

Esa Jokivuolle – Matti Viren – Oskari Vähämaa

**Transmission of macro shocks
to loan losses in a deep crisis:
the case of Finland**



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Transmission of macro shocks to loan losses in a deep crisis: the case of Finland

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Transmission of macro shocks to loan losses in a deep crisis: the case of Finland

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Abstract

Building on the work of Sorge and Virolainen (2006), we revisit the data on aggregate Finnish bank loan losses from the corporate sector, which covers the ‘Big Five’ crisis in Finland in the early 1990s. Several extensions to the empirical model are considered. These extensions are then used in the simulations of the aggregate loan loss distribution. The simulation results provide some guidance as to what might be the most important dimensions in which to improve the basic model. We found that making the average LGD depend on the business cycle seems to be the most important improvement. We also compare the empirical fit of the annual expected losses over a long period. In scenario-based analyses we find that a prolonged deep recession (as well as simultaneity of various macro shocks) has a convex effect on cumulative loan losses. This emphasizes the importance of an early policy response to a looming crisis. Finally, a comparison of the loan loss distribution on the eve of the 1990s crisis with the most recent distribution demonstrates the greatly elevated risk level prior to the 1990s crisis.

Keywords: credit risk, bank loan losses, banking crisis, macro shocks, default rates, stress testing

JEL classification numbers: C15, E37, G01, G21, G32, G33

Makrotaloudellisten sokkien vaikutus luottotappioihin kriisien aikana

Suomen Pankin keskustelualoitteita 26/2009

Esa Jokivuolle – Matti Viren – Oskari Vähämaa
Rahapolitiikka- ja tutkimusosasto

Tiivistelmä

Tässä tutkimuksessa mallinnetaan kokonaisluottotappioita, joita on aiheutunut suomalaisille pankeille yritysluotoista erityisesti Suomen suuren laman aikana 1990-luvun alussa. Työ perustuu Sorgen ja Virolaisen (2006) malliin, jota laajennetaan eri tavoin. Laajennetulla mallilla tehdään simulaatioita kokonaisluottotappioista. Simulointitulosten perusteella voidaan tehdä alustavia päätelmiä siitä, mihin suuntaan alkuperäistä mallia olisi hyödyllisintä kehittää. Tulosten perusteella keskimääräisen tappio-osuuden (LGD) määräytyminen suhdannevaiheen mukaan on mallin tärkein kehityspiirre. Työssä tarkastellaan myös luottotappiomallin historiallista selityskykyä. Skenaarioanalyysi paljastaa, että pitkittynyt syvä taantuma tai useiden makrotaloudellisten sokkien samanaikaisuus vaikuttaa kumulatiivisiin luottotappioihin kiihdyttävästi. Tämä tulos tähdentää, että uhkaavaan kriisiin on puututtava riittävän ajoissa. Lopuksi verrataan pankkisektorin kokonaisluottotappioiden vuoden 2007 lopun todennäköisyysjakaumaa siihen todennäköisyysjakaumaan, joka edelsi 1990-luvun alun kriisiä. Vertailu osoittaa, että luottoriskit olivat kasvaneet huomattavasti ennen 1990-luvun alun kriisiä.

Avainsanat: luottoriski, pankkien luottotappiot, pankkikriisi, makrotaloudelliset sokit, konkurssiaste, stressitestausta

JEL-luokittelu: C15, E37, G01, G21, G32, G33

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1 Introduction

Understanding the sources of corporate credit losses continue to lie at the heart of commercial banks' risk management as well as macro-prudential analysis conducted by financial authorities, both now and in the future. In the aftermath of the financial crisis of 2007–2008, worldwide weakened economic growth prospects threaten to increase corporate defaults and credit losses which may further burden the already troubled banking sector and impair their lending ability.

In analyzing the link between macro economy and corporate credit losses it is useful to look at earlier historic episodes when credit losses have amounted. A recent case in point is the Finnish banking crisis and great depression in the early 1990's, which have been analyzed by eg Conesa, Kehoe and Ruhl (2007), Gorodnichenko et al (2009) and Honkapohja et al (2009). The size of the Finnish crisis was exceptional even by international standards (Reinhart and Rogoff, 2009). The share of non-performing loans went up 13 per cent and annual default rates rose to 3 per cent which resulted in high loan losses (see Figures 1.1 and 1.2). The crisis cost the Finnish government almost 13 per cent of a one year GDP (Laeven and Valencia, 2008). Since the depression, economic development has been very favourable and annual default rates have come down to less than one per cent so that loan losses have been almost nonexistent.¹

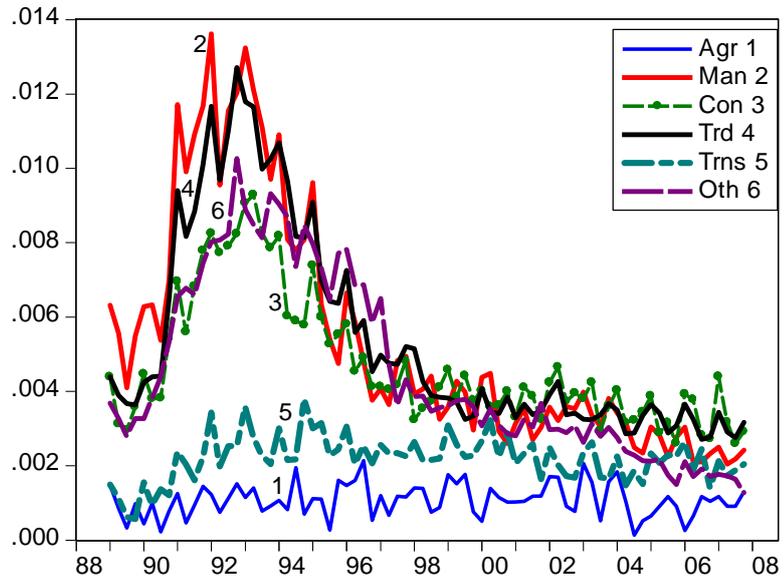
Some interesting observations as regards the relationship between defaults and loan losses can be made just by visual inspection of the Finnish evidence. In particular, the defaults-loan losses relationship appears at least to some extent to be nonlinear (cf. Figure 1.2). Even in good times there are quite many business failures; in the Finnish data, the annual default rate has not gone below 0.8 per cent, but they do not seem to have caused much loan losses. There are probably several reasons for this regularity. First, some fraction of new firms will always fail, eg, because of entrepreneurial incompetence or initial lack of resources or demand. Most of such firms are 'fortunately' small so that the effect on banks' loan losses is limited. The second reason is probably related to collateral values. In good times loan-to-value ratios are reasonably low and thus most losses can be covered by collateral. In deep recessions things are different: also some very big firms fail and falling market values of collateral reinforce the negative impact.² Thus loan losses tend to be severe only in deep recessions or depressions. That is why we also in this paper wish to further analyze the behaviour of corporate credit losses in deep and long-lasting recessions and depressions.

¹ For more details of the Finnish banking sector loan losses and comparisons with other Nordic countries, see Pesola (2001).

² That LGD tends to increase in recessions is empirically rather well established; see eg Schuermann (2004) and the references cited therein.

Figure 1.1

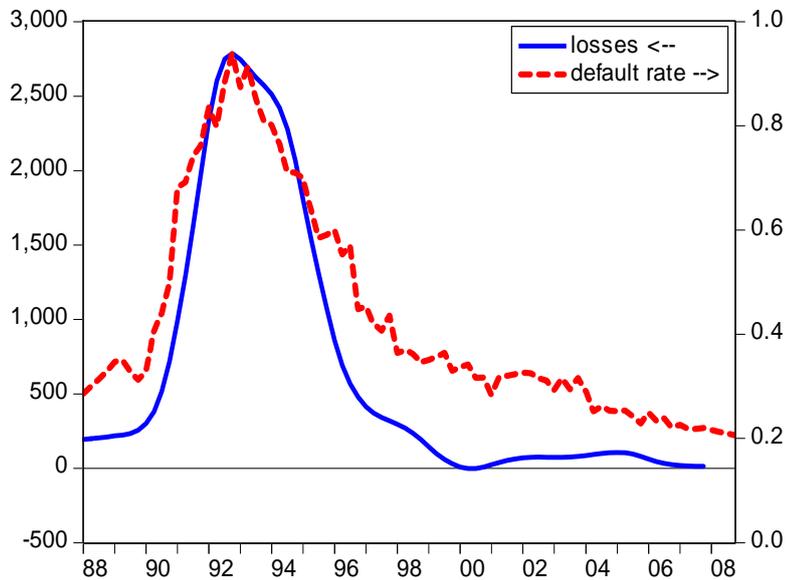
Industry-specific default rates



Agr = agriculture, Man = manufacturing,
 Con = construction, Trd = Trade, Trns = transportation, and
 Oth = Others

Figure 1.2

Relationship between loan losses and the aggregate default rate



The (seasonally-adjusted) default rate corresponds to the whole economy. Loan losses are interpolated from an annual Statistics Finland series.

Our work follows the branch of literature that has focused on the transmission of macro shocks, notably output, real interest rate and aggregate corporate indebtedness, to corporate failures and banks loan losses. We adopt the framework of Sorge and Virolainen (2006) which first models industry-specific corporate default rates with the macro variables and then simulates loan losses by using the industry-specific default rates as proxies for corporate probabilities of default (PD) in the respective industries and by assuming a constant loss given default (LGD) across all companies. Our aim is to extend their analysis of the Finnish case in several ways. First, we consider the following extensions to their model. 1) We allow LGD to depend on the state of the business cycle. 2) We consider industry-specific output shocks instead of the aggregate shock. We also take a step back and make a basic comparison by running a single-equation model for the aggregate corporate default rate, in order to investigate the importance of disaggregating to the industry-specific default rates in the first place. 3) We try an alternative times-series specification of the macro shocks. As Sorge and Virolainen (2006), we then perform Monte Carlo simulations of the macro based loan loss model to produce loan loss distributions. We investigate how the model extensions 1) to 3) affect these distributions. Taken together, these results constitute a set of robustness checks to the basic model of Sorge and Virolainen (2006), which may provide some guidance as to what may be the most crucial areas of ‘model risk’ in the basic model. The most important result here concerns the LGD, endogenous to the business cycle state, which we measure as the annual average of the entire corporate sector and which we are able to estimate by using aggregate data on the number of defaults, loan losses and the distribution of corporate debt within the corporate sector.

Second, we extend loan loss scenario analyses to further study the effects of a deep prolonged recession. Interestingly, it appears that a constant GDP shock that persists over several years has a slightly convex effect on cumulative loan losses. This nonlinear effect is further reinforced when we add a simplistic feedback mechanism from loan losses to the GDP growth. We also demonstrate a nonlinear effect from macro shocks to loan losses in that different simultaneous shocks seem to be reinforcing one another’s effect on loan losses vis-à-vis an individual macro shock of commensurate size. Third, we simulate the impact on potential aggregate loan losses of a single industrial cluster, for which Finland also provides an interesting case as a result of the central role in its economy of the newly developed ICT cluster. Fourth, we complement the analysis of Sorge and Virolainen (2006) by providing the fit of the macro based model of loan losses to the actual loan losses experienced in Finland especially during the crisis years of the early 1990’s. We find that although the endogenous LGD seems an important improvement to the fit relative to the basic model with a constant LGD, the model still falls short of capturing the full magnitude of loan losses experienced in Finland during the 90’s crisis. We discuss potential explanations for the remaining

gap. Lastly, we compute the loan loss distribution both for a pre-90's crisis period and the most recent period in our data. This comparison clearly shows the very significant impact that the prevailing macro state has on the conditional loan loss distribution. It is remarkable that in 1990 expected aggregate loan losses in Finland were roughly double what they were in the third quarter of 2008.

The rest of the paper is organized as follows. Section 2 describes the industry-specific default rate model estimation and section 3 discusses the estimation results. In section 4 we simulate the loan loss distribution and consider the effects on the loss distribution of the various extensions to the basic model. Further, we investigate a scenario of a prolonged deep recession and a scenario of simultaneous shocks. We also provide the empirical fit of the model based expected loan losses in Finland over the sample period. Finally, we contrast the pre-1990's crisis loan loss distribution with the one simulated with the most recent data. Section 5 concludes.

2 Estimation procedure

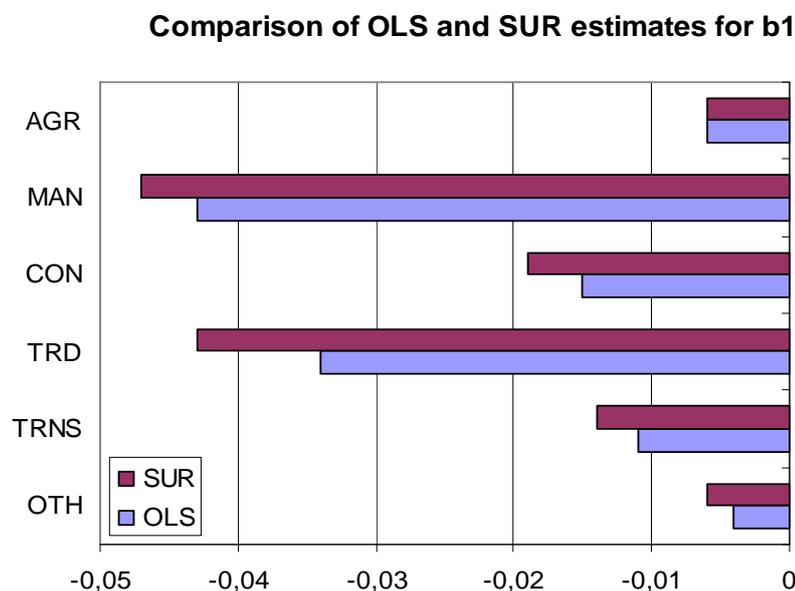
The estimated model of industry-specific default rates is in essence the same as Sorge and Virolainen (2006). It is only that we now allow for industry-specific output (output gap or output growth rate) to affect the corresponding industry-specific default rate and use industry-specific real interest rates which reflect industry-specific inflation rates. The level of indebtedness is also industry-specific. Thus, the estimated equation is of the following form

$$d_{it} = \beta_0 + \beta_1 y_{it} + \beta_2 r_{it} + \beta_3 l_{it} + u_{it} \quad (2.1)$$

where d_i denotes the default rate in industry i (agriculture, construction, manufacturing, trade, transportation and other services), y private sector output (henceforth output, for simplicity), r the real interest rate and l the indebtedness level. The estimation period is 1987Q1–2007Q4. Estimation results for (2.1) for different output variables are reported in Table 2.1. In Figure 2.1 we compare the single-equation and the system form (SUR) estimation results in the case of the basic specification where output gap is the output variable. In Table 2.2, we report diagnostic test results for this basic specification.

Figure 2.1

**Comparison of OLS and SUR estimates
of output gap for different sectors**



The default rate model (2.1) provides us with the basis for evaluating the impact of macroeconomic shocks on corporate defaults and further on banks' loan losses. To obtain empirical counterparts for the macro shocks we use alternative specifications. To begin with, we follow Sorge and Virolainen (2006) and estimate an AR(2) process for y , r and l to filter out the shocks as the residuals of the AR(2)s. Alternatively, we use a simple random walk representation for the time series of these variables. On the basis of the estimated shocks we can compute the variance-covariance matrix of the macroeconomic shocks that is needed in sampling defaults and thus loan losses from the firm level micro data.

In order to carry out the sampling procedure properly; that is, to ensure that default rates are between 0 and 1, a logistic transformation is needed for the default rate $p = 1/(1+\exp(d))$ in estimating and simulating the model (see Sorge and Virolainen, 2006). These values can then be conveniently transformed to original default rates by using the log transformation $d = \ln((1-p)/p)$.

When using Monte-Carlo methods in simulating the impact of macroeconomic shocks on loan losses we use the assumption that all random elements are normally distributed. The expected values of the macroeconomic shocks are assumed to be zero in the basic scenarios. When dealing with the depression scenarios in section 4.2, however, we change this assumption by introducing systematically negative values for output growth or, correspondingly, more positive values for real interest rates and aggregate corporate indebtedness.

In the Monte-Carlo simulation, the first step was a Cholesky transformation of the variance-covariance matrix of the stochastic terms. Although correlations

between these terms were not overly high ordering of variables (shocks) turned out to be important (see section 4.3).

Table 2.1 **Estimation results of the basic default rate model for the various industries as well as for all industries**

	Agr	Man	Con	Trd	Trns	Oth	Tot
Constant	0,002	0,000	0,003	0,001	0,002	0,001	0,000
t-value	(4.05)	(0.31)	(16.87)	(4.78)	(11.59)	(0.90)	(0.94)
total output gap	-0,008	-0,043	-0,015	-0,034	-0,011	-0,004	-0,032
t-value	(2.99)	(6.91)	(3.61)	(6.05)	(3.41)	(0.55)	(6.07)
Interest rate (real)	0,000	0,000	0,000	0,000	0,000	0,001	0,000
t-value	(0.16)	(0.20)	(1.16)	(1.41)	(0.26)	(10.71)	(0.47)
Debt	-0,025	0,210	0,099	0,141	0,005	0,096	0,235
t-value	(1.99)	(19.916)	(13.710)	(18.577)	(0.320)	(0.973)	(9.668)
R2	0,121	0,891	0,856	0,929	0,175	0,809	0,873
SEE	0,425	1,082	0,670	0,781	0,533	1,092	0,789
DW	2,020	1,308	1,451	1,141	1,497	0,982	0,495
Constant	0,002	0,000	0,003	0,002	0,002	0,001	..
t-value	(2.98)	(0.58)	(15.84)	(5.78)	(11.21)	(0.87)	..
industry-specific output gap	0,000	-0,021	-0,004	-0,027	-0,011	-0,004	..
t-value	(0.01)	(5.09)	(2.60)	(9.42)	(3.92)	(0.35)	..
Interest rate (real)	0,000	0,000	0,000	0,000	0,000	0,001	..
t-value	(0.71)	(0.48)	(2.56)	(0.76)	(0.15)	(10.92)	..
Debt	-0,014	0,209	0,097	0,119	0,006	0,098	..
t-value	(1.05)	(18.35)	(12.06)	(13.31)	(0.30)	(0.99)	..
R2	0,017	0,878	0,844	0,882	0,185	0,808	..
SEE	0,446	1,152	0,696	0,975	0,562	1,093	..
DW	1,816	0,999	1,315	0,828	1,395	0,997	..
Constant	0,002	0,001	0,003	0,001	0,002	0,002	0,000
t-value	(3.11)	(1.34)	(13.80)	(1.79)	(6.72)	(1.24)	(0.32)
growth rate of total output	-0,001	-0,018	-0,009	0,006	0,000	-0,005	-0,007
t-value	(0.45)	(2.92)	(2.75)	(1.33)	(0.11)	(0.91)	(1.30)
Interest rate (real)	0,000	0,000	0,000	0,000	0,000	0,001	0,000
t-value	(0.40)	(0.16)	(0.22)	(0.33)	(0.25)	(11.72)	(0.48)
Debt	-0,014	0,194	0,100	0,167	0,007	0,040	0,214
t-value	(1.11)	(12.89)	(13.35)	(14.82)	(0.28)	(0.34)	(6.38)
R2	0,020	0,851	0,846	0,893	0,009	0,810	0,719
SEE	0,446	1,273	0,692	0,961	0,620	1,088	1,158
DW	1,821	0,910	1,304	0,819	1,093	1,025	0,222

Agr = agriculture, Man = manufacturing, Con = construction, Trd = Trade, Trns = transportation, Oth = Others, and Tot = All industries.

When testing the coefficient restriction that the coefficients are equal for all sectors, the F statistics turns out to be 6,03 which is significant at all conventional significance levels. When comparing, the explanatory power of the sum of squares of the latter system turned out to 16 per cent larger.

Table 2.2

Diagnostic tests

	Agr	Man	Con	Trd	Trns	Oth	Tot
Correlogram squared residuals	7,700	2,254	0,914	4,361	2,530	7,710	13,131
Prob	(0.103)	(0.689)	(0.923)	(0.359)	(0.639)	(0.103)	(0.011)
Serial Correlation LM test	0,546	6,045	3,959	5,140	4,041	8,024	25,530
Prob	(0.702)	(0.000)	(0.006)	(0.001)	(0.006)	(0.000)	(0.000)
Normality test (Jarque Bera)	0,491	15,513	1,204	1,834	1,494	3,795	0,546
Prob	(0.782)	(0.000)	(0.548)	(0.400)	(0.474)	(0.150)	(0.761)
Heteroscedasticity test (BPG)	1,477	3,724	3,157	7,585	0,925	0,800	3,183
Prob	(0.228)	(0.015)	(0.030)	(0.000)	(0.433)	(0.498)	(0.029)
White	1,548	2,130	1,472	4,035	0,509	2,071	2,286
Prob	(0.220)	(0.039)	(0.177)	(0.000)	(0.862)	(0.045)	(0.027)
Chow test (1999Q1)	0,444	2,920	2,159	4,769	6,834	13,344	14,062
Prob	(0.643)	(0.027)	(0.083)	(0.002)	(0.000)	(0.000)	(0.000)
Quandt-Andrews test	1,007	5,650	3,165	5,548	6,090	9,743	17,140
Prob	(0.778)	(0.165)	(0.613)	(0.176)	(0.126)	(0.011)	(0.000)
Chow forecast test (2003Q1)	1,440	0,468	1,244	0,730	1,024	2,084	2,935
Prob	(0.145)	(0.967)	(0.259)	(0.775)	(0.454)	(0.018)	(0.001)
Ramsey RESET test	1,380	2,855	3,335	2,023	5,911	4,667	3,320
Prob	(0.258)	(0.064)	(0.041)	(0.141)	(0.004)	(0.013)	(0.042)
CUSUM	+	+	+	+	+	-	-
CUSUM ²	+	-	+	-	+	-	-
Recursive coefficient of GDP	+	+	+	+	+	-	+

Agr = agriculture, Man = manufacturing, Con = construction, Trd = Trade, Trns = transportation, Oth = Others, and Tot = All industries.

Cusum (+) means that the assumption of coefficient stability cannot be rejected. Accordingly, recursive coefficient (+) means that the coefficient of output gaps seems to be stable over time.

3 Estimation results

In this section we comment on our estimation results presented in Table 2.1. To start with, the model fits the data on industry-specific default rates reasonably well. Only in the case of agriculture, and to some extent, other services, there are some problems. Thus, in the case of default rates in agriculture we are not able to obtain coefficients of the correct sign for the real interest rate and indebtedness. We suspect that this failure reflects some data problems: it is quite difficult to distinguish family (household) farming and firm-type farming.³ ‘Other industries’ is also a bit difficult because it really represent a mix of various activities. It is thus no big surprise to us that the main diagnostic problems, related to stability,

³ For the simulation analysis, we changed the equation for agriculture by setting the coefficients of incorrect signs equal to zero and re-estimating the equations with this/these restriction(s).

appear in this sector. Even so, the coefficient estimates make sense as well as the simulation results in the next section.

Interestingly, one may notice that the data quite strongly favours the disaggregated model. When we just focus on the aggregate default rate model (titled ‘TOT’ in the last column of Table 2.1) and use the corresponding aggregate equation several diagnostic problems arise. In particular, the stability properties of the aggregate equation seem dubious (see Table 2.2). Moreover, the explanatory power seems to suffer from aggregation, though not dramatically.

One may go deeper in the disaggregated structure by using industry-specific output instead of aggregate output in explaining each industry-specific default rate (the second block in Table 2.1) but it appears that the gain is not significant (in either direction). This notion is confirmed when we carry out the loan-loss simulations in the next session and see that essentially the same results are obtained for both aggregate output and industry-specific output. Obviously, industry-specific output model is required when we want to examine the role of sector-specific shocks (see section 4.3). Finally, we may note that the output measure of the basic specification, the Hodrick-Prescott measure of output gap, performs much better than just the output growth. Hence, we hold to this measure.

The models are first estimated with basic OLS which may be subject to certain well-known pitfalls. First of all, the right-hand side variables may depend on the default rates creating a classical simultaneity problem. The problem is particularly relevant for output, not so much for interest rates or indebtedness because these variables have been lagged in the final estimation specification. As for output, corporate failures probably affect output by destroying productive capacity and firm-specific human capital. The bias is probably smaller when we use aggregate output instead of industry-specific output but it is hard to say more on the magnitude of this bias without proper instruments. In one of our loan loss simulations, we allow for a simple feedback mechanism, meant to capture the effect of defaults on output. Another problem with OLS estimation is related to correlation of residuals of equations for different industries. To see the effect, we have used the more efficient SUR estimator instead of OLS (see Figure 2.1). Overall, differences in the estimated coefficients do not appear to be very big so that we may as well use the OLS estimated coefficients in the simulation exercise of section 4. This choice is also supported by the notion that the data for agriculture may contain some deficiencies that could in the SUR estimation contaminate parameter estimates of other sectors’ equations. The important message of Figure 2.1 is perhaps not the fact that the two estimators produce similar estimates but the fact that the coefficients for different sectors are indeed very different and hence it seems necessary to have a disaggregated model when evaluating loan loss risks with simulations.

To sum up results from diagnostic tests, it seems that the basic model for industry-specific default rates passes muster rather well. In particular, we may

notice that the stability properties of the equations are rather good in spite of the huge changes in the default rates which have taken place in the early 1990's. This also shows up in recursive estimates of the coefficient of the output gap, although in the interest of brevity we do not report the results here.⁴

3.1 On estimating the endogenous LGD

It is well known that LGD is not a constant across defaulted loans, and that LGD tends to increase in economic downturns (see eg Schuermann, 2004, and the literature surveyed therein). We therefore relax the assumption of the basic model of a constant LGD and replace it with a time-varying annual LGD which is a function of the state of the business cycle, measured with output gap. In other words, we assume that the LGD is the same for all defaulted loans in a given year, but it can vary from year to year according to the business cycle. If the expected annual LGD equals the constant LGD of the basic model, then we should expect a fatter tail to the loan loss distribution, given that both PDs and the annual LGD are decreasing functions of the output gap.

Because we do not have data from Finland on individual loans' loss given default, we have estimated the annual average LGD from aggregate data by using a method based on random sampling. We make use of the following equality in which we assume that LGD is a constant in a given year t

$$\begin{aligned}
 \text{Total loan losses}_t &= \sum_i^{N_t} D_i l_{i,t} \text{LGD}_t \\
 &= \text{LGD}_t \sum_i^{N_t} D_i l_{i,t} \sum_{i=1}^{N_t} D_i l_{i,t} \text{LGD}_t \\
 &= \text{LGD}_t \sum_{i=1}^{N_t} D_i l_{i,t}
 \end{aligned} \tag{3.1}$$

where D equals one if firm i is in default, zero otherwise, and where l denotes the amount of firm i 's loans. N is the total number of firms. In other words, total loan losses in year t simply equal the sum of loans of bankrupt firms in that year, multiplied by the common LGD in that year. We have data on annual total loan losses, the number of defaulted companies in each year and the loan size distribution across companies. In order to estimate the LGD_t for each year, we

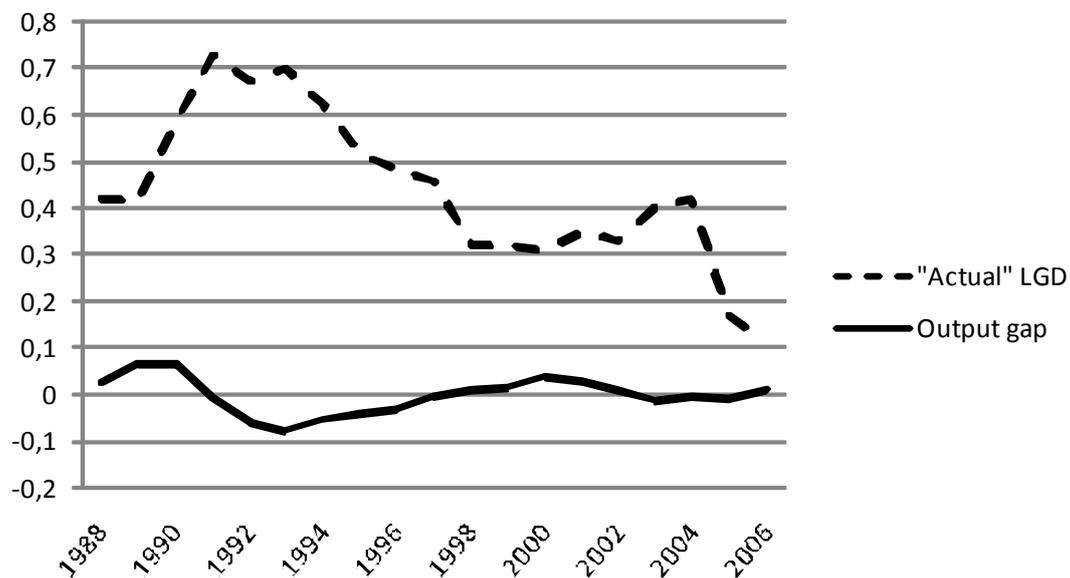
⁴ This result seems to be in striking contrast with some preliminary estimation results with the model for aggregate loan losses. Thus, if loan losses are explained by the aggregate default rate (d) the explanatory power is reasonably high (0.93) but the RESET test clearly suggests that the functional form is mis-specified ($F(2,76) = 43.54$). The relationship seems to be very strongly nonlinear which also shows up in the fact that if the second and third powers of d are introduced as additional explanatory variables the R^2 goes up to 0.97.

draw random samples of size k_t out of the annual population of N_t firms such that k_t is the number of defaulted firms in that year. For each round of sampling, the LGD_t which equates (3.1) is computed. After a sufficient number of random samples, we obtain a distribution of LGD_t s. The mean of this distribution is then used as our final estimate of the LGD_t . To our knowledge, this type of method has not been previously used in empirical studies on LGD and it might be interesting to explore it further in future work.⁵

Figure 3.1 depicts the estimated ‘actual’ annual LGD series against the output gap, and provides in the legend the results of regressing the ‘actual’ LGD on the output gap. This model is then used to endogenize the LGD in our loan loss simulations. We find that during the sample period the annual estimated LGD ranges between 12% (in 2006) and 73% (in 1991), the average being 47%, which is well in line with, say, the 45% reference point used in Basel II.

Figure 3.1

The estimated annual average LGD (‘Actual’ LGD) against the output gap. The regression of the ‘Actual’ LGD on the output gap obtains the following parameter estimates: ‘Actual’ $LGD_t = 0.43 - 2.03 * \text{Output gap}$. The significance level of the coefficient on the Output gap is 0.044% and the R2 of the regression is 22%.



⁵ Further details of the LGD estimation procedure are available from the authors upon request.

4 Simulation results

As Sorge and Virolainen (2006) describe, the macro based empirical model for industry-specific default rates can be used to simulate loan losses. Here we give just a brief account of the procedure and refer the reader to Sorge and Virolainen (2006) for further details. We take a representative bank loan portfolio of the Finnish corporate sector and group the included companies according to their industry. In the absence of firm-specific balance sheet data, each company in each period of the simulation is then assigned the default rate of its industry, obtained from the default rate model. An independent binary random draw is then carried out for each company to determine whether it survives or defaults in a given simulation period. If a company defaults, a share of its outstanding credit, determined by the LGD, either constant or endogenous, is taken as a loss. The multi-period simulation procedure keeps track of defaulted firms in the portfolio so that each company can only default once during the simulation horizon. Individual firms' credit losses are then summed to obtain the aggregate cumulative bank loan losses of the corporate sector at the end of the simulation horizon.

As to the representative bank loan portfolio of the Finnish corporate sector, Sorge and Virolainen (2006) used data of the 3000 biggest Finnish companies from the year 2002.⁶ Together these companies accounted for more than 90 per cent of the total loans granted by MFIs (henceforth banks, for brevity) to the corporate sector that year. Unfortunately, it has not been possible to us, due to its non-public status, to update or extend further back into the history the portfolio data used in Sorge and Virolainen (2006). However, we have had access to a more limited data source of the 500 biggest companies in Finland which, on the other hand, does not provide the division of corporate credit into bank loans and other credit.⁷ Simulation experiments with this alternative data set indicated that changes in the loan size distribution across companies have only minor effects on the resulting loan loss distributions in our modelling framework. Therefore, our final choice was to use the portfolio composition in Sorge and Virolainen (2006) as the representative corporate loan portfolio throughout the entire sample period.

⁶ Data also includes some information from 2003.

⁷ The data source is Talouselämä 500.

4.1 Loan loss distributions with extensions to the basic model

Our first set of simulation results compares the basic model of Sorge and Virolainen (2006) with the various extensions we have considered: 1) the endogenous LGD, 2) industry-specific output shocks, and 3) two alternative shock specifications; the standard AR(2) case used by Sorge and Virolainen (2006) and a random walk. These extensions are grouped in Table 4.1 in the following way. The two alternative shock specifications (cases a and c) and the case of industry-specific shocks (b) are each run with both a constant and an endogenous LGD. Hence a total of six cases are considered. The case with the aggregate output shock, modelled with AR(2), and constant LGD, corresponds to the case considered by Sorge and Virolainen (2006). In each case we have computed three descriptive statistics of the simulated loan loss distribution three years ahead, starting at the beginning of 2008: the expected loss and the unexpected loss at both 99 and 99.9 per cent confidence (or ‘value-at-risk’) level. The expected endogenous LGD is always adjusted (approximately) to the same level as the constant LGD so that the most interesting case of how endogenous LGD affects the ‘tail’ of the loan loss distribution can be considered. The number of simulation rounds in each case is fifty thousand (50 000).⁸

⁸ This may still leave room for some inaccuracy stemming from the finite number of simulation rounds so that some caution is in order when interpreting particularly the unexpected loss figures at the far end of the loan loss distribution.

Table 4.1

Summary of simulations

			<i>Expected loss</i>	<i>Unexpected loss (VaR 99%)</i>	<i>Unexpected loss (VaR 99.9%)</i>
a) Aggregate output					
AR(2)		LGD = 0.43	1.72	2.56	3.69
		LGD endogenous LGD min/mean/max = 0.26/ 0.43/ 0.59	1.74	2.69	3.97
b) Industry-specific output					
AR(2)		LGD = 0.43	1.73	2.56	3.73
		LGD endogenous LGD min/mean/max = 0.25/ 0.43/ 0.60	1.75	2.67	3.91
c) Aggregate output					
RW		LGD=0.43	1.59	2.51	3.78
		LGD endogenous LGD min/mean/max = 0.18/ 0.43/ 0.70	1.61	2.67	3.85

In a) the (weighted) aggregate PD is 0.0033, in b) 0.0034 and in c) 0.0031. Simulation horizon is 3 years starting at the beginning of 2008.

When examining the results in Table 4.1 we first note that, overall, differences in magnitude between the various cases are not very big. However, as expected, the endogenous LGD clearly has an effect of widening the loan loss distribution. This is manifested as higher unexpected losses. In the base case model (a) with aggregate output and AR(2) shocks, the endogenous LGD increases the 99% and the 99.9% unexpected losses by 5–8%. Similarly, in cases (b) and (c) the endogenous LGD increases the unexpected losses. One reason that the effect of the endogenous LGD is not very big is that the explanatory power of the LGD-output regression model is ‘only’ 22% (see Figure 3.1). In actuality, further experiments with the LGD-model revealed that a much higher coefficient on output and thus a much higher explanatory power is achieved if we use the first lead of the output as the explanatory variable. Such a lead structure may be understood as resulting from, say, certain loan loss accounting conventions but it is problematic to implement in the loan loss simulation model. Therefore we have held to the original LGD-output specification in the simulations. However, should one want to experiment with loan loss simulations using the higher coefficient on output in the LGD model, the resulting widening of the loan loss distribution would naturally be more pronounced.

When we make a comparison across the cases (a), (b) and (c), either with the constant LGD or the endogenous LGD, we see that the unexpected losses stay roughly at the same level for the different model versions. The highest 99.9% unexpected loss (the unexpected loss being 3.97% of the loan stock) is obtained for the base case model (a) with endogenous LGD. One may conclude from these results that it seems to matter less whether we use industry-specific or aggregate output shocks or how the shock processes are specified. What does matter is that we replace the constant LGD with the endogenous LGD. We also investigated the effect on the loan loss distribution of increasing the standard deviation of a shock (in this case the output shock). As we expected, unexpected losses increased correspondingly in a roughly linear manner.

4.2 Prolonged recession and simultaneous shocks

After the analysis of unconditional loan loss distributions we wish to study the impact on loan losses of a prolonged deep recession. Figure 4.2 illustrates the results of this exercise. The main message is that, if a constant negative shock to output persists over several periods (up to 5 years), the cumulative impact on expected loan losses is significantly convex. Roughly speaking, if cumulative expected losses are 1% of the loan stock at the end of the first year, they are more than 10% at the end of the fifth year, while a linear extrapolation would suggest cumulative expected losses of 5% (see Figure 4.2). Figure 4.2 further compares the base case with a case in which we have added a simplistic feedback mechanism from defaults to output; GDP is decreased at a constant quarterly rate which is thought to correspond to the loss of productive capacity of the corporate sector as a result of cumulating defaults. Clearly, the convex impact on the expected losses of the prolonged recession is reinforced. The convex effect is probably at least partially the result of the fact that the indebtedness increases as output decreases because output affects directly the denominator in the indebtedness variable. The policy implication of these simulation results would appear to be that long-lasting shocks causing an economic downturn should be dealt with at an early stage before they develop into prolonged recession.

Figure 4.1

Distribution of loan losses (fixed LGD)

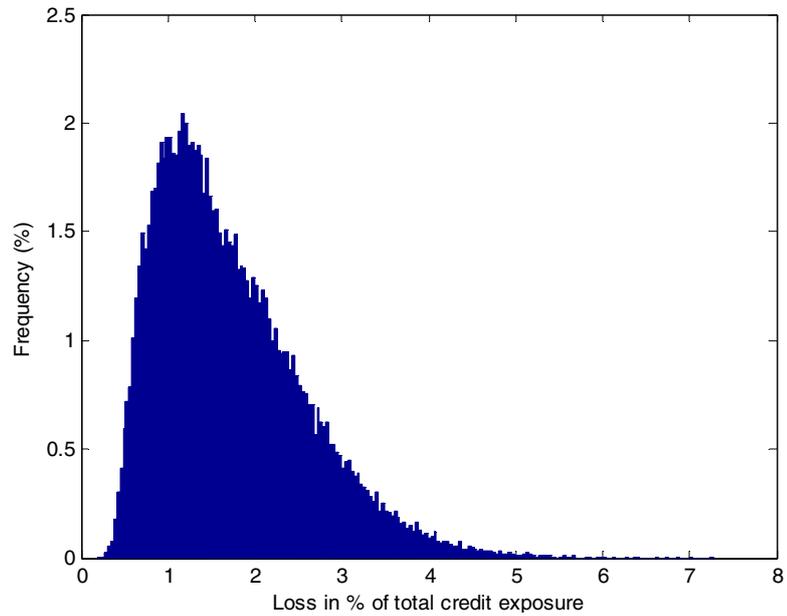
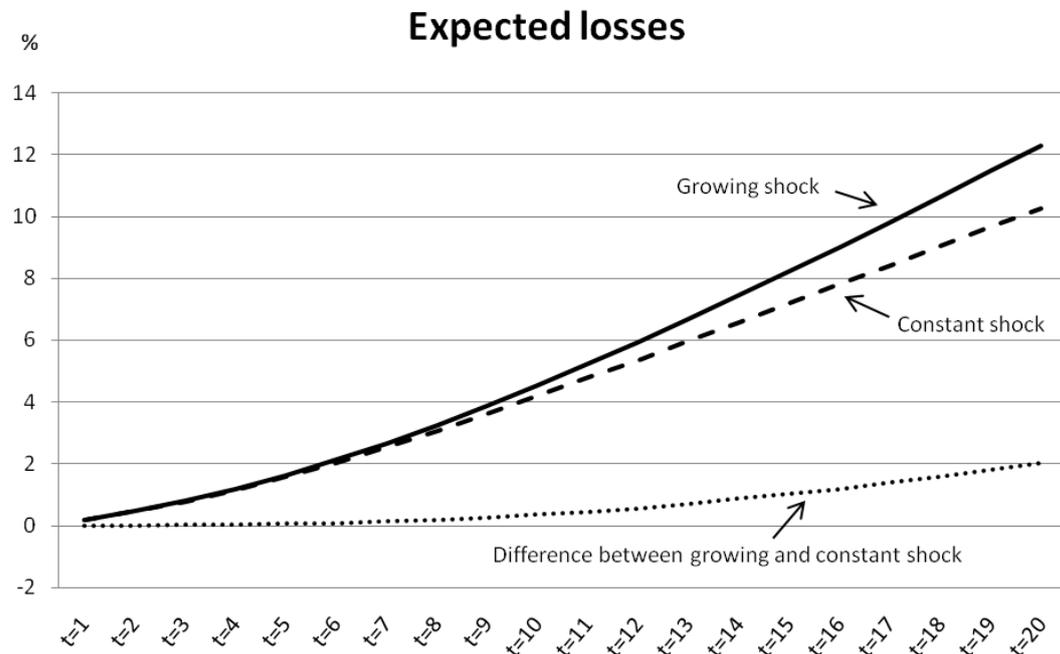


Figure 4.2

**Expected losses and the length of depression:
feedback from defaults to output**

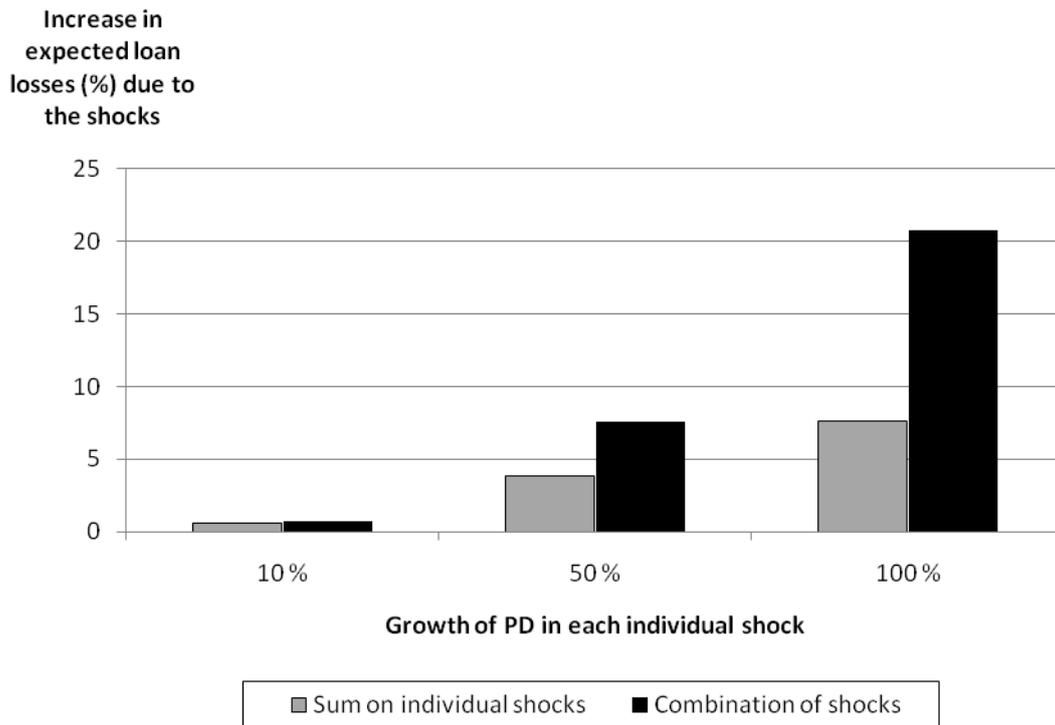


Feedback means here that GDP is decreased at a constant quarterly rate which is thought to correspond to the loss of productive capacity (firms) along with prolongment of depression.

In Figure 4.3 we illustrate another important effect related to simultaneity of shocks. In other words, the question is whether it makes a difference whether shocks that are known to increase loan losses take place simultaneously or whether they happen one at a time. In order to study this question in a meaningful manner we have first chosen shocks to output, real interest rate and the corporate sector indebtedness in such a way that each individual shock alone would produce an equal size increase in the weighted average of the industry-specific PDs. We then make the following comparison. We run our basic model of loan losses separately with each individual shock and take the sum over the three model runs of the increase in the aggregate expected loan loss. This sum of expected losses is then compared to a single run of the basic model in which all the three previous shocks take place simultaneously. This comparison is depicted in Figure 4.3 for three different shock sizes, corresponding to a 10, 50 and 100 per cent increase in the PD. Clearly the combined effect is much larger. This result obviously reflects the correlations between individual shocks. This analysis may also provide one way to better understand what happened in the Finnish crisis of the early 1990's and how the situation is different from today's perspective. In the early 90's, clearly a combination of shocks hit Finland: output dropped as a result of a big export shock, effective indebtedness increased dramatically as a result of the devaluation of the currency, and interest rates sky-rocketed. In contrast, today's conditions seem essentially less severe as corporate indebtedness remains moderate and interest rates are low, making the Finnish banking sector better prepared to weather the negative export demand shock resulting from the 2007–2008 global crisis.

Figure 4.3

Comparison of effects of macro shocks



Sum of individual shocks denotes the sum of differences between the simulated values and the base in terms of the expected losses due to the three macro shocks (of equal size in terms of the PD). Combination of shocks denotes the analogous difference in expected loss due to a simultaneous occurrence of these three macro shocks (all of equal size).

4.3 Effect on loan loss risk of an industrial cluster

When assessing the risk of aggregate loan losses in an economy, we also like to draw attention to the fact that particularly in many small economies single industrial clusters or even individual companies can make a sizeable portion of total output. Finland is a good example of such a situation as the ICT and forestry-related industrial clusters are central to the economy. If such clusters which operate globally make decisions to move their production to other countries, it is in principle possible to have large output effects within a relatively short time period. Although such moves in themselves would not necessarily induce any credit risks to materialize, the second-round effect via overall decline in output could entail increasing loan losses as our empirical model would suggest.

For the purpose of loan loss scenario analysis it may be wise to consider such shifts in production and output as separate risk events because the probability of such events may not be properly captured on the basis of historical output fluctuations. In the following we consider the effect on loan losses that a single industrial cluster, the ICT cluster in Finland, could have. To this end, the version

of our empirical model with industry-specific output, discussed in section 4.1, is quite useful. We first assess how the ICT cluster affects output in the respective industry (manufacturing). The shock then spreads to other industries, having an effect on their respective outputs, through the model's shock correlation structure. For simplicity, we consider an extreme scenario of the Finnish economy with an exit of the ICT cluster. Because the ICT cluster makes up ca. 22% of the manufacturing industry in Finland, we consider a 22% cumulative negative output shock to the manufacturing industry that would take place over the three-year horizon; our standard simulation horizon in this study.⁹ Such a shock turns out to have the largest spillover effect on output in construction and trade industries as well as in agriculture and other services industry in each of which output falls by about 7%. The effect on aggregate loan loss distribution is that the expected loss is 3.22% while the 99% and 99.9% unexpected losses are at 4.01% and 5.85%, respectively. As we have used the model version with endogenous LGD, these numbers should be compared, respectively, to 1.75%, 2.67% and 3.91% from Table 4.1, section b), second line. Thus the ICT cluster shock almost doubles the expected aggregate loan losses relative to the unconditional expected losses. The size of the effect on loan losses suggests that the type of approach to stress testing taken in this subsection may be important. Lastly, as already discussed in section 2, when modeling an output shock which originates from a certain industry and then spills over to the rest of the economy, this has to be taken into account by setting the original shock as the first one in the matrix of the Cholesky decomposition. Our experiments showed that ignoring the proper order of shocks may greatly bias the results downwards.

4.4 Empirical fit of the loan loss model

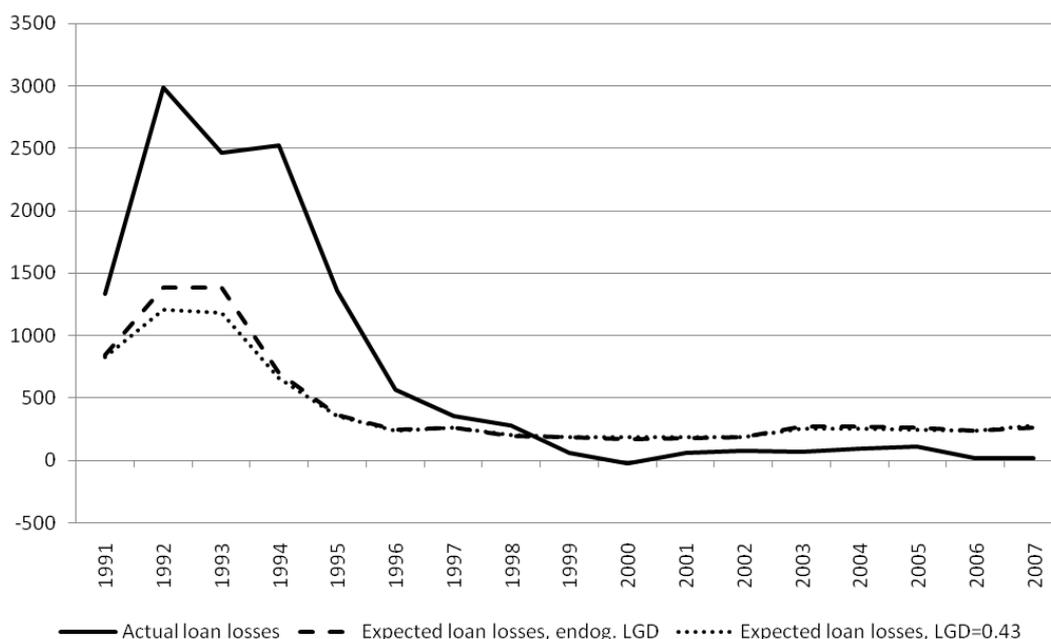
Because the Finnish loan loss experience of the first half of the 1990's is so extraordinary, it is very tempting to try to get at least a rough idea of how well the current macro based model could capture that episode. As already discussed in the beginning of this section we effectively assume that the individual loan size distribution of the aggregate bank loan portfolio has stayed invariant.

The results are depicted in Figure 4.4. Although the model can follow the overall profile of the aggregate loan losses, it exaggerates loan losses in normal times and falls greatly short of them in the 1990's crisis years. This was partly to be expected: although our default rates model fits quite well to actual default rates (cf. the high R^2 s mostly in the range of 80% to 90% in Table 2.1), the fluctuations in the aggregate loan losses are larger than in the aggregate default rate, as shown

⁹ For an alternative way of quantifying the output contribution of the Finnish ICT cluster, see Ali-Yrkkö et al (2000).

in Figure 1.2. The endogenous LGD explains part of the gap, as expected, but not much in relation to the size of the gap. One possible explanation for the remaining gap is that the effects of the large devaluation of the Finnish currency during the crisis are not fully controlled for in the calculation of loan losses. Namely, a number of non-exporting companies had taken foreign currency denominated loans from Finnish banks (cf. the recent experience in Iceland). As a result of the devaluation the nominal value of these loans rose in terms of the domestic currency. Unfortunately we do not have sufficiently disaggregated data to control for these effects. A second potential explanation is that during the Finnish crisis, many big export-oriented companies went bankrupt. Obviously, their relative weight is not sufficiently reflected in the industry-specific default rates we have used. For instance, given that the almost over-night collapse of trade with the Soviet Union was a central reason for the Finnish crisis (see eg Gorodnichenko et al, 2009), we should have data on firm-level exposures to the Soviet trade to have a more disaggregated model of defaults and hence to better capture the actual loan loss behaviour. Clearly, back then the collapse of the Soviet Union was a big unexpected event and, with hindsight, a big single risk factor to the Finnish economy. In the same vein as we argued in section 4.3, macro based credit risk models might benefit from trying to incorporate single risk factors related to single institutions, markets or products which form a sizable part of the economy and which are vulnerable to discrete events that might dramatically change their role in the economy.

Figure 4.4 **Fit of the constant LGD and the endogenous LGD loan loss model**



4.5 Loan loss distribution: 2008 vs pre-1990's crisis

Finally, it is tempting to make a comparison between the loan loss risk outlook prior to the Finnish crisis in the early 1990's and today. Again, we simply use the sample portfolio from 2002 as a proxy for the portfolio prevailing prior to the 1990's crisis.

In particular, we considered the state of the banking sector at the end of 1989 and took the starting values for the macro variables from the first and the second quarter of 1990. With the basic constant LGD version of the model, the expected loss and the 99% and 99.9% unexpected loss, respectively, were 3.65, 3.53 and 4.95. These results can then be compared with the more recent situation as of the end of 2007. In Table 4.1, the corresponding numbers are 1.72, 2.53 and 3.58. In terms of the expected loss, we can see that the aggregate loan loss risk was more than two times bigger just before the 1990's crisis hit than it was at the end of 2007. The difference in risks is effectively a result of the different macroeconomic position then and now. Particularly the indebtedness of the corporate sector in Finland was much higher on the eve of the 1990's crisis than it is now. Total corporate sector indebtedness in the second quarter of 1990 was almost double and the indebtedness of the manufacturing industry alone was almost three-times the respective indebtedness in the second quarter of 2008. In general, these results emphasize the role played by the prevailing macroeconomic conditions in assessing risks of future loan losses.

It is tempting to speculate with what might have been done differently, had the awareness of the size of the aggregate credit risk been better at the end of the 1980's. Clearly, knowledge and use of the current type of credit risk portfolio models started their international proliferation only in the latter half of the 1990's. Of course, the crisis of the 2007–2008 has revealed severe inadequacies also in the current credit risk models. Nevertheless, the comparison for Finland that we have carried out here by using the current modeling framework is justified on the basis that for Finland the current crisis came almost entirely as an external (export-driven) shock. The Finnish banking sector was not much affected by the contagion in the global banking sector.

5 Concluding remarks

This study has illustrated how macroeconomic shocks affect banks' loan losses from the corporate sector by revisiting and extending the model of Sorge and Virolainen (2006). In the base model, the central macroeconomic factors that drive industry-specific default rates and hence loan losses are the output gap, the real interest rate and the corporate sector indebtedness. The empirical model for default rates is then used in simulating the aggregate loan loss distribution.

We have considered the following extensions to the base model and have studied their effect on the loan loss distribution. First, instead of aggregate output we considered industry-specific outputs; second, we relaxed the constant LGD assumption used in the simulations and make LGD depend on the output gap; and third, we considered alternative ways of specifying shocks to the explanatory macro variables. It turned out that in terms of the loan loss distribution; mainly the endogenized LGD had a material impact. We also showed that disaggregation significantly improves the properties, including stability properties, of the model but it does not have a significant quantitative impact on the loan loss simulation results. Moreover, the model with industry-specific outputs is useful when we consider the potential second-round effects on the aggregate loan loss risk of a single industrial cluster, particularly the ICT cluster which is quite central to the Finnish economy. We also considered the empirical fit of the model based expected loan losses with actual loan losses and found that although the endogenous LGD improves the fit, the model nevertheless falls short of explaining the large loan losses experienced in the early 1990's crisis in Finland. Identifying the missing risk factors that could explain the gap remains an issue for future research.

We also emphasize that the severity of a crisis, in terms of mounting loan losses, may very much depend on the exact nature of the crisis. That is, the combination of simultaneous macroeconomic shocks as well as the duration of these shocks may be important. We have studied these issues with the help of scenario based analyses. We found that prolonged deep recessions as well as a combination of simultaneous shocks both seem to have a convex effect on loan losses. This suggests that policy actions should be designed in a way that prevents acceleration of a looming crisis. Finally, a comparison of the loan loss distribution on the eve of the 1990's crisis with the most recent distribution demonstrated the greatly elevated risk level prior to the 1990's crisis. More generally, the comparison emphasizes the effect of prevailing macroeconomic conditions on potential future loan losses.

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