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Macro stress testing with sector specific bankruptcy models

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(Makro stressz teszt ágazat-specifikus csődráta modellekkel)

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Contents

Abstract

This paper employs the methodology of Wilson (1997) on Hungarian data to conduct a macro stress test in relation to banks' corporate loan portfolio. First, sector specific models of bankruptcy are estimated, where the bankruptcy frequency is linked to the general health of the economy. Data on bankruptcy filings in Hungary between 1995 and 2005 are used. Then, after identifying relevant shocks, the estimated models are employed in Monte Carlo simulation to conduct a stress test on the Hungarian banking sector. Various loss measures are defined to quantify the impact of shocks and evaluate the resilience of the Hungarian banking sector. The sensitivity of the stress test results to the endogeneity of LGD and the prevailing macro environment are also examined.

JEL: C32, G21, G33.
Keywords: credit risk, bankruptcy, macro stress testing.

Összefoglalás

A tanulmány Wilson(1997) módszertanára építve végez stressz teszteket a magyar bankok vállalati hitelportfolióján. Először ágazat-specifikus csődmodelleket becslünk, ahol a csőd gyakoriságát a gazdaság általános állapotát leíró makro változókkal magyarázzuk. Az elemzéshez az 1995 és 2005 között benyújtott csőd- és felszámolási eljárások adatait használjuk fel. Majd azonosítjuk a hazai bankszektor számára releváns sokkokat. E sokkok hatásának számszerűsítéséhez Monte Carlo szimulációt végzünk a becsült csődráta modellek segítségével. A sokkok okozta veszteségek azonosításához több mutatót is definiálunk. Ezen túlmenően megvizsgáljuk, hogy érzékenyek-e a stressz teszt eredményei arra, hogy aggregált vagy ágazat specifikus modellekkel dolgozunk; hogy az LGD-t állandónak vagy endogénnek tekintjük; és arra hogy mennyire kedvező a makro környezet induló állapota.

1. Introduction

For assuring financial stability the assessment of the banking sector's vulnerability as a whole is indispensable. One method of identifying potential vulnerabilities is through stress testing the system – observing how it would operate under abnormal (extreme but plausible) conditions. Stress testing is a risk management tool originally developed by commercial banks to assess how their portfolio values would react to a sudden crisis situation. This method, however, can also be applied to entire financial systems to reveal which systemic factor might be a source of vulnerabilities and how resilient the banking sector is to relevant macro shocks. Typically stress tests are run by risk types (market risk, credit risk, liquidity risk, etc.). This paper focuses on the credit risk assumed in the corporate loan portfolio of Hungarian banks. As credit risk is still the major source of losses for banks, it is vital to have models which can explain what drives credit risk at a systemic level. There is a growing body of literature presenting evidence about the importance of the macro environment on credit risk assumed in banks' loan portfolio.

The key building blocks of stress tests are (1) the relevant macro shocks or scenarios; (2) models which link a measure of financial distress (and credit risk) to systemic risk factors; and (3) loss measures, used to assess the shock's impact on banks. The main contribution of this paper is twofold. First, we estimate sector specific bankruptcy models on Hungarian data (2nd building block). The bankruptcy models are not only useful in macro stress tests, they can be used in forecasting and commercial banks can utilise our results as well. Second, these credit risk models in turn are used to conduct a stress test on the Hungarian banking sector's corporate loan portfolio. The results of the macro stress tests can be built into the regular assessment of financial stability.

We seek answers on the following questions. Is there a link between bankruptcy frequency and the macro environment? How heterogeneous are various sectors with respect to this relationship? How resilient is the banking sector to relevant shocks? Is it straightforward what measures to use in assessing the impact of shocks? How sensitive are our results to various assumptions?

In this paper we follow the method proposed by Wilson (1997). His credit risk model links sectoral probability of defaults (PD) to systemic variables, which are modelled separately. This methodology allows one to capture two important dimensions of credit risk: its dependence on common, systemic risk factors (such as GDP and interest rates) and the specific features of the sectors. That is, different sectors have diverse sensitivity to macro variables and are exposed to sector specific shocks as well. Moreover, the methodology also allows one to take into account the correlation between sectors beyond the common exposure to systemic risk drivers (e.g. coming from direct links between sectors).

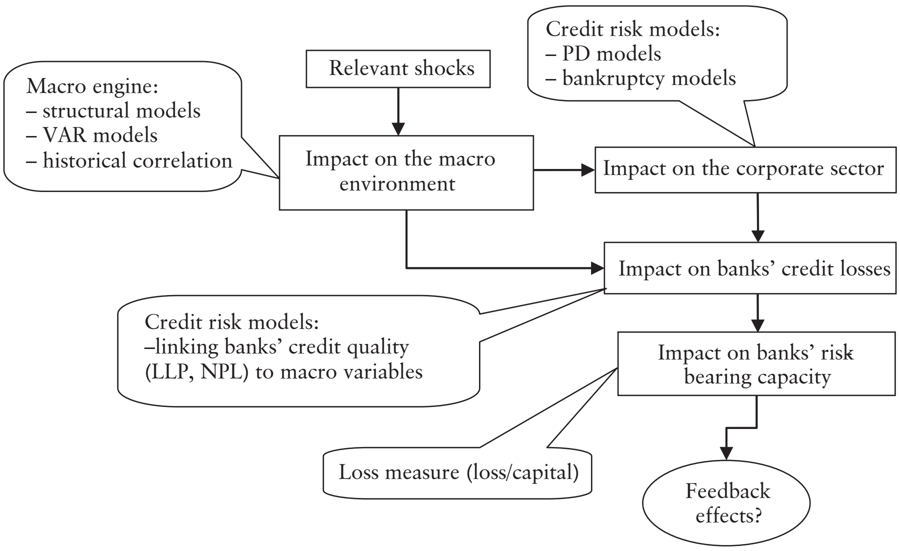
The paper is organised as follows. Section 2 reviews some of the relevant literature. Section 3 presents our methodology. In section 4 we describe our dataset, followed by the presentation of some stylised facts in section 5. Results from the estimation are discussed in section 6. The stress testing exercise is reported in section 7, and then we conclude.

2. Related literature

Sorge (2004) gives an excellent review on the methodology of stress testing.[1] Figure 1 displays the building blocks of macro stress testing for (the corporate) loan portfolio and the typical modelling approaches.

Figure 1

Framework of macro stress tests



The first step of stress testing is to identify the relevant shocks (e.g. demand shock, oil price increase), which then need to be translated into consistent macro scenarios with the help of a macro engine. This macro engine could be the macro-econometric model of the central bank used for monetary policy purposes, a VAR model, or simple historical correlations could be imposed. In the next step various credit risk models are used to calculate the impact of the macro scenarios on the financial sector. In the last step loss measures are identified and estimated (credit losses/capital), which are suitable for evaluating the impact of shock from a financial stability point of view.

The methodology of stress testing raises several issues – among the challenges we should mention are the problem of integrating credit and market risk stress tests, incorporating feedback effect, and dealing with the potential response of banks on shocks. Nevertheless, here we focus on issues in credit risk modelling, which are more relevant to our paper.

One of the major findings of the literature is that the macro environment, in particular the business cycle has a major impact on the credit risks banks are exposed to. In other words, credit risk is procyclical. In the **credit risk models developed by the banking industry** – for a detailed comparison see Crouhy et al. (2000) – this common exposure to the macro environment is captured in various, often implicit ways. In the KMV (Merton type) model common exposure comes from the correlation of firms' equity return. The transition matrix, used for example in CreditMetrics, can be made dependant on the business cycle. The new Basle 2 framework is based on a single factor model, assuming a latent systemic risk factor. The CreditPortfolioView (hereafter referred to as the Wilson model) was the first and only one in the 1990s which explicitly linked the (sector specific) PDs to the macro environment. However, having acknowledged the importance of macro variables, many of the models used by banks in either risk management or pricing have been recently enhanced by explicitly taking into account the impact of the macro environment (see, for example, Kamakura and KMV model developments).

[1] Those interested in more details or references, see the paper of Sorge.

In developing credit risk models, **central banks** have a primary focus on systemic risk, thus on the common exposure[2] to systemic risk drivers (business cycle, interest rate, exchange rates, etc.). As for empirical studies conducted at central banks, two basic approaches can be distinguished – see the 'Credit risk model' bubbles on Figure 1. (1) Either the relationship between **bank credit losses and the macro environment** is modelled directly. Here credit risk in banks' portfolio is usually measured by the ratio of non-performing loans or the loan loss provisioning (LLP) to total loans. This methodology is followed by, among others, Delgado-Saurina (2004), Gambera (2000), Quagliariello (2004) – they use the ratio of non-performing loans as a credit risk measure. Others, using the provisioning ratio (LLP/TL-t) are Kaliari-Scheicher (2002), Bikker-Metzemakers, Laeven-Majnoni (2002), Pain (2003) and Marcucci-Quagliariello (2006). Among the variables proved to be significant appear the business cycle, interest rate and the leverage of the corporate sector.

In the other branch of the literature (2) the **credit risk of borrowers** (individual companies, sectors or the entire corporate sector) is linked to the macro environment and other sector- or firm-level characteristics. This methodology often goes back to the models developed by the industry, obviously altering the methodology to cater for the special interest of central banks and to accommodate to data limitations. Credit risk of the company/or sector is often captured by the product of three parameters: E*PD*LGD. Where E is the exposure, PD is the probability of default and LGD is loss given default. The bulk of the literature focuses on the estimation of PD. Where no data on default is available (as in our case), the bankruptcy frequency is investigated instead. Several studies have proved that firm-level financial ratios (profitability, leverage, liquidity) have predictive power with respect to failure. This literature started with the seminal work of Altman (1968). Since then the literature has been enhanced by employing other econometric approaches – logit model is used for example in Ohlson (1980), Lennox (1999) and Hamerle et al. (2004); hazard models are employed in Shumway (1999) and Chava and Jarrow (2004). The most recent advances in this area highlight the importance of combining the micro and macro approaches – see the work of Carling et al. (2007). One of their major findings is that the model which uses only firm-specific characteristics is outperformed by the models which also condition on the macro environment. On the other hand, even when one intends to model aggregate default rate instead of firm-level probability of default, the best solution is again to combine the macro and micro approach – see Jacobson et al. (2005).

The method we chose to follow in this paper is the one suggested by Wilson (1997) as described in the next section. This paper and similar studies link financial distress of companies (mainly) to macro variables using bankruptcy data on individual sectors. As with the majority of the literature the focus is on estimating PD.[3]

Wilson's method has been applied by Boss (2002) to the Austrian banking sector, and Virolainen (2004) to Finland, as well as Misina et al. (2006) to the Canadian banks' corporate loan portfolio. All three of these studies investigate default or bankruptcy rates (as opposed to default probabilities used by Wilson), but while the latter two estimate sector specific models, Boss (2002) models aggregate default rates. Boss (2002), however, like Virolainen (2004), uses individual loan data for banks' exposures in contrast to Misina et al. (2006), who employ aggregate data. Boss (2002) stress tests his model using historically observed maximum changes in the macro indicators. He finds that expected losses within three years are up to 6 percentage points higher than in the baseline scenario, while the maximum loss, occurring with a probability of 99%, comes to 26.6% of banks own funds at the most. From this Boss concludes that the risk bearing capacity of the Austrian banking sector is adequate. Virolainen (2004) likewise finds that credit risks stemming from the Finnish corporate sector are modest after observing the response of loss distributions to GDP and interest rate shocks. Misina et al. (2006) also look at the effects of domestic and foreign (US in their case) GDP and interest rate shocks, and use loan-loss provisions to assess banks' ability to withstand these shocks.

The other risk measure, LGD, is rarely investigated in empirical works, due to the scarcity of information. The empirical findings are mostly based on observations on bond defaults, as in Schuerman (2004). He considers the impact on LGD of collateral, seniority of claim, industry, size and the business cycle. As to the last factor, he shows that the mean LGD in recession could be 10 percentage points larger than in boom. Turning to the theoretical developments in this field, in a very recent paper Kupiec (2007) developed a single factor risk model where not only PD but the LGD is made dependent on the systemic risk factor. The endogeneity of LGD hugely increases the skewness of the portfolio loss distribution and results in significantly larger capital estimates.

[2] Systemic risk has two major sources: common exposure and contagion – see De Bandt and Hartmann (2000). Here only the former is considered.

[3] Note that the existence and magnitude of feedback effects from the financial sector to the real economy cannot be investigated within this framework.

3. Methodology

As mentioned earlier, we rely on the methodology proposed by Wilson (1997a and 1997b), the so-called CreditPortfolioView, developed at McKinsey's. This was the first industry model which explicitly took macroeconomic variables into consideration when tracing the evolution of credit risk. This feature of the model makes it an ideal tool for macro oriented stress testing. The main idea behind the model is linking default probabilities to macroeconomic factors. In addition, it also recognises that the sensitivity of different sectors to aggregate shocks may differ. Once the model is estimated, it is used to simulate the evolution of default probabilities in response to shocks. In what follows we will briefly describe Wilson's methodology. For a more detailed description please refer to the above mentioned studies.

Wilson's (1997a and 1997b) model consists of the following steps. First the default probabilities are assumed to be a logistic function of an index *y:*

$$d_{i,t} = \frac{1}{1+\exp(y_{i,t})} \tag{1}$$

where $d_{i,t}$ is the default probability in sector i at time t and $y_{i,t}$ is a sector specific macroeconomic index. This logit transformation is necessary because it assures the default probability will fall between *0* and *1*. Otherwise the simulation might produce unreasonable values.[4] In our paper the default probability is replaced by the observed bankruptcy frequency in each sector, as we do not have access to default data. Obviously, the two might deviate – not all defaulted companies go bankrupt, and not all the bankrupt companies have loans – but it is reasonable to assume strong positive correlation between them.

The macro index, y can be interpreted as an indicator of the overall state of the economy. As the default probability is observed, but not the y, we can obtain the macro index by applying the inverse of the logistic function:

$$y_{i,t} = \ln\left(\frac{1-d_{i,t}}{d_{i,t}}\right)$$

The y index in turn is assumed to be determined by a number of key macroeconomic variables which influence the state of the economy. More specifically the index takes the following form:

$$y_{i,t} = \beta_{i,0} + \beta_{i,1}x_{1,t} + \beta_{i,2}x_{2,t} + \ldots + \beta_{i,n}x_{n,t} + \nu_{i,t} \tag{2}$$

Where the β_i's are the regression coefficients to be estimated for sector $i = 1,\ldots, I$ and $x_{j,t}$ represents the jth macroeconomic factor at time t, where $j = 1,\ldots,n$. The $\nu_{i,t}$'s capture sector and time specific surprises and are assumed to be serially independent and identically normally distributed. A high value of y implies a good state, while low values imply a bad state of the macro environment. This specification has two main advantages; it allows the sensitivity to different shocks to differ across sectors and the individual error terms to capture idiosyncratic shocks that are sector specific. Notice that in this form the model can be interpreted as a segment specific multi-factor model that describes the 'health' of a particular sector as a weighted 'sum' of macroeconomic variables. The betas represent these 'weights' the particular variables take for each segment, with the error term capturing a sector specific surprise. The model links the health of a sector to current economic developments. It rests on the observation that during 'bad times' the default probability tends to be higher than in good ones.

Until now we have specified a static model. The next step is modelling the dynamics of the macro factors themselves. Wilson (1997) assumes that all variables can be reasonably well described by an AR(2) process. Instead of using AR(2) uniformly, we look at the actual data and fit an ARMA(p,q), where p and q are selected by combining several approaches (we use the Akaike information Criterion (AIC) to select the best model up to 4 lags; we also follow the Box-Jenkins methodology).

[4] The logit transformation also has other advantages when applied here. This is because the linear model on the macro index will turn into a non-linear model for the BR. The impact on BR is level dependent, that is the impact on BR of one unit increase in the macro index depends on the level of the macro index – the lower the macro index, the larger the effect. This can be observed in the relationship between BR and the macro variables. For example, it is often found that the macro shocks have more pronounced impact on credit risk in recession than in boom – see, for example, Bangia et al. (2004), Jacobson et al. (2005).

$$x_{j,t} = \delta_{j,0} + \sum_{k=1}^{p} \delta_{j,k} x_{j,t-k} + \sum_{l=0}^{q} \delta_{p+l+1}\, \varepsilon_{j,t-l} \tag{3}$$

Where δ_j is a set of regression coefficients that need to be estimated and $\varepsilon_{j,t}$ is the error term assumed to be distributed as $N(0,\sigma_j)$.

Let us define the vector of errors as: $\mu_t = [v_{1,t} \dots v_{i,t}\ \varepsilon_{1,t} \dots \varepsilon_{j,t}]'$. The covariance matrix Σ_μ is

$$\Sigma_\mu = \begin{pmatrix} \Sigma_v & \Sigma_{v,\varepsilon} \\ \Sigma_{v,\varepsilon} & \Sigma_\varepsilon \end{pmatrix} \tag{4}$$

It should be mentioned that the elements of the Σ_v sub-matrix could be highly significant, since bankruptcies in different sectors correlate not only because of their common dependence on systemic risk factors – captured in eq (1) – but also because of the direct connections between the sectors.[5] The other sub-matrices account for the possible interdependence of macroeconomic shocks and their impact on the segment specific macro index.

Equations (1) to (3) together with Σ_μ define a system that describes the joint evolution of default probabilities and the macroeconomic factors. This system can be used to conduct Monte Carlo simulations of the bankruptcy rate. The simulation is carried out in the following steps:

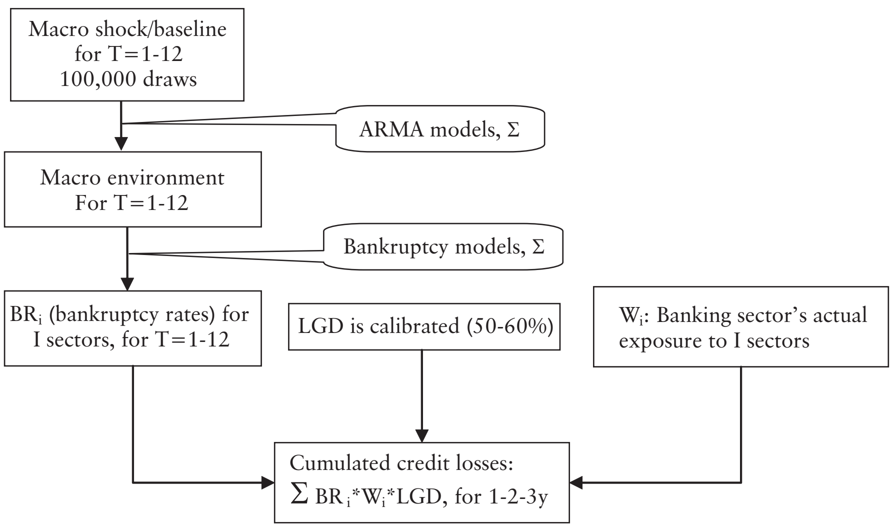
(i) Generate $\mu_t \propto N(0,\Sigma_\mu)$ by using Cholesky factorisation of Σ_μ. In this way we obtain a vector of random shocks that have the same variance-covariance structure as the models' error terms.

(ii) Given some initial values of the macro variables, calculate their 'forecasts'[6] for t+1 using the parameter estimates of equation (3) and the generated macro innovations (ε_j).

(iii) Use the forecasts from step (ii), the generated sector specific innovations (ε_j) and equation (1) and (2) to determine the forecast of the bankruptcy rates for t+1.

Figure 2

Steps of the simulation



[5] Actually that is what we find in our data.

[6] We add the generated innovations to the forecasted values. Therefore, the concept of 'forecast' is not used entirely properly here.

To obtain forecasts for the desired time horizon (H), repeat steps (i) to (iii) H times, using the values obtained in each step to make the next forecast.

To obtain a loss distribution, the model is simulated 100,000 times. Once the simulated path of the implied default probabilities is obtained, the credit loss distribution for loan portfolios and various risk measures (expected or unexpected losses) are determined. To do so the actual portfolio weights of each sector in the loan portfolio are used. The simulated losses are cumulated through time for 1-2-3 years. The steps of the simulation are outlined in Figure 2.

In addition to the baseline forecasts generated above, stress scenarios of interest can be fed through the model by shocking the error term of the macro variable(s). In practice the generated innovations of the macro variable (j) are replaced by the normalised shock (z)

$$z_{j,t+h} = \varepsilon_{j,t+h}/\sigma_j,$$

where $\varepsilon_{j,t+h}$ is the assumed shock at time $t+h$ and σ_j is the standard deviation of the error in the ARMA equation of the jth macro variable. Then follow the steps outlined above.

4. The Data

Bankruptcy rates. To construct bankruptcy rates as the ratio of defaulted firms to surviving ones, we made use of the OPTEN database, which includes court announcements of various forms of bankruptcy proceedings instituted against firms from 1992 to 2005.[7] The database contains the timing and type of proceeding, as well as links between consecutive procedures against the same firm. There are four major types of bankruptcy procedures:

– liquidation due to insolvency, initiated by the creditors – Felszámolás, (F);

– the company is dissolved due to reasons other than insolvency[8] – Végelszámolás, (V);

– termination by court order[9] – Bírósági eljárás, (B);

– restructuring, initiated by the debtor, which aims to ensure the going concern of the troubled (insolvent) firm by reaching agreement among creditors and the firm – Csőd.

Two features of the Hungarian practice should be mentioned here. First, restructuring is hardly existent in Hungary.[10] Second, the bulk of the announcements are either V or F; however, many of the V later turn into F – the involved firm turns out to be insolvent, thus a liquidation procedure is initiated against it.

To identify bankrupt cases, we started with the number of Fs, using the date of announcement. Then whenever V precedes F we use the starting date of V instead of F.

Usually the bankruptcy rate is calculated by dividing the annualised number of bankrupt firms by the number of firms active in the same period. We have made a slight modification of this convention, however. BR is calculated as follows:

$$BR = \frac{bankrupt_t * 4}{total_{t-n}}$$

Where n = 0 or 4. The reason why two alternative rates are used is that periods of very high growth (above 10%) in the number of active firms occurred in our sample. This can distort the bankruptcy rate through its impact on the denominator. We estimate our models using the ratios calculated with n=4 and n=0, then compare the results (they are called index1 and index2 respectively).

The bankruptcy *rates* show high volatility and some seasonal pattern. Even so, seasonal adjustment models such as tramo/seats or X11 failed to find significant seasonal variation. To reduce volatility we have applied the HP-filter. Since the goal was to reduce volatility (in contrast to extracting the trend) a considerably lower value of λ was used. (For a comparison of the original and the HP-smoothed series, please see the Appendix.)

In our analysis only corporations with a legal entity (limited liability + joint stock companies) are included.[11] We have excluded all financial institutions, offshore companies as well as activities typically run by the government in Hungary (education, health and social care). We dropped some small sub-sectors, such as unclassified manufacturing activities. All the remaining cases have been divided up into the following five major categories: (1) agriculture (AGR), (2) construction (CONS), (3) manufacturing (MAN), (4) trade (TRD), and (5) services (SER). In addition 'services' was broken up into three

[7] The first 'modern' bankruptcy regulation was effective from 1991. Since then there have been two major changes in the regulation. The first one in 1993 eliminated the obligation of self-bankruptcy; the second took place in 2006, which reshaped the incentives and procedures dramatically. However, those changes have no effect on our estimation period. Other, minor alterations of the law mainly aimed to ensure transparency of procedures, to change seniority of claims (in particular that of lenders with collateral), to ensure funding of direct bankruptcy costs, etc.

[8] Such as closing down or re-establishing a firm.

[9] Many registered companies are not active; liquidation by court order aims to find those companies.

[10] This serious shortcoming is aimed to be remedied by the new regulation of 2006.

[11] At the end of 2006, 98% of bank loans were granted to companies with legal entity.

sub categories, because its different components show a quite different pattern and also because the real estate sector makes up a significant share of banks' portfolios. These sub-categories were: hotels and restaurants (TOUR), transport and communication (TRA) and real estate (HOUSE). Manufacturing was also disaggregated into smaller units, but without much success in the estimation. For a more detailed description of our industrial categorisation see the Appendix.

Macroeconomic variables.[12] The following groups of macroeconomic variables were chosen, as they are likely to have an impact on firms' creditworthiness and probability of default.

Several **business cycle indicators** and demand factors were experimented with – such as the output gap, industrial production (IP), exports (EXP), investment (INV), GDI, consumption (CONS) and unemployment (UNEMP) – to capture the impact of the changing macro environment on firms' net worth or cash flow.

Interest rates actuate via increasing the debt burden of firms in addition to changing their net worth. We use domestic short nominal rate (IR), the 3m BUBOR, which is the benchmark rate banks use in pricing variable rate loans. The short rate is used because bank loans typically had a short repricing during the investigated period. For the real interest rate (RIR) this rate was discounted by the same period's CPI index – also our measure of inflation (INFL). Foreign short interest rate (IRF) was added as well (EURIBOR 3m), because the corporate sector takes around 40% of its loans from abroad. In addition, almost half of the loans raised at home are denominated in foreign currency.[13]

Real and nominal effective **exchange rate** (NEER and REER) might exert its influence via several channels. Appreciation or depreciation of the currency alters the competitiveness of both net exporters/net importers and those competing with imported goods. In addition, firms with foreign currency denominated debt are also affected through changes in the value of their debt. Irrespective of the direction of FX change, the volatility of the exchange rate (EU_VOL) in itself can have harmful impacts due to increased volatility of firms' cash flow. We have also investigated whether changes in the terms of trade (TOT) have any significant impact on the BRs.

Leverage (LEV) increases the fragility of the firm. The more geared a firm, the more likely that sudden shocks decrease the value of its assets below its debt (e.g. the firm goes bankrupt). Here leverage is calculated as a ratio of total loans (domestic and foreign) and nominal GDP. In contrast to domestic loans, unfortunately, we do not have the sector composition of loans raised abroad. Therefore we use the aggregate leverage.

Unit root tests were employed to detect trending variables. We used ADF, PP and KS tests. The KS test has a null of stationarity and therefore proves to be very useful as a double-check on the other two tests, which have low power – they tend not to reject I(1) when they should. According to the results the explanatory variables are de-trended when needed, either by the Hodrick–Prescott (HP) filter (for GDI) or differencing (interest rate, house permit).

[12] The abbreviations of macro variables can be found in the Appendix.

[13] Two major currencies of denomination are the Euro and the Swiss franc. As the value of the two currencies and also the respective short interest rates are highly correlated (see Figure in the Appendix), we include only the Euro rates in the calculations.

5. Stylised facts

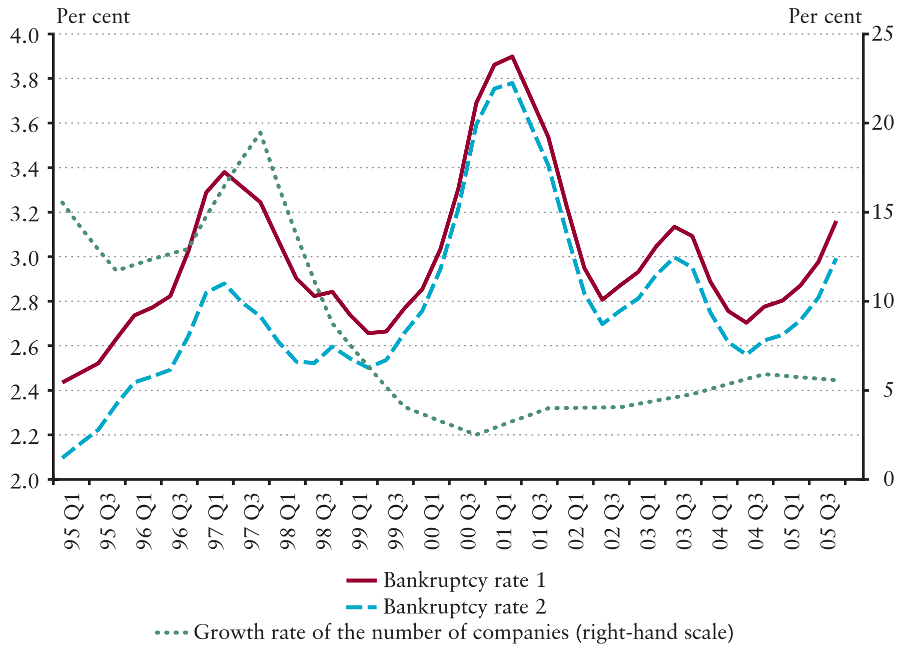
In the estimation we use the transformed bankruptcy rate;[14] however, for summarising the stylised facts the HP-filtered bankruptcy rate is preferred (for ease of interpretation).

As mentioned earlier, during some sub-periods dramatic increases in the number of firms can be observed. Therefore we used two definitions of the bankruptcy rate, the difference being the time index of the denominator (total number of firms at time t or t–4). The resulting ratios diverge significantly during the first years (especially in 1996–1997). This is not surprising, as the growth rate of companies reached very high levels (see Figure 3) at that time.

There are several peaks in the BR; the largest is in 2001, the three others – in 1997, 2003 and at the end of the period – are more modest. The highest level of BR is likely to be caused by the coincidence of various detrimental moves (rise in foreign interest rate, drop in external demand, high leverage). Detailed explanation will follow later.

Figure 3

Aggregate bankruptcy rate



The sector specific BRs are heterogeneous. One might expect various sectors to have varying sensitivity to general macro shocks. In addition, certain sectors also faced idiosyncratic shock (see construction in 2005). Nevertheless the turning points in BR observed on the aggregate level can also be detected for most of the sectors.

To further illustrate the differences among sectors, the next table presents the descriptive statistics by sectors. Formal tests also reject the equality of means and variances at a very high level (results are not reported here). As one can see, both the average and the volatility of the BRs are very divergent across sectors. For example, construction and manufacturing have the highest average bankruptcy rate; furthermore, they are above the average most of the time.

[14] The bankruptcy rate is annualised – the numerator is multiplied by 4.

Figure 4

Bankruptcy rates by sectors

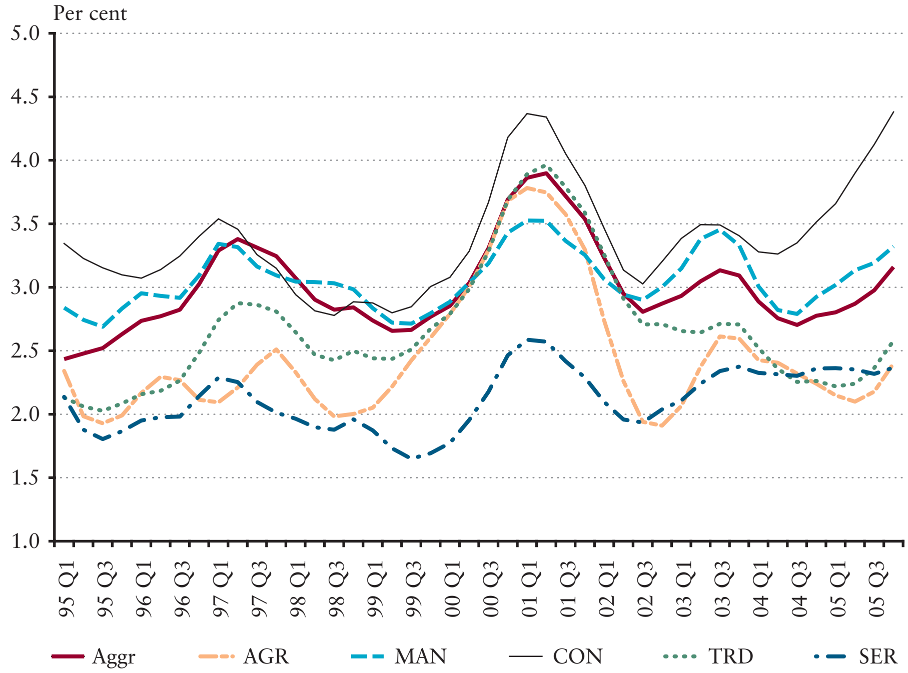


Table 1

Descriptive statistics of sectoral bankruptcy rates

	Mean	Median	Standard deviation
Total	3.00%	2.90%	0.35%
AGR	2.45%	2.31%	0.51%
MAN	3.06%	3.03%	0.23%
CON	3.38%	3.28%	0.43%
TRD	2.68%	2.61%	0.49%
SER	2.12%	2.10%	0.24%

6. Estimation

When selecting the variables for our model there were several issues that had to be taken into consideration. First, because of the short time span of our data the number of variables used had to be kept low due to degrees of freedom considerations. Also, if the number of macro factors is high, the corresponding covariance matrix becomes very large, which makes the simulation very time consuming and cumbersome. Second, to ensure the model is well specified and misspecification bias is avoided (or at least reduced) enough variable should be introduced (watch for Durbin Watson statistics). Third, our aim was to model sector level bankruptcy rates using common macro factors. Therefore, although the fit of certain models could have been improved by adding more sector specific variables – cyclical component of sector specific output or investment, for example – these were only used if the improvement in the model was considerable and/or the explanatory power and the diagnostics of the model was otherwise poor.

To obtain final models we combined variables from the following groups:

– business cycle, real variables (GAP, unemployment, industrial production, consumption, investment, gross disposable income, export);

– interest rates – domestic and foreign, real and nominal;

– exchange rates and terms of trade index (nominal and real effective exchange rate, exchange rate volatility, terms of trade);

– leverage;

– a dummy for year 1997, when the growth rate of companies was extremely high.

Because of potential multicollinearity more than one model (various combinations of explanatory variables) was considered.

As to the lag length, we used two alternative specifications. First, only first lags were allowed. These are the results reported in the paper. Allowing more lags made the results very sensitive to the starting set of variables, which is not a surprise given the size of the sample, the potential multicollinearity between variables and the persistence of the individual macro factors. Models including only contemporaneous values have been estimated, too. For some sectors these models provided better fit. Nevertheless, we decided not to use them as it is very unlikely that the change in the macro environment significantly moves the bankruptcy frequency within such a short time span. Even if payment problems arise quickly, in order to have long enough payment delays[15] to initiate bankruptcy some time needs to elapse.[16] Table 2 and Table 3 summarise the parameter estimates, their significance, the reported Rbar^2 and the Durbin–Watson statistic (DW). Robustness is investigated by changing the estimation period (starting in 1997 and 2000) and comparing the results for the two definitions of the macro index (reminder: macro index1 and 2 use the number of companies as denominator at time t-4 and t respectively to calculate the bankruptcy frequency). First, the general findings are summarised, and then specific features of individual sectors are discussed.

The major determinants of the macro index seem to be the business cycle *(gap),* the *leverage* and the *foreign interest rate.* They all tend to be significant, have a strong impact with the expected sign on the macro index and enhance the explanatory power of the models considerably (in terms of R^2). According to the result, in boom/recession the macro index is increasing/decreasing, implying lower/higher bankruptcy frequency. At the same time, the leverage of the corporate sector, which usually moves with the business cycle (positive correlation between the two) partly offsets this impact – lowers the macro index in boom but raises it in recession. The foreign interest rate is likely to have a role due to the high share of FX denominated debt (foreign and domestic). In contrast to IRF, domestic nominal and real interest rates are rarely significant, and even when they are (not in the final models) their sign is sometimes positive (intuitively wrong).

[15] One condition of initiating insolvency is that the borrowers should have at least 60 days delay of payment.

[16] The findings and the stress test results gained by using the contemporaneous models are very similar to the ones reported in the paper.

Table 2

Estimation results for the aggregate model

	index 1			index 2		
	1995–2005	1997–2005	2000–2005	1995–2005	1997–2005	2000–2005
C	5.482***	4.65***	4.722***	5.76***	5.075***	4.68***
IRF(–1)	–0.074***	–0.106***	–0.115***	–0.076***	–0.111***	–0.128***
REER(–1)	–0.007***	–0.002	–0.003	–0.008***	–0.004	–0.003
TOT(–1)	0.014**	0.022***	0.031**	0.017**	0.024**	0.031**
EU_VOL(–1)	–0.015*	–0.016	–0.003	–0.024*	–0.022	–0.007
GAP(–1)	0.106***	0.064	0.186***	0.101***	0.096*	0.196**
LEV(–1)	–0.026***	–0.015***	–0.015**	–0.029***	–0.022**	–0.013*
D97	–0.166***	–0.079*	–	–0.134***	–0.034	–
Rbar^2	0.705	0.802	0.839	0.693	0.718	0.788
DW	1.142	1.235	1.695	1.044	1.144	1.344

*Stars next to the estimates indicate significance levels; ***: significant at 1% level, **: significant at 1%-5% level, *: significant at 5%-10% level.*

A dummy to control for the extremely high growth rate of the number of companies in 1997 was found to be significant in most of the cases.

The *EUR/HUF volatility* has a detrimental impact. It is rather surprising that the real depreciation of the currency also lowers the macro index in the aggregate model and thus increases the bankruptcy frequency. To interpret the result one has to take into account that another alternative measure of competitiveness is also included in the model (terms of trade), which has the expected positive sign. This means that improving export prices relative to import prices enhance the macro index. As to the sign of REER, it appears that the potential net improvement in competitiveness due to real depreciation abroad and at home (on markets with import competition) is offset by other, potentially harming influences of the depreciation (such as an increase in the interest burden for unhedged borrowers).

One striking feature of our results is that besides leverage and gap, 'external' variables play a significant role in driving the macro index (IRF, REER, TOT, EU_VOL). This is due to the fact that Hungary is a small open economy, heavily dependant on external demand and subject to changes in international competitiveness. Furthermore, the corporate sector assumes more than two-thirds of its debt in foreign currency.

The models have nice diagnostics – no remaining autocorrelation in the error (in most of the cases), relatively high adjusted R^2, and the model captures the lows and highs pretty well. The estimated parameters are usually robust to changes in the estimation period and the definition of the macro index.

Comparing the estimates for various sectors the following was found. Relative to the aggregate models here some additional variables were needed to be able to get reasonable fit and uncorrelated errors.[17] All the sectors are exposed to GDP, some also to GDI. The macro index of CONS also depends on the changes in the number of house permits (HPERMIT). The foreign interest rate is highly significant in each model, although with different parameters. We do not have data on the denomination of loans by sectors. It could be that all the sectors have a high portion of debt in foreign currency. The least satisfactory is the model for manufacturing (much lower R^2 and some positive autocorrelation in the errors).[18]

We were altogether unsuccessful in finding any robust result for the housing sector. Therefore, it was dropped in the simulation – exposure and capital data were adjusted accordingly. One reason for this could be that the number of bankruptcies is very small, especially in the first part of the period covered.

[17] Remaining autocorrelation of the error term is often a sign of misspecification; it was mostly removed by adding explanatory variables. There was no need to use dynamic model specification.

[18] One reason could be that manufacturing industry is very heterogeneous, some sub-sectors (like textiles and food) have been exposed to sector specific shocks. Nevertheless, we were no more successful with the sub-sectors either. For MAN, however, the contemporaneous model leads to much better results.

Table 3

Estimation results by sectors (sample 1995–2005)[19]

	MAN	CON	AGR	TRD	TRA	TOUR
C	4.373***	4.190***	6.831***	6.498***	5.570***	5.787***
IRF(–1)	–0.041**	–0.062***	–0.152***	–0.103***	–0.077***	–
REER(–1)	–	0.003**	–0.013***	–0.013***	–0.006***	–0.012***
TOT(–1)	–	0.036***	–	–	–	–
IR_d(–1)	–	–	–	–	–	–0.023**–
EU_VOL(–1)	–	–	–0.049***	–0.031**	–	–
HPERMIT_d(–1)	–	0.010	–	–	–	–
GAP(–1)	0.089***	0.094***	0.158***	0.128***	0.194***	0.190***
GDI_hp(–1)	–	0.019**	0.050***	–	–	–0.032
LEV(–1)	–0.018***	–0.025***	–0.034***	–0.033***	–0.027***	–0.030***
D97	–0.091***	–0.153***	–	–0.228***	–0.035***	–0.160***
$Rbar^2$	0.385	0.739	0.745	0.737	0.646	0.534
DW	0.699	1.107	1.197	1.088	1.035	0.797

*Stars next to variables indicate significance levels; *** significant at 1% level, ** significant at 1%-5% level, * significant at 5%-10% level.*

The estimated parameters link the explanatory variables to the macro index. However, one would also like to see how these estimates translate into sensitivities of the BR. Due to the logit transformation, this will always depend on the level of the macro index. Therefore, the marginal effects were calculated at the macro index's overall average, as well as its 2005 year average value. As the two resulted in almost identical marginal impacts, only the former ones are reported. Given the average value of the macro index, according to the aggregate model a 1 percentage point increase in foreign interest rates/gap leads to a 0.2% increase/0.31% decrease in the bankruptcy frequency a quarter later.

As a last step, needed to run the simulation, the ARMA equations generating the macro environment (for all the explanatory variables that appear in either the aggregate or the sectoral models) and the covariance matrix of the error terms are calculated. The ARMA estimates and the correlation coefficient with their test statistics on their significance are found in the Appendix. The ARMA models show that many of the explanatory variables are highly persistent. As to the covariance matrix,

Table 4

The marginal effects on the bankruptcy rate

	AGGR	MAN	CON	AGR	TRD	TRA	TOUR
IRF(-1)	0.21%	0.12%	0.18%	0.44%	0.30%	0.22%	0.03%
REER(-1)	0.02%		–0.01%	0.04%	0.04%	0.02%	
TOT(-1)	–0.04%		–0.10%				
IR_d(-1)							0.07%
EU_VOL(-1)	0.04%			0.14%	0.09%		
HPERMIT_d(-1)			–0.03%				
GAP(-1)	–0.31%	–0.26%	–0.27%	–0.46%	–0.37%	–0.56%	–0.55%
GDI_hp(-1)			–0.06%	–0.14%			0.09%
LEV(-1)	0.08%	0.05%	0.07%	0.10%	0.10%	0.08%	0.09%

[19] Results for the alternative macro index and estimation periods can be found in the Appendix.

two findings should be highlighted. First, we see significant, positive correlation between all sectors, implying that there is dependence among the sectors beyond the common exposure to the same macro factors. Second, regarding the correlation between the innovations of macro variables, those few which were significant are also intuitive. For example, leverage and the output gap are positively correlated, which is often found in practice. Euro volatility is also found to move with changes in the domestic interest rate.

7. Results of the stress test

Equipped with the estimated system of equations – including the sector specific bankruptcy models and the ARMA models describing the macro environment – Monte Carlo simulation[20] is run. We make some strong **assumptions** in the stress tests:

– The 'default rate' on corporate loans is made equal to the estimated BR. Default occurs when the firm does not meet its obligation – does not pay the due interest or repayment of its loan.[21] The reason behind the default could be short-term financial difficulties, not necessarily insolvency, which eventually will lead to bankruptcy. That is, not only bankrupt firms default.

– We assume that the banking portfolio is representative of the corporate sector; thus the default rate (in the sub-portfolio of each sector) can be well approximated by the generated bankruptcy rates. However, the two might deviate. If banks cherry-pick customers, the estimated BR might overstate the default rate. However, as competition in the corporate loan market is rather strong and many companies don't have a long history, the actual bank (sub)portfolio might even be of worse quality than the entire sector.

– A probably more severe limitation of our approach is that, given the lack of data on individual exposures, the concentration risk (large exposures) of the portfolio is ignored.[22] The presence of large exposures makes the loss distribution much skewed.

– The loss given default (LGD) is set to 50 and 60%.[23] This is a very conservative LGD and might overstate the actual losses banks suffer. From our model we calculated so-called implied LGDs, which are in the range of 55-70%. Implied LGD was estimated as EL/W, where EL is the forecasted median of losses over 1 year horizon in the baseline scenario; W is the value of the loan portfolio. We made four calculations, using both the aggregate and the sector specific models for BR, and end of 2005 and end of 2006 data for W. The LGD parameters used in other studies are in a rather wide range. Basle II also gives guidelines for those who will employ the Foundation IRB approach.[24]

– The timing of losses is ignored here. On average it takes three years to close bankruptcy proceedings in Hungary – it was even longer in the 1990s. Although banks have to classify the debt of bankrupt firms as bad and provision for it properly at the time of the announcement, the actual loss they suffer could turn out to be either larger or smaller.

– We assume that the composition of the loan portfolio does not change over the investigated time horizon.

Two (series of) loss distributions are obtained: one by aggregating the results for individual sectors (hereafter referred to as **'portfolio'** or **'sector specific'** model) and the other by making use of the aggregate BR model (hereafter referred to as **'aggregate'** model). As was seen before, sector BR models show similarities but also differences. One question we seek to answer here is whether using sector specific or aggregate BR models in a stress test makes any difference.

The calculated loss distributions are evaluated with the help of standard risk measures (e.g. expected loss). The expected loss is approximated by the median of the loss distribution. That gives the losses with 50% probability.

[20] In the MC simulation normality of error terms of equations (1) and (2) are assumed. Testing the residuals questions this normality only for the AR equation of leverage, and even in that case the results depend on the test used.

[21] Typically, 90 days overdue is used in the definition of default.

[22] Ideally, when data about individual loan exposures are available, one can use the generated bankruptcy rate as a proxy for PD for each loan. In addition, assuming an LGD and the binomial distribution of defaults, the loss distribution of banks' entire portfolio can be generated. Unfortunately, we do not have access to credit register (individual data).

[23] No estimation for LGD is available for Hungary. We have no information at all about defaulted loans of solvent firms. As to bankrupt firms, there is only one calculation providing information enabling a judgement about banks' recovery rate – see Lóránth and Frank (2006) – which gives a lower bound of 36%; that is what is left after taking into account all costs during the bankruptcy.

[24] For unsecured senior claims LGD=45%; for secured claims it can be lowered by taking into account the effect of risk mitigation.

Stress tests are run on the **2006 year-end portfolio** of the entire banking sector. We also considered conducting stress tests on individual bank's data; however, the quality of various bank's portfolio in the same sector was very different (reflected by the ratio of net/gross value of loans). This, on the one hand, can mirror the true differences in portfolio quality, the risk appetite or the quality of credit decisions. Alternatively, this might suggest that individual sector sub-portfolios are too small, not granular enough, and therefore do not represent the sector well. Collateralisation and provisioning policy might also be very heterogeneous across banks. Therefore we decided not to use individual bank data.

As to the **correlation structure** (**Σ**) we use the full covariance matrix. When the results are compared to calculations with Σ_{signif}, – where only the significant elements of the covariance matrix are included (test of significance of correlation coefficient is applied) – no major differences are found. However, ignoring correlations altogether would alter the result of the stress test, especially in the case of a gap decline, where the leverage (LEV), by moving into the same direction,[25] partly offsets the impact of the deteriorating gap.

The decision on time horizon of stress tests faces one with tradeoffs. Even when a shock lasts only for 1-2 quarters, its impact on credit losses can be detected in the 2nd or even 3rd year. This is also confirmed by our simulation. Accordingly, some studies use a 3-year horizon. However, the longer the time horizon the more questionable other assumptions of the methodology become. How can we accept that the portfolio remains the same? What do we assume about the changes in profit and capital during this period?

To help make the decision about time horizon, one also has to take into account that for risk management purposes the time horizon is typically the one which is needed to liquidate the position in question. In the case of credit risk this often equals the maturity of the loan, as banks tend to hold the loan till its expiry.[26] Based on our estimation,[27] the average maturity of the corporate loan portfolio in Hungary is close to two years.

In an effort to circumvent these issues, results over 1-2-3 years are all reported. Nevertheless, a preferred time horizon for the stress test is set at 2 years, which corresponds to the average maturity of loans.

THE MACRO SHOCKS

Two real shocks were investigated:

Gap1: the gap[28] decreases by 2 percentage points for 2 consecutive quarters

Gap2: the gap falls by 1 percentage point for 2 quarters

As the foreign interest rate was found to be a major determinant of bankruptcy probability, this was the other variable shocked in the stress test. IRF is increased by 200 basis point, but in

Irf1: during 1 quarter (+200bp per quarter)

Irf2: during 2 quarters (+100bp per quarter)

An increase of 200 basis points is in line with the supervisory recommendations for developed countries' interest rates and with the practice of large investment banks. This is a typical shock used for market risk stress tests.

In order to illustrate the severity of these shocks, Figure 5 shows the time series of GAP and IRF extended with the generated medians over the forecast period.

[25] Remember that GAP and LEV are positively correlated; however, their impact on the macro index is of opposite sign.

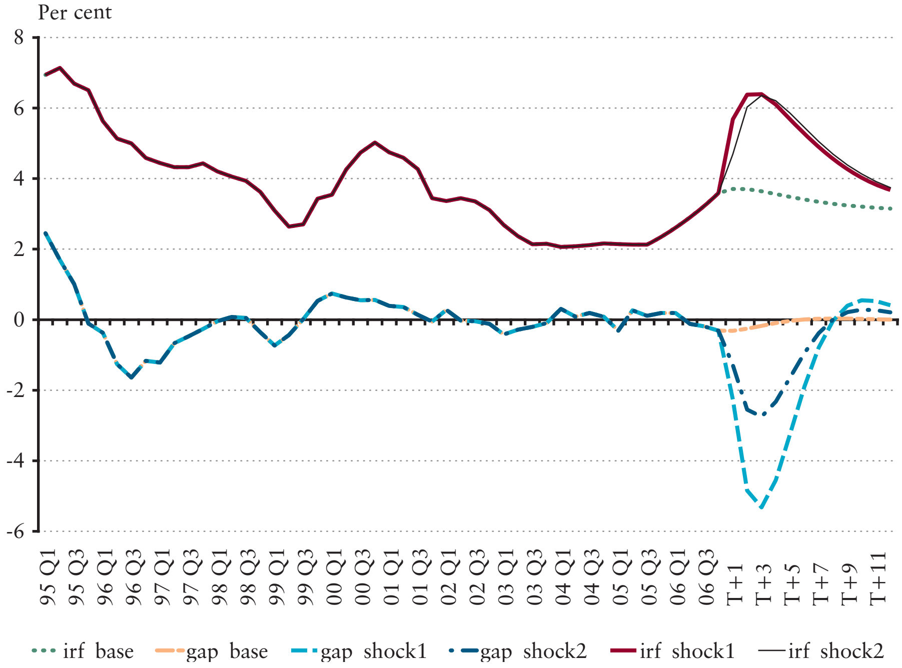
[26] The sale of non-performing assets – Hungarian banks used this often in the past – can shorten the maturity of loans. However, loans are usually sold only when they are already in default. Credit derivatives can be an alternative, although they are not used extensively in Hungary.

[27] Unfortunately, we do not have a precise figure on the maturity composition of corporate loans.

[28] Typically, real GDP is shocked. Supposing there is no major change in potential GDP (e.g. no change in factor productivities or available labour and capital), then real GDP shock translates into a similar move in gap.

Figure 5

The simulated path of GDP gap and foreign interest rate



The decline in GAP exceeds the fall in GAP caused by the Bokros measures in 1995-1996. In this sense even in historical terms the shock can be considered as extreme enough.

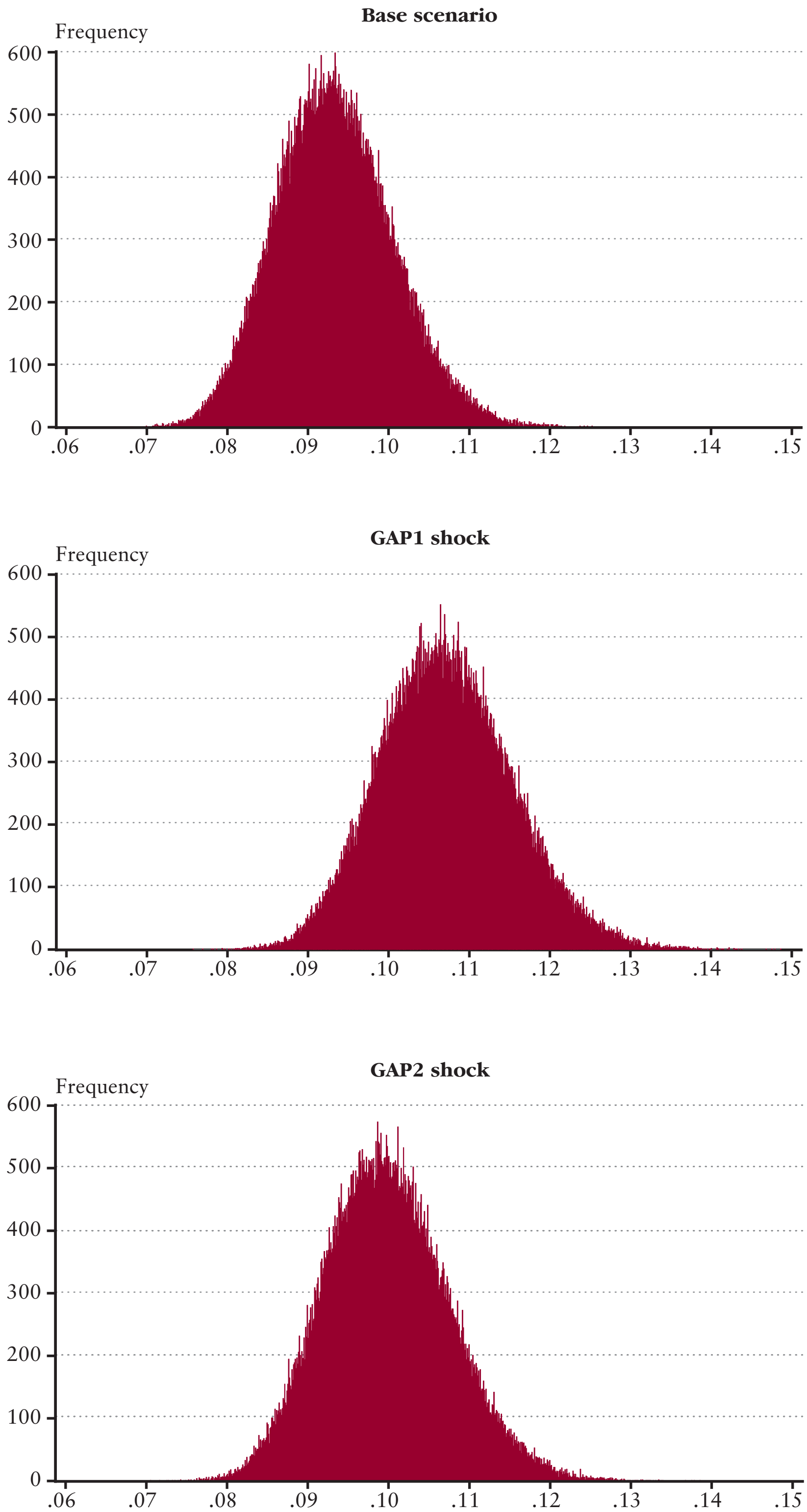
An interesting issue is how the **shocks change the distribution of loan losses.**

Figure 6 shows the distribution of the BR's under the baseline scenario and the two GDP shocks on a 2-year horizon. As the graphs reveal, the macro shock's main effect is to shift the distributions out to the right. Their effect on the shape of the graphs is only minor. The descriptive statistics on skewness and kurtosis[29] show that discrepancy from the normal distribution appears in the form of fat tail at the right end. The distribution of credit losses is supposed to exhibit very strong skewness and fat tail. The reason why we cannot detect this is that we use aggregate instead of individual loan data. Therefore, we fail to account for the presence of large exposure, which would make the distribution skewed and have a fatter tail.

[29] For descriptive statistics please refer to the Appendix.

Figure 6

Histogram of cumulated credit losses



STRESS TEST RESULTS

Finally, let us report the result of the stress test. The question we seek to answer is to what extent each shock would undermine the capital position of the banking industry.

The loss measure is defined as follows

$$(EL_{t+j}^{shock} - EL_{t+j}^{base}) / capital_t$$

where *EL* is the 'median' of the cumulated loss distribution and *j* is the time horizon=1, 2, 3 years.

In the credit risk literature two basic risk measures are used: expected and unexpected losses. The former is the median or mean of losses and is supposed to be covered by provisioning. The unexpected losses are to be backed up by the capital. In our set-up we take the expected losses in the baseline scenario. As to the shocks, the expected losses conditional on the extreme realisation of the risk drivers are calculated. In the baseline scenario we assume that banks always provision enough to make up expected losses (they have enough profit, on the one hand, and follow prudent provisioning on the other). Thus to calculate the impact of the shock the difference between the EL in the shocked and the baseline scenario is taken. These extra losses caused by the shock should be covered by the capital.

With respect to the denominator, we use only part of the regulatory capital, which can be thought to cover corporate loan losses.[30] To calculate that we assume that the share of capital, which can be allocated to cover corporate loan losses, equals the share of corporate loans in total risk weighted assets. The capital defined in this way turns out to be about half of the regulatory capital. This is a very simplified approach; however, we prefer this to using the entire capital (which is needed to cover other losses as well, such as losses on the household portfolio or trading positions).[31] This approach is also in line with the conservative nature of stress tests. Throughout the paper capital is used as defined above.

In addition to capital, future profit can also serve as a shock absorber. As forecasting future profit is not an easy task (especially not when banks are hit by a shock), we ignore this here. Nevertheless, one has to keep this in mind when evaluating the results.

As suggested by current literature – Schuerman (2004), Kupiec (2007) – not only PD (here BR) but **LGD is endogenous** as well. Taking this endogeneity into account in credit risk models has a huge impact on risk measures. This is why we decided to investigate the impact of changing the LGD in the base and shocked scenarios. Based on the empirical observations in Schuermann (2004), we assumed a 10 percentage point (a likely) and a 20 percentage point (less likely) increase in LGD due to the GDP shock.

The results of the stress tests are displayed in Figure 7. According to this, the banking sector seems to be resilient to the investigated shocks. Even the largest losses are just above 10% of the capital. It is also interesting how persistent the impact of shocks is – although these shocks last only for 1 or 2 quarters, the losses are largest in the 2nd or 3rd year.

The figure also reveals the difference between the sector specific and the aggregate model. The latter always leads to larger stress losses, although the difference is more pronounced in the case of the GAP than the IRF shock. For example, while the GAP1 shock results in a loss of about 8% in the aggregate model, it compares to a 6% loss calculated by the sector specific models. One would expect the sector specific models to give more reliable estimates, as a more detailed, larger information set is used in the estimation. However, as we saw in the previous chapter, it was easier to find a model with good fit for the aggregate than for the sectoral bankruptcy rates.[32] Unfortunately, this does not help in making an unambiguous choice between the models.

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[30] Since other studies usually use the entire capital, caution should be taken when comparing the stress test results.

[31] Implicitly we assume that other parts of the portfolio will be affected by the shocks as well.

[32] We should also add that when contemporaneous models were used this relationship reversed: the sectoral models (which actually had nicer diagnostics, in particular better R^2 then the lagged models) led to larger losses then the aggregate one.

Figure 7

The impact of shocks

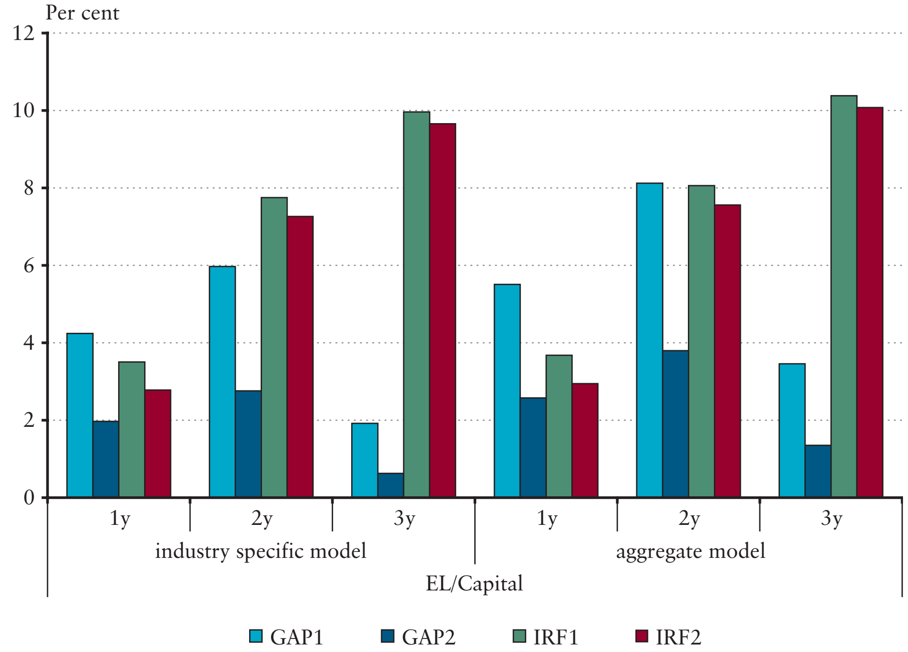
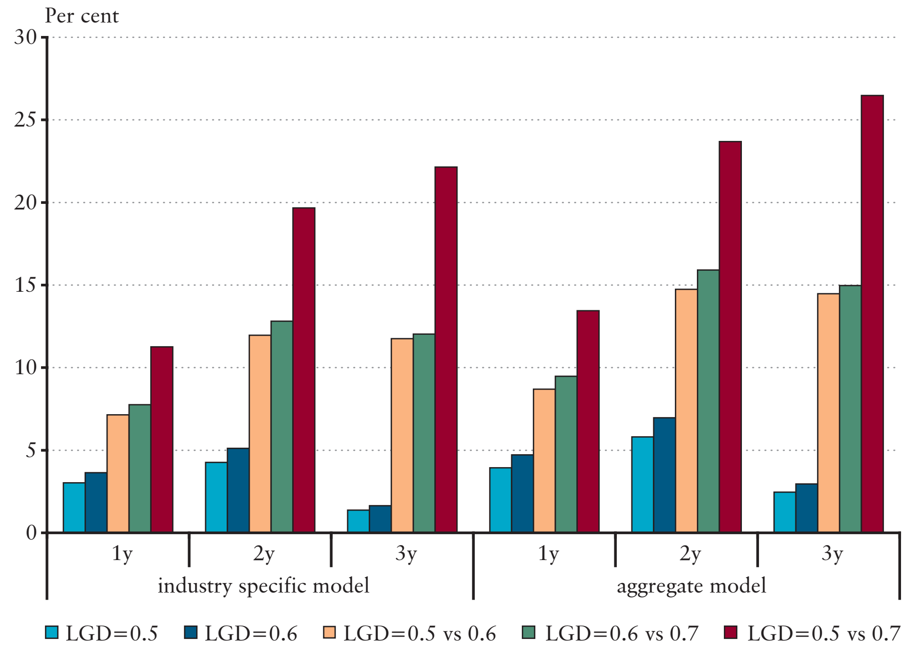


Figure 8

The impact of endogenous LGD (gap1 shock)

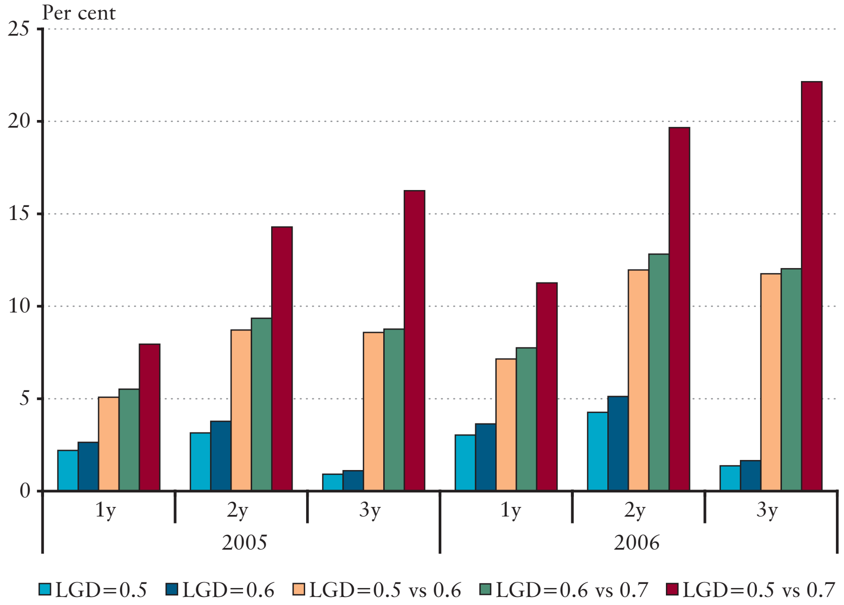


Our third result (see Figure 8) highlights the importance of dealing with the endogeneity of LGD. The empirical findings of Schuermann (2004) indicate that during recession the LGD could be around 10% higher than during boom. As the figure reveals, using 50% or 60% LGD does not make a huge difference in terms of stress losses. However, using 50% (60%) LGD in the base line scenario and a 10 percentage point higher LGD in the shocked case more than doubles the losses. It is also striking that changing the endogenous baseline LGD from 50% to 60% (column 3-4) has very little impact relative to the change caused by the endogenous assumption itself (column 4 and 3 relative to 2 and 1 respectively). When assessing the implication of this result one also has to consider the following. After the implementation of CRD,[33] banks have to use a downturn LGD in the calculation of their capital requirement. Unless the regulatory recommendations or the banks own calculations are wrong (they understate downturn LGD), this is likely to reduce the above concerns. This does not mean that the stress loss calculated with endogenous LGD shrinks, but rather implies that the banks are more likely to have enough capital to absorb the losses.[34] Nevertheless, there is an additional underlying assumption behind this reasoning: we also assume, that banks are provisioning properly. That is, both at the time of the stress test and during the entire time horizon of the simulation banks put up enough provisions to cover their expected losses for the baseline scenario. According to our implied LGD calculations, we do not see signs of under-provisioning in the Hungarian banking sector.

So far end-2006 data were used in the calculation. Many studies have pointed out that the often mild impact of stress tests could be partly due to the benevolent macro environment at the time of the exercise. Comparing the end of 2005 and 2006 results, it is striking that a more benign macro environment (lower IRF and slightly larger output GAP in 2005)[35] lowers the losses by about one third.

Figure 9

Stress test at end-2005 and end-2006



As we mentioned earlier, not only the capital but future profit can also be relied on to absorb credit losses. The average after-tax profit of the Hungarian banking sector keeps increasing as the sector expands. If we take the last 7/3 years average, this amount is the equivalent of 50%/77% of the end of 2006 capital. Taking that into account would significantly increase the shock absorbing capacity of the banking sector.

[33] The Credit Risk Directive will be implemented in Hungary in 2008.

[34] Obviously, it all depends on the ability of the CRD methodology/banks' internal model to capture unexpected losses properly.

[35] Capital adequacy was slightly better as well. However, its impact is negligible.

8. Conclusion

This paper focuses on credit risk, the major potential source of losses banks face in their operation. Court announcements between 1995 and 2005 have been used to define historical bankruptcy rates and then estimate sector specific bankruptcy models. As we have information about the industrial composition of the banks' loan portfolio, those models in turn are used to conduct a macro stress test on the Hungarian banking sector. Relevant macro shocks are identified, then Monte Carlo simulation is used to generate the loss distribution of the actual loan portfolio.

As to the bankruptcy models, we sought for parsimonious models, which are well suited for application in macro stress tests. The estimation results show that, although sector specific determinants of bankruptcies do exist (their mean level, volatility and sensitivity to the macro environment differ), financial distress in each sector is driven by common systemic risk factors. The most influential drivers of credit risk are the business cycle (GAP), the foreign interest rate and leverage. The importance of the foreign interest rate can be attributed to the high share of foreign currency denominated debt in the corporate sector.

The stress test results reveal that the Hungarian banking sector is robust and resilient to the relevant shocks. Even a sharp decline in real GDP or an increase in foreign rates would at the most cause an approximately 10 percentage point loss of capital. We also highlighted the importance of taking into account the endogeneity of LGD. When a reasonable change in LGD along the business cycle is taken into account, the calculated losses at least double. In some cases it is wise to report more than one loss measure.

The comparison of results from the sector specific and the aggregate bankruptcy model revealed that the aggregate model tends to result in a larger calculated impact of shocks.

Although the results are sensitive to the various, sometimes fairly strong assumptions we made, we have tried to follow the conservative nature of stress testing, i.e. rather overestimating than underestimating the losses.

The methodology we developed here suffers from many limitations. Some of them cannot be easily remedied. These models are subject to the Lucas critique as their parameters and functional forms are probably quite unstable. We assumed that banks do not respond to the shocks. Due to the short time series, we were not able to model the likely regime switching nature of the relationship between credit risk and the business cycle. Many of the other shortcomings can be dealt with, but often at a cost. The macro environment can be described by more sophisticated reduced form or structural models. The feedback effects from the bankruptcy rate on the macro environment can be explicitly modelled as well, however, in this case we need to work with aggregated data and sacrifice the information contained in more disaggregated (sector specific) data. It would be important to obtain a more precise estimate on LGD and its changes during the stages of the business cycle. Finally, should we have access to information on individual loans, the concentration of the loan portfolio could be taken into account as well. All these are left for future research.

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Appendix

Table A1
Macro variables (all expressed in percentage points)

IRF	EURIBOR 3m	Level
REER	ULC-based real effective exchange rate	Level
TOT	Terms of trade (export price index/import price index-1)	Level
IR	3m BUBOR	Difference
EU_VOL	relative 90 days MA volatility of EUR/HUF exchange rate	Level
HPERMIT	number of house permits	Difference
GAP	HP-filtered real GDP at 2000 prices, seasonally adjusted	Level
GDI	Gross Disposable Income	HP-filtered
LEV	corporate loans/nominal GDP	Level

Sources: MNB.

Table A2
Sectoral decomposition

Industry	Abbreviation	eteaorf code 1992–1999	eteaorf code 2000–
Agriculture	AGR	1–4	1–3
Construction	CON	15	20
Manufacturing	MAN	5–12	5–17
Food and Tobacco	–	5–6	5
Textiles, Wood, paper and printing	–	7–8	6–9
Chemical industry, Other non-metallic products, Metal products	–	9–11	10–14
Machinery	–	12	15–17
Trade	TRD	16–17	21–22
Services	SER	18–20, 22	23, 25, 26, 29
Hotels and restaurants	TOUR	18	23
Transport and communication	TRA	19–20	25–26
Real Estate	HOUSE	22	29

Table A3
Other abbreviations used in the paper

BR: bankruptcy rate

EAD: exposure at default

PD: probability of default

LGD: loss given default

EL: expected loss

UL: unexpected loss

F: liquidation due to insolvency

V: the company is dissolved due to reason(s) other than insolvency

NPL: non-performing loans

LLP: loan loss provisioning

Table A4

Results of unit root tests

	ADF	PP	KPSS
GAP	I(0)	I(0)	I(0)
GDI	I(1)	I(1)	I(1)
GDI_hp	I(0)	I(0)	I(0)
IRF	I(1)	I(1)	I(0)
LEV	I(1)	I(1)	I(0)
HPERMIT	I(1)	I(1)	I(1)
HPERMIT_d	I(0)	I(0)	I(0)
IR	I(1)	I(1)	I(1)
IR_d	I(0)	I(0)	I(0)
REER	I(1)	I(1)	I(0)
EU_VOL	I(0)	I(0)	I(0)

Significance level is set at 10%.

Table A5

Estimation results of the ARMA models

	IRF	REER	TOT	IR_d	EUVOL	HPERMIT_d	GAP	GDI_hp	LEV
C	3.059***	90.766***	–	–0.636**	2.945***	–	–	–	56.352**
AR(1)	1.356***	1.293***	0.536***	0.327**	0.683***	2.18***	1.354***	0.674***	0.974***
AR(2)	–0.446***	–0.357**	0.332**	–	–0.424**	–2.160***	–0.549***	–	–
AR(3)	–	–	–	–	–	1.156***	–	–	–
AR(4)	–	–	–	–	–	–0.285**	–	–	–
Adj.R^2	0.954	0.922	0.0396	0.098	0.338	0.947	0.833	0.447	0.922

*Stars next to variables indicate significance levels; ***: significant at 1% level, **: significant at 1%-5% level, *: significant at 5%-10% level.*

Table A6

Descriptive statistics of the simulated loss distributions

Shock	Time horizon	Mean	Skewness	Kurtosis	St.Dev./Mean
Baseline	1Y 2Y 3Y	0.048 0.093 0.138	0.21 0.25 0.28	3.09 3.10 3.12	0.0628 0.0778 0.0864
GDP1	1Y 2Y 3Y	0.057 0.107 0.144	0.20 0.25 0.27	3.09 3.10 3.11	0.0637 0.0770 0.0831
GDP2	1Y 2Y 3Y	0.052 0.100 0.140	0.20 0.25 0.28	3.09 3.10 3.12	0.0626 0.0771 0.0846
IRF1	1Y 2Y 3Y	0.054 0.107 0.156	0.20 0.24 0.27	3.08 3.07 3.11	0.0618 0.0761 0.0845
IRF2	1Y 2Y 3Y	0.053 0.106 0.155	0.19 0.23 0.27	3.07 3.06 3.11	0.0609 0.0748 0.0836

Table A7

Sectoral regression results and robustness check

	Manufacturing			Construction			Agriculture		
	1995–2005	1997–2005	2000–2005	1995–2005	1997–2005	2000–2005	1995–2005	1997–2005	2000–2005
C	4.373***	4.369***	4.098***	4.190***	3.981***	3.954***	6.831***	6.132***	6.371***
IRF(–1)	–0.041**	–0.070***	–0.074***	–0.062***	–0.079***	–0.079**	–0.152***	–0.179***	–0.140***
REER(–1)	–	–	–	0.003**	0,004	0.002	–0.013***	–0.008**	–0.016**
TOT(–1)	–	–	–	0.036***	0.045***	0.06***	–	–	–
IR_d(–1)	–	–	–	–	–	–	–	–	–
EU_VOL(–1)	–	–	–	–	–	–	–0.049***	–0.055***	–0.039**
HPERMIT_d(–1)	–	–	–	0,010	0.016**	0,019	–	–	–
GAP(–1)	0.089***	0.130**	0.171***	0.094***	0.135***	0.196**	0.158***	0,096	0,108
GDI_hp(–1)	–	–	–	0.019**	0.027**	0,025	0.050***	0.06***	0,030
LEV(–1)	–0.018***	–0.016***	–0.010**	–0.025***	–0.021***	–0.018	–0.034***	–0.026***	–0.020**
D97	–0.091***	–0.011	–	–0.153***	–0.079	–	–	–	–
Adjusted R^2	0.385	0,422	0.412	0,739	0.768	0,590	0.745	0,786	0.848
DW	0,699	0.719	0,732	1.107	1.085	1.458	1.197	1.152	1.135

	Trade			Transportation			Tourism		
	1995–2005	1997–2005	2000–2005	1995–2005	1997–2005	2000–2005	1995–2005	1997–2005	2000–2005
C	6.498***	5.393***	5.223***	5.570***	4.873***	4.99***	5.787***	5.413***	6.063***
IRF(–1)	–0.103***	–0.155***	–0.164***	–0.077***	–0.081***	–0.089***	–	–	–
REER(–1)	–0.013***	–0.005***	–0.006***	–0.006***	–0.002	–0.002	–0.012***	–0.010**	–0.019**
TOT(–1)	–	–	–	–	–	–	–	–	–
IR_d(–1)	–	–	–	–	–	–	–0.023**	–0.033	–0.006
EU_VOL(–1)	–0.031**	–0.031***	–0.018*	–	–	–	–	–	–
HPERMIT_d(–1)	–	–	–	–	–	–	–	–	–
GAP(–1)	0.128***	0.065	0.145**	0.194***	0.097***	0.143***	0.190***	0.024	0.128
GDI_hp(–1)	–	–	–	–	–	–	–0.032	–0.055***	–0.076*
LEV(–1)	–0.033***	–0.020***	–0.015***	–0.027***	–0.018***	–0.020***	–0.030***	–0.024**	–0.022
D97	–0.228***	–0.1111**	–	–0.035***	–0.029	–	–0.160***	–0.233**	–
Adjusted R^2	0.737	0.872	0.929	0.646	0.643	0.666	0.534	0.327	0.366
DW	1.088	1.308	1.828	1.035	1.025	1.113	0.797	0.833	0.754

*Stars next to variables indicate significance levels; ***: significant at 1% level, **: significant at 1%-5% level, *: significant at 5%-10% level.*

Figure A1

Original and HP-smoothed aggregate bankruptcy rate

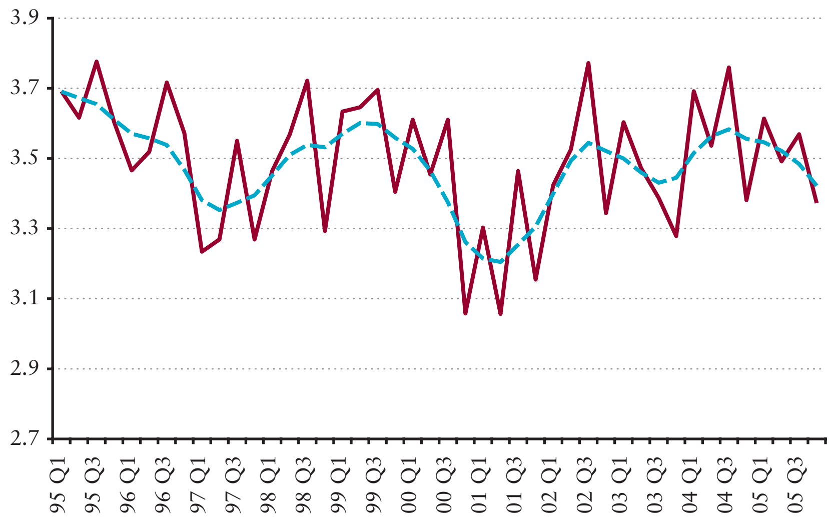


Table A8

Correlation between the error terms

Between the error terms of sectoral bankruptcy models

	AGR	MAN	TRD	CON	TRA	TOUR
AGR	1					
MAN	0.466***	1				
TRD	0.625***	0.645***	1			
CON	0.450***	0.726***	0.472***	1		
TRA	0.490***	0.567***	0.632***	0.455***	1	
TOUR	0.320**	0.627***	0.412***	0.522***	0.373**	1

*Stars next to variables indicate significance levels; ***: significant at 1% level, **: significant at 1%-5% level, *: significant at 5%-10% level.*

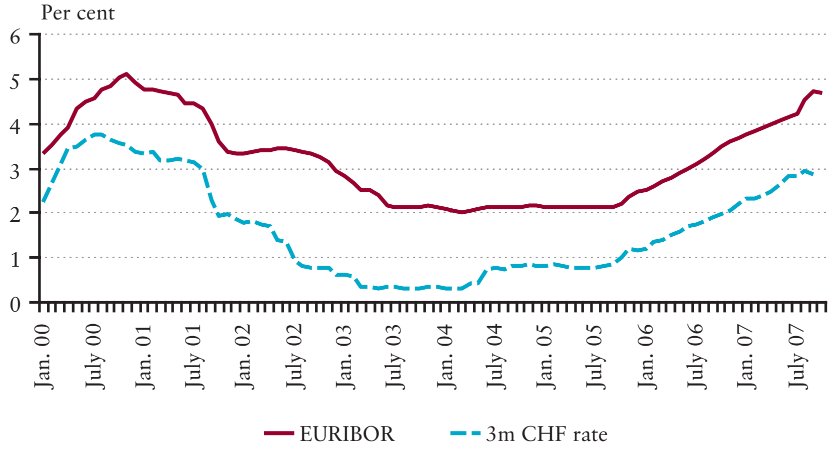
Between the error terms of the ARMA equations of macro variables

	IRF	REER	TOT	IR_d	EU_VOL	Hpermit_d	GAP	GDI_hp	LEV
IRF	1								
REER	0.087	1							
TOT	0.165	–0.256	1						
IR_d	0.246	0.062	0.257*	1					
EU_VOL	–0.07	0.282	–0.238	0.479**	1				
HPERMIT_d	–0.015	0.01	0.1	0.069	0.002	1			
GAP	0.134	–0.029	0.013	0.270*	0.03	–0.096	1		
GDI_hp	0.173	–0.07	–0.053	0.036	0.195	–0.22	–0.039	1	
LEV	0.053	0.046	–0.033	0.078	0.225	–0.291*	0.265*	–0.074	1

*Stars next to variables indicate significance levels; *** - significant at 1% level, ** - significant at 1%-5% level, * - significant at 5%-10% level.*

Figure A2

Euro and CHF interest rates



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