and 1.55%/2.72% (2.67%/4.82%), respectively. The ratings-based estimate of expected losses is significantly lower than that obtained with the macroeconomic credit risk model. On the other hand, the ratings-based estimates of unexpected losses, with a conservative assumption of a constant 20% default correlation, appear to be rather well in line with those obtained with the macroeconomic credit risk model.

Of course, the estimate of expected losses obtained with the simulations is strongly dependent on the assumption of the LGD parameter. By varying the LGD between 0% and 100%, we can get estimates of expected losses ranging between 0% and 1.2% with the macroeconomic credit risk model. As the period of a severe banking crisis in the early 1990s in Finland is included in the "memory of the model", we would expect to get rather conservative loan loss estimates with it. The significantly higher estimate of expected losses obtained with the macroeconomic credit risk model as compared to an estimate based on firms' current credit ratings lends some support to this belief. We next turn to carrying out some stress testing with the model.

6 Stress testing with the model

For stress testing purposes, an artificial shock can be introduced in the vector of innovations. The corresponding element in the vector $Z_{t+s} \sim N(0,1)$ of (pseudo) random numbers is replaced by the assumed shock (normalised by the respective standard deviation). This shock, or a sequence of shocks, is introduced in the first step(s) of each simulation round, and it impacts the other macro factors through the variance-covariance matrix. Loss distributions for the assumed stress scenario can then be calculated with the simulated default rate paths as in the baseline case.

In the following, we consider three examples of macro stress testing with the model. First, we analyse the impact of a temporary negative GDP shock. Second, the effect of an increase in the short term interest rate is examined. Finally, we perform a stress test with an extreme negative GDP shock resembling the developments in the early 1990s in Finland.

6.1 GDP shock

Starting from the macroeconomic environment prevailing in the second quarter in 2003 in Finland, we assume that for some exogenous reason – eg a negative export shock – the quarterly real GDP declines by one per cent for four consecutive quarters, and after that continues again at the trend growth rate, approximately +0.5% per quarter, for a two-year period. This corresponds approximately to a two per cent decline in the annual GDP in the first year, then zero growth in the second year, and trend growth of +2 % p.a. in the third year.

The simulated loss distributions of the aggregate credit portfolio of the Finnish corporate sector over a one-year and a three-year horizon are presented in figures 6.1 and 6.2, respectively. Comparing the outcome with the baseline results, we can see some, but not dramatic, increase in the expected losses, while the impact on the unexpected losses is proportionally more modest.

Table 6.1 **Expected and unexpected losses of the Finnish corporate credit portfolio in the GDP shock scenario as of 2003Q2, in percent of total credit exposure**

	1-year horizon	3-year horizon
Expected loss	0.69%	2.17%
Unexpected loss (VaR 99%)	1.91%	2.92%
Unexpected loss (VaR 99.9%)	2.90%	4.22%

Figure 6.1 **Simulated loss distribution of the Finnish corporate credit portfolio in the GDP shock scenario, 1-year horizon**

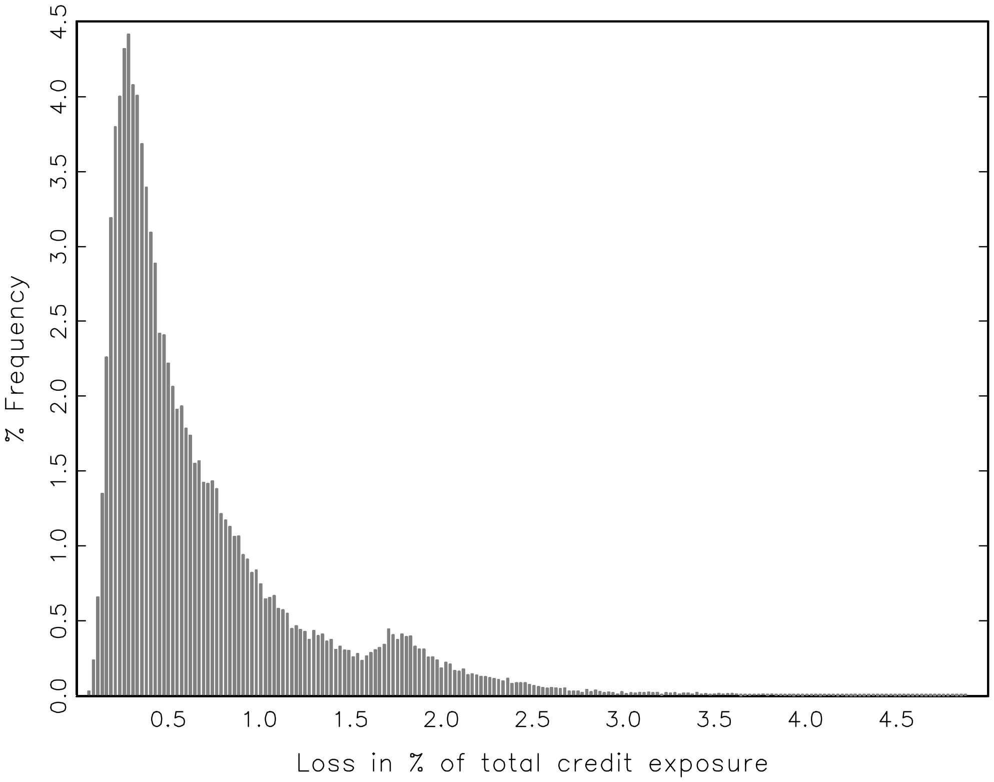
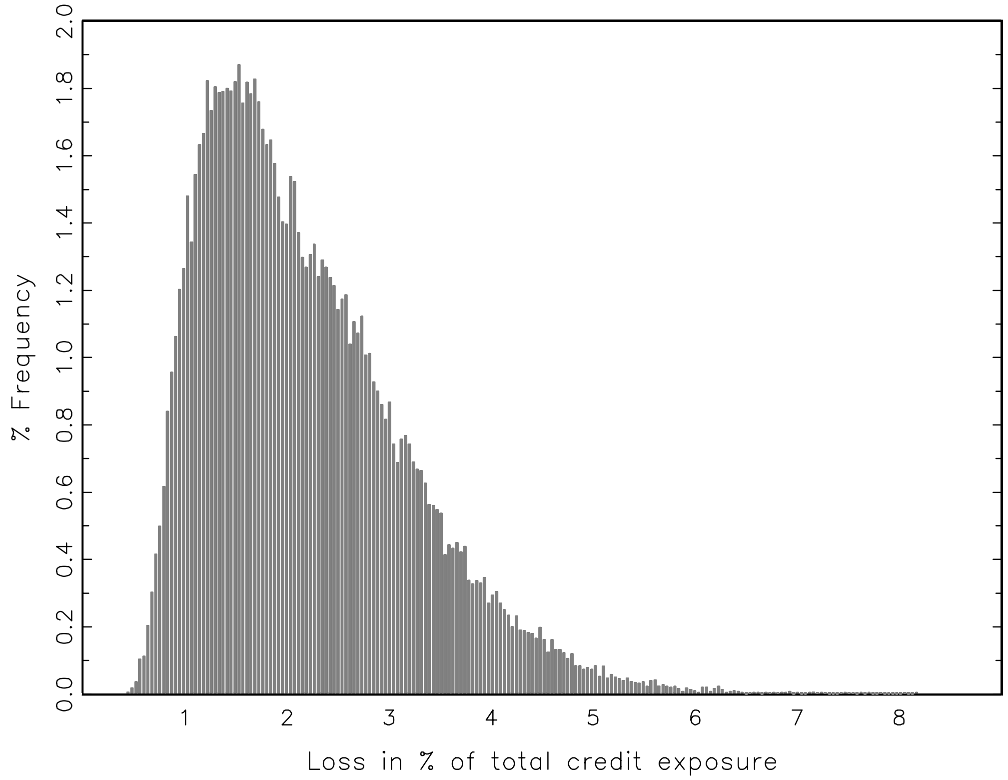


Figure 6.2 **Simulated loss distribution of the Finnish corporate credit portfolio in the GDP shock scenario, 3-year horizon**



6.2 Interest rate shock

For the interest rate shock, we assume that the short term interest rate suddenly increases by one percentage point for four consecutive quarters, and then remains at this higher level for a two-year period. Table 6.2 reports the expected and unexpected losses, and figures 6.3 and 6.4 depict the simulated loss distributions over a one-year and a three-year horizon, respectively.

A four percentage point increase in the nominal short term interest rate appears to have a rather modest effect on the loss distribution. Expected credit losses increase hardly at all over a one-year horizon and by some 0.10 percentage points only over a three-year horizon. As in the case of a temporary GDP shock, the impact on the unexpected losses is also modest.

Table 6.2 **Expected and unexpected losses of the Finnish corporate credit portfolio in the interest rate shock scenario as of 2003Q2, in percent of total credit exposure**

	1-year horizon	3-year horizon
Expected loss	0.60%	1.92%
Unexpected loss (VaR 99%)	1.86%	2.97%
Unexpected loss (VaR 99.9%)	2.87%	4.39%

Figure 6.3 **Simulated loss distribution of the Finnish corporate credit portfolio in the interest rate shock scenario, 1-year horizon**

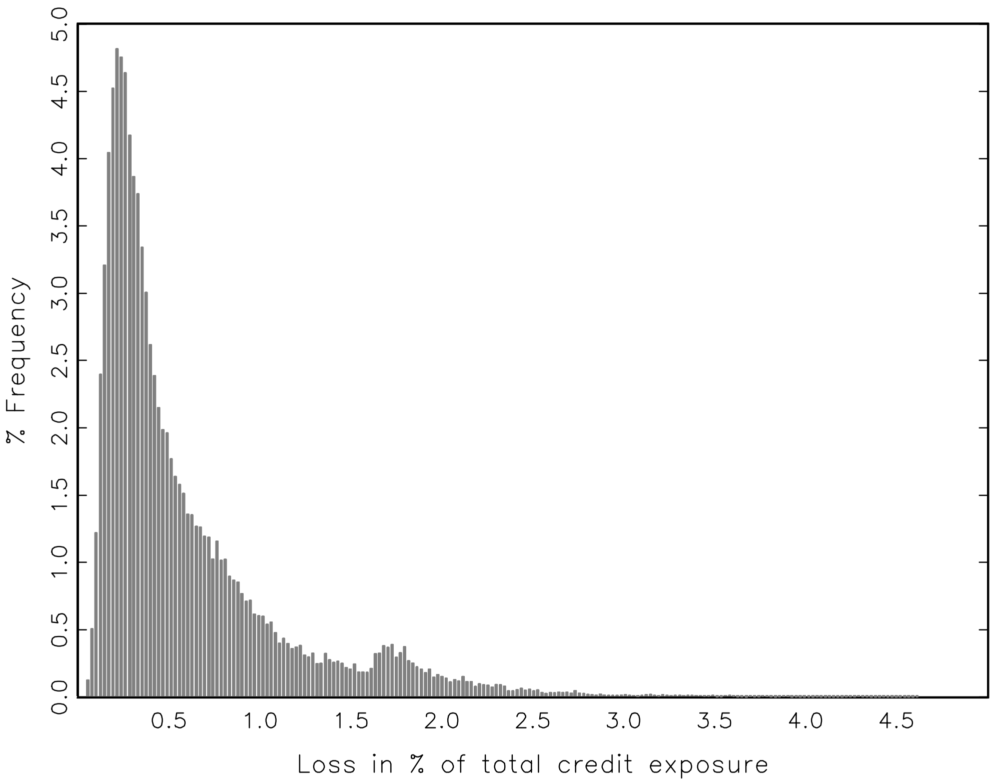
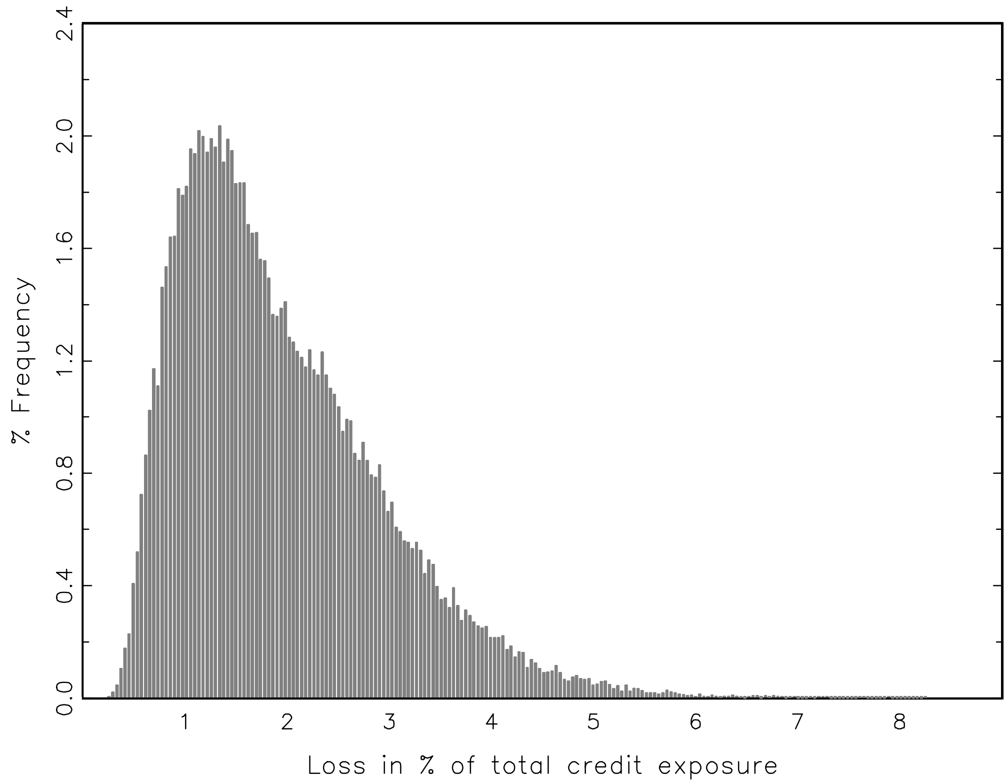


Figure 6.4 **Simulated loss distribution of the Finnish corporate credit portfolio in the interest rate shock scenario, 3-year horizon**



6.3 Extreme GDP shock

As a final example, we analyse the impact of an extreme stress scenario – similar in nature to the early 1990s recession – on the aggregated credit portfolio of the Finnish corporate sector in 2003Q2. More specifically, we assume that the quarterly real GDP declines by two per cent for eight consecutive quarters, after which the GDP is allowed to develop without artificial shocks in the third year. This corresponds approximately to a four per cent decline in the annual real GDP in the first year, then a seven per cent decline in the second year, and –1.5% change in the third year. Table 6.3 reports the expected and unexpected losses, and figures 6.5 and 6.6 show the simulated loss distributions over a 1-year and a 3-year horizon, respectively.

Quite realistically, the assumed extreme GDP shock appears to have a rather modest impact over a one-year horizon, but over a three-year horizon the resulting loan loss estimates become significant. Over three years, the expected losses amount to 3.5% of the overall corporate credit exposure. Moreover, the 99th percentile of the simulated loss distribution implies that another 3.5% of the overall corporate credit exposure would be required as a capital buffer to avoid bank default in 99 cases out of 100. In fact, given the magnitude of the assumed GDP shock, it is likely that a number of banks' income components would be adversely affected, and the required capital buffer would likely need to be even larger than that to cover part of the expected losses also.

Table 6.3 **Expected and unexpected losses of the Finnish corporate credit portfolio in the extreme GDP shock simulation, in percent of total credit exposure**

	1-year horizon	3-year horizon
Expected loss	0.80%	3.52%
Unexpected loss (VaR 99%)	2.04%	3.50%
Unexpected loss (VaR 99.9%)	3.09%	4.94%

Interestingly, the estimated losses in the extreme GDP shock scenario are significant but still rather modest compared to the experiences during the banking crisis in the early 1990s (with cumulative loan loss provisions of almost 12% of banks' total lending over the worst three-year period). The explanation for these results is the fact that the Finnish macroeconomic environment in the second quarter in 2003 was clearly more favourable than that in 1990-1991: the level of indebtedness in the Finnish corporate sector today is low compared to the levels observed in the early 1990s, and the current interest rates are low in historical comparison.[23]

[23] A shortcoming of the simulation is that the effect of a deep decline in the GDP on the corporate sector indebtedness – measured as a proportion of the value added – is assumed to be captured by the historical correlation between the real GDP and corporate indebtedness. A more realistic modelling of this effect might yield somewhat higher loan loss estimates.

Figure 6.5 **Simulated loss distribution of the Finnish corporate credit portfolio in the extreme GDP shock scenario, 1-year horizon**

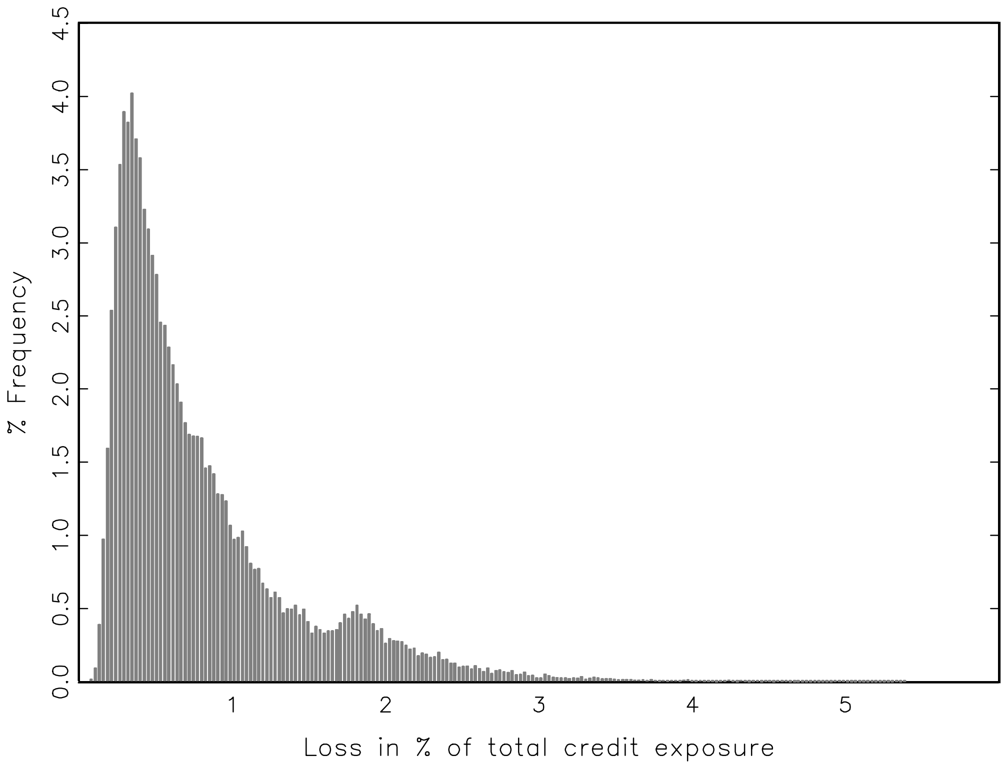
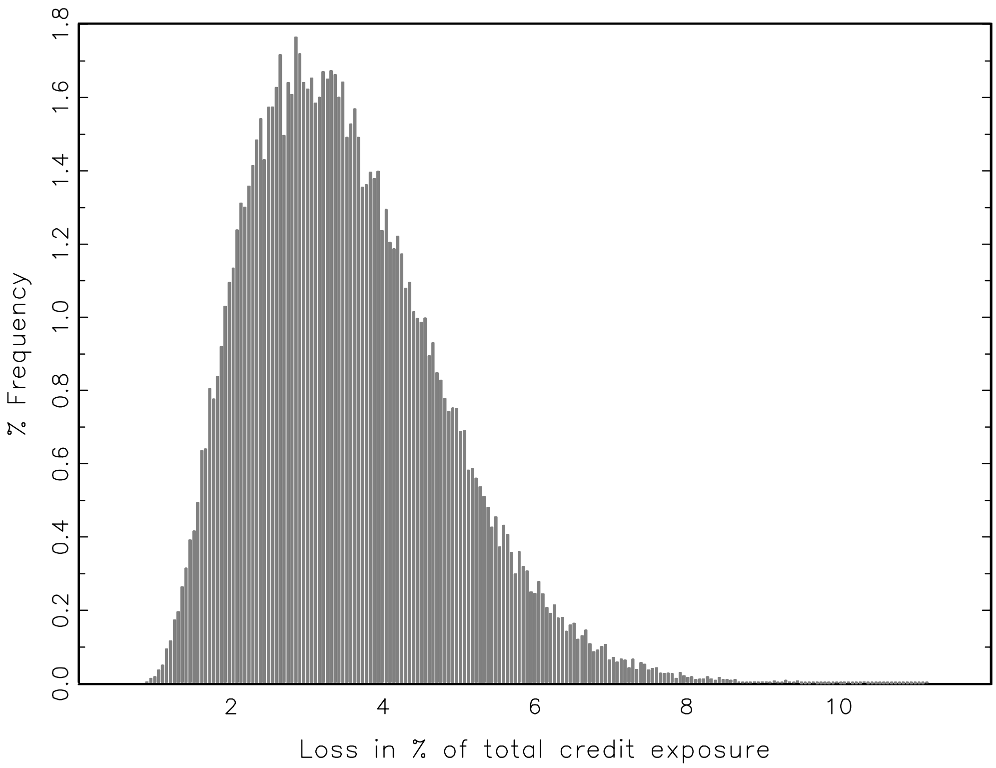


Figure 6.6 **Simulated loss distribution of the Finnish corporate credit portfolio in the extreme GDP shock scenario, 3-year horizon**



7 Conclusions

We have modelled and estimated a macroeconomic credit risk model for the Finnish corporate sector. A distinguishing feature of the study is that the sample period employed to estimate the model includes a severe recession and a banking crisis. Thus, we avoid the shortcoming of performing stress tests with a model based on "too benign historical data". Another distinctive feature of the study is that we model and estimate industry-specific default rates, which makes it possible to obtain more accurate credit loss estimates than those obtained with more aggregated models.

The empirical results suggest a significant and fairly robust relationship between industry-specific default rates and key macroeconomic factors including the GDP, the interest rate and the corporate sector indebtedness. These findings are in line with previous studies using observed bankruptcies for default rate measures. The nominal interest rate effect is not equally strong across all industries, however. For one industry, agriculture, macroeconomic factors appear to play only a marginal role in explaining default rates.

The macroeconomic credit risk model with explicit links between default rates and macro factors is well suited for macro stress testing purposes. We use the model to analyse the impact of stress scenarios on the credit risks of an aggregated Finnish corporate credit portfolio. The results of the stress scenario analyses suggest that the current credit risks stemming from the Finnish corporate sector are modest. An explanation for this finding is that the current macroeconomic environment in Finland is favourable with a strong financial position of the Finnish corporate sector and low interest rates. Of course, for a comprehensive picture of the credit risks faced by the Finnish banks, the analysis would also need to cover the household sector.

Some aspects of our macroeconomic credit risk model would certainly require further elaboration. First, it is unfortunate that we cannot find any role for the real interest rate. Some other measures than the ex post real interest rate might be more suitable for a sample period that covers two significantly different inflation regimes. Second, the AR(2) modelling of the evolution of the macro factors is simplistic. A more consistent picture could be obtained by the use of a macro model, although this would complicate the analysis. Finally, estimating the model with "industry-specific GDP" (value added) variables instead of using the aggregate real GDP for each industry would make it possible to analyse the impact of industry-specific shocks.

It should also be noted that the industry breakdown of the default rate data is still a relatively crude approximation, and there is likely to be quite a lot of heterogeneity in default probabilities across firms within an industry. A useful extension of the model would be to include company-level rating information and link the whole matrix of industry-specific rating transition probabilities and macroeconomic factors, as in Wilson's (1997a) original formulation. However, in Finland, rating data currently exist for short periods of history only.

As regards the application of the model, it is likely to be better suited for relatively homogeneous corporate credit portfolios, like those consisting of SME sector firms only. Moreover, in macro stress testing exercises attempting to detect indications of potential crises, sufficiently long time horizons would be needed. However, extending the time horizon poses a number of new challenges from the modelling point of view, as feedback issues become more relevant.

In the current credit risk models employed by financial institutions macroeconomic factors play a limited role. Hence, it is important that the public authorities examine the impact of macroeconomic developments on financial institutions' credit risks as part of their financial stability analysis.

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Appendix 1

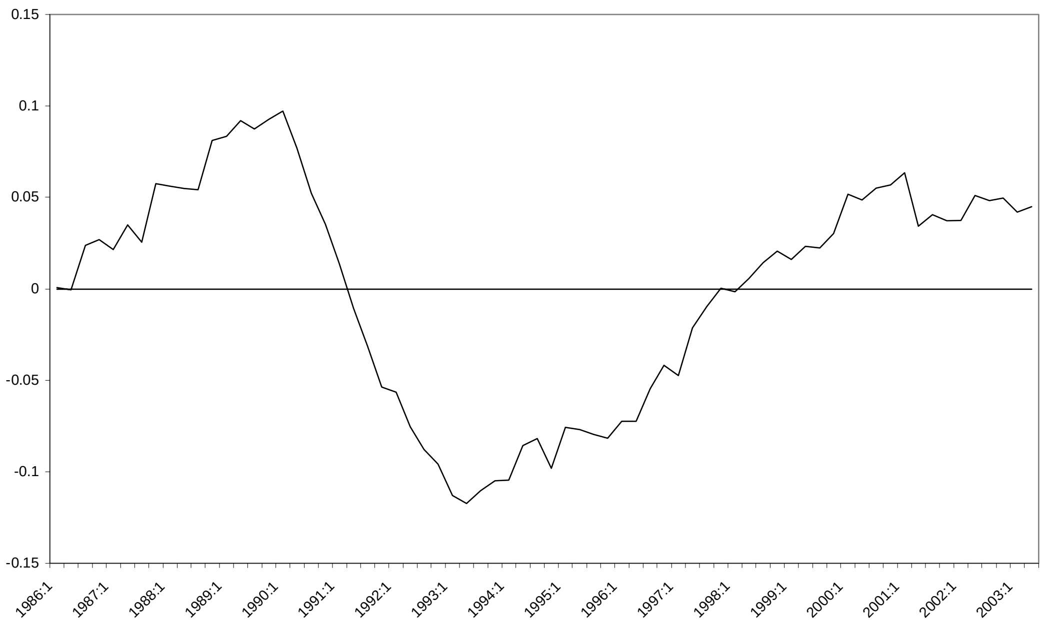
Data description and descriptive statistics

Quarterly default rate data

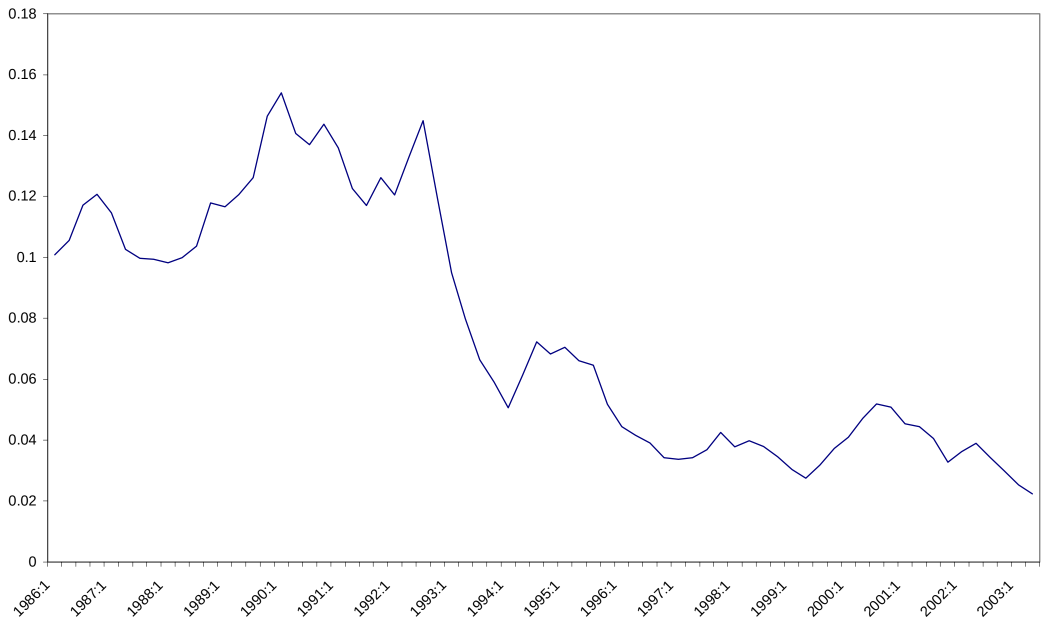
Default is defined to take place when a bankruptcy proceeding is instituted against an enterprise for the first time. This can be instituted either by the enterprise itself or by a creditor. Quarterly information on the number of bankruptcy proceedings by sector is published by the Statistics Finland and is available from 1986Q1 onwards. Sectoral classification is the following (TOL-02): Corporate enterprises total (A–X); Agriculture (A–B, agriculture, hunting, forestry and fishing); Manufacturing (C–E, mining and quarrying, manufacturing, electricity, gas and water supply); Construction (F); Trade, hotels and restaurants (G–H, wholesale and retail trade, repair of motor vehicles, motorcycles and personal and household goods); Transport, storage and communication (I); Other industries (J–X, Financial intermediation; real estate, renting and business activities; public administration and defence; compulsory social security; education; health and social work; other community social and personal service activities; private households employing domestic staff and undifferentiated production activities of households for own use; extra-territorial organisations and bodies; industry unknown). Information on the number of corporate enterprises is published by the Statistics Finland. Two different data sources are available: "Enterprises in Finland" (annual data) and "Enterprise openings and closures" (quarterly data); these are derived form different sources and are not directly comparable. We adopted the "Enterprises in Finland" concept of corporate enterprises and personal businesses subject to trade tax which operated for more than six months in a given year and employed more than half a person, or their turnover exceeded a certain threshold (EUR 9134 in 2002). The total number of companies was 226,593 in 2002. This definition excludes farms without hired employees, which totalled 67732 in 2002. Annual data was linearly interpolated into quarterly data. Observations for 2003 were calculated by adding the net quarterly changes as given by the "Enterprise openings and closures" statistics to end-2002 figures.

Macroeconomic factors

GDP – residuals of log real GDP regressed on constant and time trend. GDP data are seasonally adjusted at constant prices.



R – nominal short-term interest rate (12-month Helibor / Euribor).



$DEBT_j$ – gross debt of industry j divided by the (seasonally adjusted) value added of industry j. Quarterly observations show the debt stock as a proportion of the annualised value added. Intra-corporate sector credits are excluded.

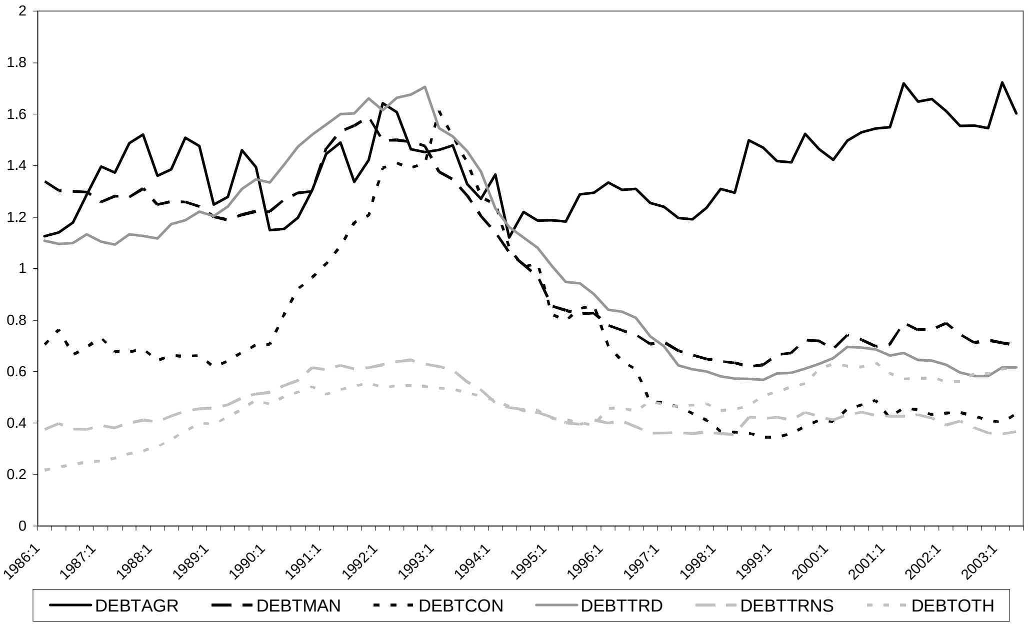


Table A1.1 **Descriptive statistics**

	Mean	Medium	Maximum	Minimum	Std. Dev.
YAGR	6.504	6.478	7.612	5.695	0.461
YMAN	5.089	5.164	5.833	4.159	0.459
YCON	5.182	5.286	5.715	4.507	0.336
YTRD	5.315	5.424	5.853	4.419	0.432
YTRNS	6.075	6.025	6.972	5.415	0.350
YOTH	5.583	5.755	6.178	4.753	0.385
GDP	0.000	0.021	0.097	-0.117	0.062
R	0.076	0.065	0.154	0.022	0.040
DEBTAGR	1.390	1.395	1.724	1.120	0.156
DEBTMAN	1.020	0.993	1.588	0.621	0.311
DEBTCON	0.731	0.664	1.612	0.345	0.341
DEBTTRD	1.018	1.087	1.707	0.568	0.370
DEBTTRNS	0.454	0.425	0.644	0.357	0.087
DEBTOTH	0.476	0.488	0.634	0.218	0.107

Table A1.2 **Correlation matrix**

	YAGR	YMAN	YCON	YTRD	YTRNS	YOTH	GDP
YAGR	1.000	0.132	0.182	0.254	0.433	0.334	0.292
YMAN	0.132	1.000	0.915	0.891	0.275	0.782	0.630
YCON	0.182	0.915	1.000	0.912	0.392	0.843	0.710
YTRD	0.254	0.891	0.912	1.000	0.487	0.945	0.832
YTRNS	0.433	0.275	0.392	0.487	1.000	0.601	0.615
YOTH	0.334	0.782	0.843	0.945	0.601	1.000	0.898
GDP	0.292	0.630	0.710	0.832	0.615	0.898	1.000
R	0.254	-0.587	-0.452	-0.342	0.385	-0.137	0.119
DEBTAGR	-0.186	0.293	0.155	0.264	-0.085	0.236	0.256
DEBTMAN	0.147	-0.764	-0.680	-0.543	0.198	-0.337	-0.140
DEBTCON	-0.081	-0.903	-0.895	-0.892	-0.282	-0.792	-0.661
DEBTTRD	0.064	-0.839	-0.757	-0.699	0.054	-0.522	-0.293
DEBTTRNS	-0.088	-0.701	-0.655	-0.654	-0.148	-0.532	-0.285
DEBTOTH	-0.256	0.194	0.133	0.008	-0.383	-0.084	-0.005

	R	DEBTAGR	DEBTMAN	DEBTCON	DEBTTRD	DEBTTRNS	DEBTOTH
YAGR	0.254	-0.186	0.147	-0.081	0.064	-0.088	-0.256
YMAN	-0.587	0.293	-0.764	-0.903	-0.839	-0.701	0.194
YCON	-0.452	0.155	-0.680	-0.895	-0.757	-0.655	0.133
YTRD	-0.342	0.264	-0.543	-0.892	-0.699	-0.654	0.008
YTRNS	0.385	-0.085	0.198	-0.282	0.054	-0.148	-0.383
YOTH	-0.137	0.236	-0.337	-0.792	-0.522	-0.532	-0.084
GDP	0.119	0.256	-0.140	-0.661	-0.293	-0.285	-0.005
R	1.000	-0.218	0.897	0.566	0.870	0.650	-0.365
DEBTAGR	-0.218	1.000	-0.117	-0.133	-0.175	0.112	0.517
DEBTMAN	0.897	-0.117	1.000	0.770	0.951	0.729	-0.346
DEBTCON	0.566	-0.133	0.770	1.000	0.879	0.812	-0.030
DEBTTRD	0.870	-0.175	0.951	0.879	1.000	0.849	-0.186
DEBTTRNS	0.650	0.112	0.729	0.812	0.849	1.000	0.301
DEBTOTH	-0.365	0.517	-0.346	-0.030	-0.186	0.301	1.000

Appendix 2

Further econometric results

Table A2.1 **Estimates for the AR(2) macro factor models**

	C	x_{t-1}	x_{t-2}	Adj.R^2	SEE	DW
GDP	0.0005	1.203	-0.227	0.957	0.013	2.10
	(0.32)	(9.96)	(-1.88)			
R	0.001	1.372	-0.400	0.964	0.008	1.86
	(0.53)	(12.1)	(-3.46)			
$DEBT_{AGR}$	0.315	0.802	-0.02	0.611	0.095	1.99
	(2.80)	(6.46)	(-0.18)			
$DEBT_{MAN}$	0.006	1.288	-0.299	0.982	0.042	2.14
	(0.32)	(10.9)	(-2.53)			
$DEBT_{CON}$	0.011	1.213	-0.234	0.962	0.067	1.99
	(0.58)	(10.1)	(-1.94)			
$DEBT_{TRD}$	0.003	1.444	-0.451	0.988	0.041	2.31
	(0.17)	(13.0)	(-4.03)			
$DEBT_{TRNS}$	0.012	1.232	-0.261	0.953	0.024	2.05
	(1.00)	(10.4)	(-2.19)			
$DEBT_{OTH}$	0.029	1.105	-0.156	0.960	0.020	2.03
	(2.48)	(9.04)	(-1.32)			

Note: t-statistics in parenthesis.

Table A2.2 **Initial SUR estimates for the static model without dummies for structural break**

	y_{AGR}	y_{MAN}	y_{CON}	y_{TRD}	y_{TRNS}	y_{OTH}
C	7.761	6.032	5.677	5.914	6.371	6.078
	(17.8)	(75.7)	(116.6)	(141.3)	(39.9)	(89.2)
GDP	2.750	4.352	2.351	4.772	2.525	5.806
	(3.28)	(11.9)	(4.57)	(19.3)	(5.00)	(24.5)
R		-2.635	-2.110		4.751	-3.071
		(-2.41)	(-2.95)		(5.08)	(-8.57)
$DEBT_j$	-0.905	-0.729	-0.458	-0.588	-1.448	-0.550
	(-2.91)	(-5.17)	(-4.20)	(-15.3)	(-3.33)	(-5.03)
Adj.R^2	0.132	0.864	0.827	0.916	0.535	0.893
SEE	0.429	0.169	0.140	0.125	0.239	0.126
DW	1.878	1.675	1.680	1.445	2.068	1.435

Note: t-statistics in parenthesis.

Appendix 3

Assets and liabilities of bankrupt companies in Finland

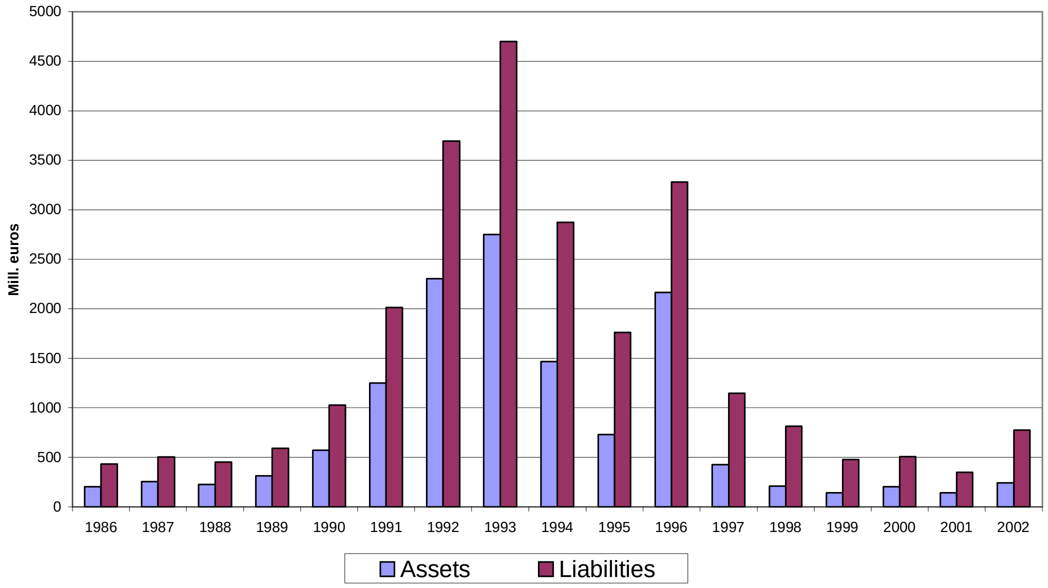
Table A3.1 **Total assets as a percentage of total liabilities of bankrupt companies per industry**

Year	TOTAL	AGR	MAN	CON	TRD	TRNS	OTH
1986	46.4%	16.0%	51.3%	46.4%	41.9%	40.2%	43.8%
1987	50.5%	61.5%	52.5%	51.5%	45.4%	59.7%	50.2%
1988	49.9%	60.6%	51.9%	55.4%	48.9%	48.2%	39.2%
1989	53.1%	81.2%	50.3%	35.7%	46.0%	37.5%	65.7%
1990	55.8%	33.9%	61.5%	40.6%	47.3%	66.0%	69.2%
1991	62.1%	49.2%	63.6%	63.0%	59.5%	38.4%	65.9%
1992	62.4%	45.8%	63.2%	64.4%	52.8%	48.1%	69.7%
1993	58.5%	71.6%	64.1%	58.5%	52.0%	40.5%	59.9%
1994	51.0%	81.6%	47.9%	63.6%	46.3%	20.4%	47.9%
1995	41.5%	30.7%	47.5%	40.8%	37.3%	33.0%	41.9%
1996	66.0%	35.8%	40.1%	50.2%	31.4%	25.5%	75.3%
1997	37.0%	93.2%	29.2%	29.8%	41.6%	63.6%	28.7%
1998	25.9%	32.8%	39.4%	29.3%	29.3%	38.5%	21.0%
1999	30.1%	44.0%	43.8%	31.3%	41.3%	39.3%	14.8%
2000	39.8%	56.5%	54.4%	30.9%	40.5%	17.4%	37.4%
2001	40.7%	54.1%	39.7%	44.9%	54.6%	33.8%	29.0%
2002	31.3%	44.3%	48.6%	34.1%	29.9%	16.1%	34.7%
Average	47.2%	52.5%	49.9%	45.3%	43.9%	39.2%	46.7%

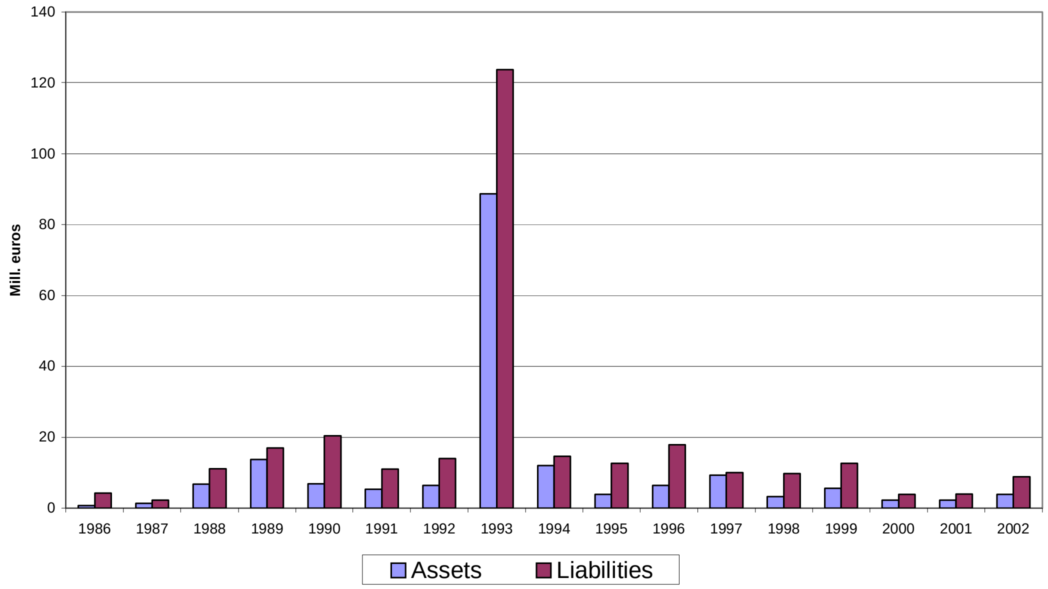
Source: Statistics Finland. Data are based on completed bankruptcy proceedings.

Figures A3.1–7 **Assets and liabilities of bankrupt companies per industry**

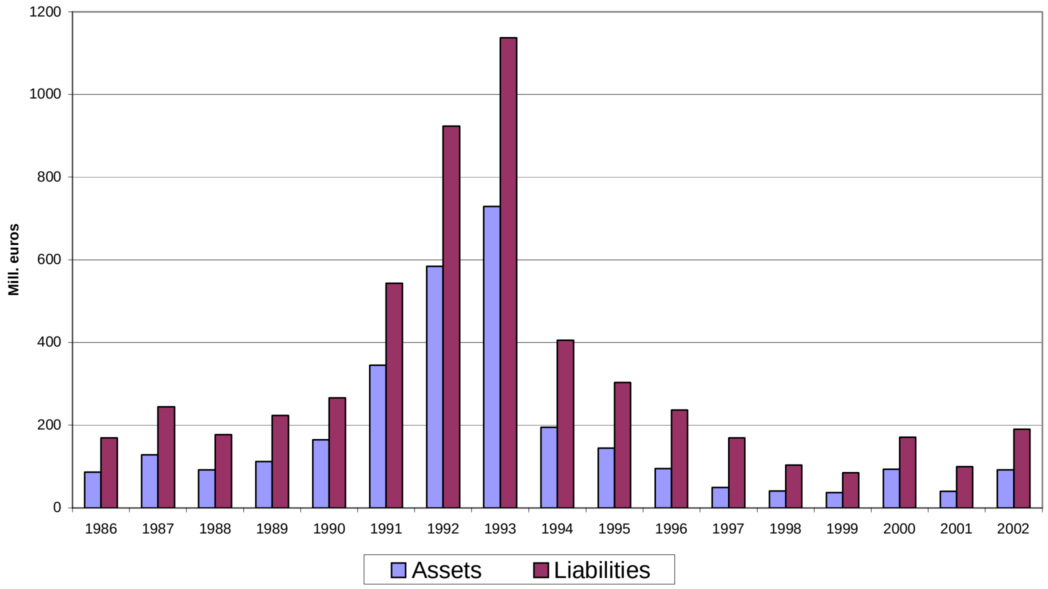
Total corporate sector



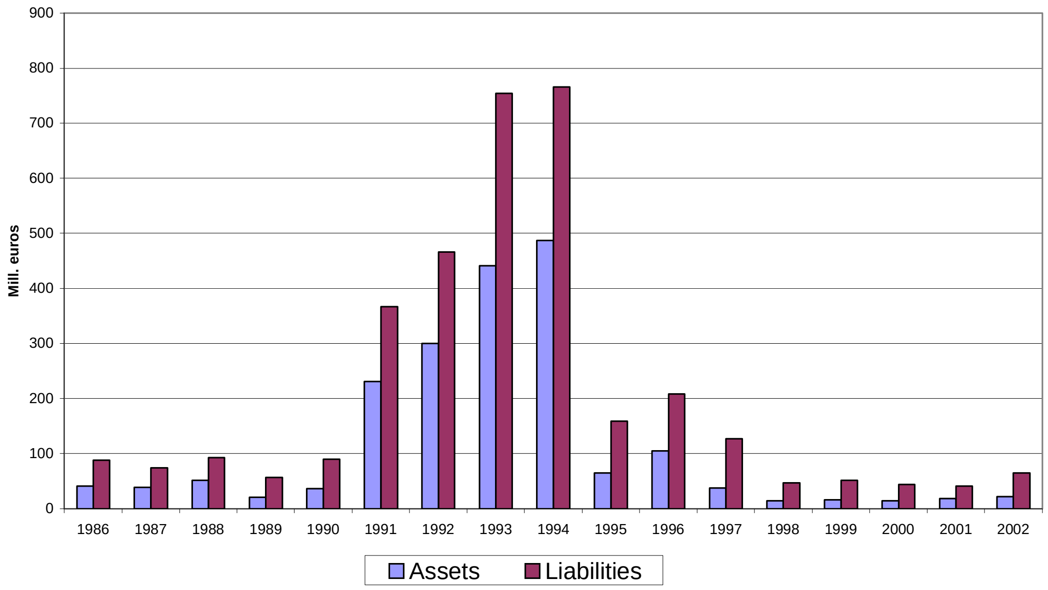
Agriculture



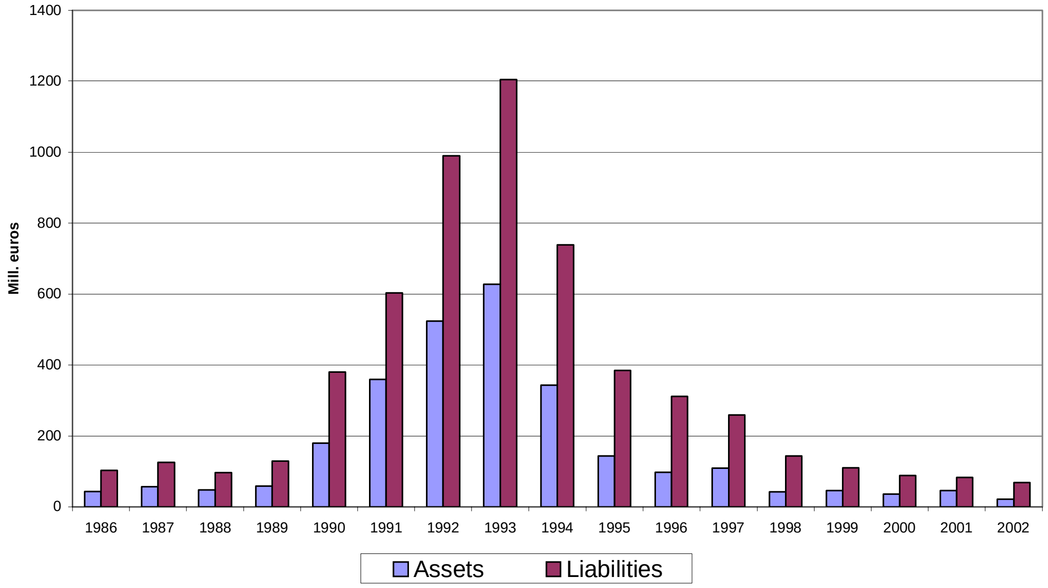
Manufacturing



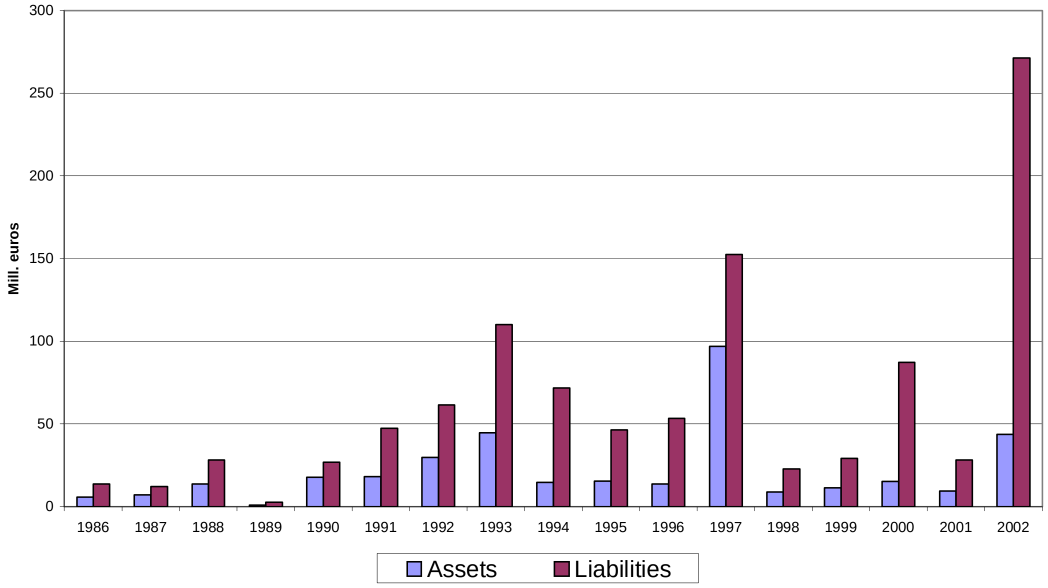
Construction



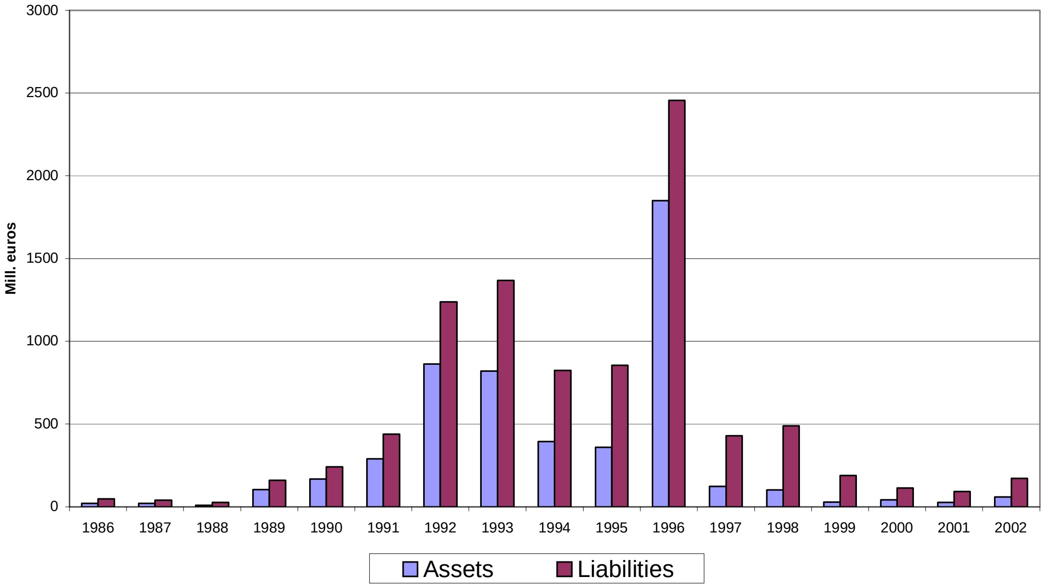
Trade, hotels and restaurants



Transport and communication



Other industries



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