

# **The impact of bank concentration on financial distress: the case of the European banking system**

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**(Preliminary version)**

## **Abstract**

This paper examines the impact of bank concentration (measured by the Herfindahl-Hirschman Index) on bank financial distress using a dataset consisting of 18,159 bank year observations for six European countries (Austria, Belgium, France, Germany, Italy and Spain). Financial distress is defined as a switch from two consecutive period ( $t-1$ ;  $t$ ) into the bottom 5 percentile of the Economic Value Added (EVA) empirical distribution in a given country. In order to account for an omitted variable bias, we impose a factor model to the correlation structure of the binary indicators of distress in each country. This leads to a multivariate probit model estimated by GMM. Our findings suggest that, on average, there is a negative effect of bank concentration on financial distress. However, the impact of bank consolidation turns out to be positive (relative to the average) when considering either commercial or listed banks.

**Keywords:** *EVA, Banking, Systemic Risk, Multivariate Probit, Stochastic simulation*

**JEL codes:** *C15, C35, G21, G32*

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# **The impact of bank concentration on financial distress: the case of the European Banking system**

## **1. Introduction**

Given the recent wave of consolidation in the European banking system (see Figure 1 reporting recent data on the increasing importance of M&A) there is an increasing concern on the impact of bank concentration on the stability of the overall banking system. There are contrasting views about the impact of banking concentration on financial stability. Under the “competition-fragility” view, some authors (see Allen and Gale, 2004, among the others) argue that bank concentration, by keeping safe profit margins for banks, does not give the incentive to bank to finance risky projects. On the other hand, the “competition-stability” view (Boyd and De Nicolo’, 2005 among the others) argues against bank concentration, given that, the sizeable market power of the only few existing banks will give the incentive of banks to raise the interest rate on loans, and consequently, this will adversely select the firm with risk projects, with a negative impact on the stability of the banking system.

In order to address this issue, we use 18,159 bank year observations for the 1997-2005 sample period (annual frequency) for six European countries: Austria, Belgium, France, Germany, Italy, and Spain. As far as we are aware, this is the first paper to analyse the impact of bank consolidation on financial distress, considering not only commercial and, or listed banks, but also non listed, savings and cooperative banks. These type of banks have a key role in many banking industry in the Continental Europe (eg. Germany and Italy). As for the empirical analysis, we are interested in studying the effect of bank concentration [proxied by the Herfindahl-Hirschman Index<sup>1</sup> (HHI)] on the migration into distress, defined as a move over two consecutive periods ( $t-1$ ;  $t$ ) into the bottom 5 percentile of an indicator of shareholder value. Creating value for shareholders has been the main strategic objective of banks over the last decade or so and has important policy implications for academics, practitioners and regulators: over ten years ago, Greenspan

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<sup>1</sup> The Herfindahl-Hirschman Index is the sum of squared values of each bank asset market share.

(1996) affirms “you may well wonder why a regulator is the first speaker at a conference in which a major theme is maximising shareholder value... regulators share with you the same objective of a strong and profitable bank system”. Shareholder value measures are also superior to profit measures to assess the if banks are healthy and sound since the first account for both bank profitability and the cost opportunity of capital (that reflect the bank risks). Crises of U.S. investment banks in 2008 provide clear evidence that profitable banks may be unsound. While shareholder value is usually assessed for listed companies using stock market returns, we use the Economic Value Added (EVA) since we choose to consider both listed and non-listed banks: the number of quoted banks in Europe is still small and our aim is to have a broad view of the European banking systems, especially in those countries where cooperative and savings bank have a key role. EVA is a measure of the value created by firms for their owners. The studies of Ferguson and Leistikow (1998), Machuga et al. (2002), Adsera and Vinolas (2003), Abate et al. (2004), Ferguson et al., (2005 and 2006) provide evidence that EVA is particularly useful in assessing shareholder value considering the opportunity cost of capital as well as bank economic performance. As a consequence, we estimate EVA following the procedure outlined in Fiordelisi (2007) for banks (see figure 2). While previous studies control for an omitted variable bias using observable common factors (such as GDP growth), we allow explicitly for contemporaneous correlation among the binary endogenous indicators of distress driven by an unobservable common factor. Therefore, the model we propose has the flavour of an high dimensional multivariate probit. While bivariate probit modelling can nowadays be easily implemented, modelling higher order multivariate probit, involves multi dimensional integrals and this can be very computationally intensive. The use a single common factor driving the latent variables underlying the endogenous binary variables indicators of financial distress can reduce the number of parameters underlying extreme events correlation. The use of common factors underlies the Maximum Likelihood, ML, approach of Bock and Gibbons (1996), and Gibbons and Wilcox-Gok (1998) to estimate high order multivariate probability models. However, given six countries under investigations, the computational intensity of the ML is still very high and, therefore we suggest a two stage procedure. In the first stage, the common factor loading are obtained via a GMM type of analysis (see Bertschek and

Lechner, 1998 for an application to GMM for the purpose of estimating probit models). The moment conditions we use are based upon both marginal and joint probabilities of observing financial distress (while Bertschek and Lechner, 1998, focus only on moment conditions based upon marginal probabilities). We find that, on average, there is a negative effect of bank concentration on financial distress (supporting the view of Boyd and De Nicolo', 2005). However, by using slope dummies into the GMM estimation, we also find that, while concentration decrease financial distress for savings and cooperative banks, bank consolidation increase banking instability for commercial and listed banks (supporting the view of Allen and Gale, 2000 and 2004).

The paper is organised as follows. Section 2 and 3 provide a literature review on the effect of bank consolidation on the overall banking systemic risk and a description of the econometric methodology, respectively. Section 4 data and empirical analysis. Conclusions are in section 5.

## **2. Literature Review on the impact of bank consolidation on bank stability**

In this section, we first review the studies that support the concentration-stability view. Allen and Gale (2004) show that less concentration in the banking system should erode bank market power, hence affecting the net present value of profits (franchise value) of a bank. This would give an incentive to banks to pursue risky policies (by, for instance, increasing the loan portfolio credit risk) in an attempt to maintain the former level of profits (Marcus 1984, Keeley 1990, Demsetz, Saidenberg, and Strahan 1996, Carletti and Hartmann 2003). Consequently, riskier policies should increase the probability of higher distress in the banking system. Therefore, this literature, argues in favour of a more concentrated banking system which should encourage banks to pursue safer strategies, given the possibility for banks to protect their higher franchise values ("competition-fragility" view). Furthermore, another argument put forward to support the concentration-stability view relies upon observing that monitoring and supervision of a banking system can be facilitated especially when there are few banks have sizeable market shares. A number of studies provide empirical evidence in favour of the concentration-stability view. Bordo et al. (1995) compare the performance of the U.S. and Canadian banking

system between 1920 and 1980. The authors (op. cit.) find an higher degree of systemic stability in Canada compared to the U.S. banking system and they conclude that this finding could be ascribed to the higher degree of concentration in the Canadian banking sector. Hoggarth et al. (1998) compare the performance of the UK and German banking sector for the period of 1965-1997. They find the German banking system less competitive but more stable (given less variable aggregated banking profitability) and also more competition but less stability (given the more volatile aggregated banking profitability) in the U banking system. More recently, Beck et al. (2006) examine the effect of banking market concentration on the likelihood of suffering a systemic banking crisis using data on 69 countries over the period from 1980-1997. In particular, Beck et al. (2006) classify as systemic banking crisis an episode when the ratio of total non-performing loans to total banking system assets exceed ten percent, or when the government has taken extraordinary steps, such as declaring a bank holiday or nationalizing much of the banking system. The authors (op. cit.) fit a logit model to the pooled dataset and find that an increase in banking concentration does not result in higher banking system fragility. This result is robust when controlling for differences in bank regulatory policies and national institutions affecting market structures. Heimeshoff and Uhde (2008) apply panel data analysis to bank balance sheet data from banks across the EU-25 for the period of 1997-2005. Heimeshoff and Uhde (2008) use the z-score (which is based on bank returns on assets (ROA), on its dispersion measured as  $\sigma(\text{ROA})$ , and on the ratio of equity to total assets ) as a proxy of banking stability and they find that market concentration has a negative impact on banks' financial soundness. The empirical study of Jimenez et al. (2007), based upon a rich dataset of Spanish banks, suggests a positive relationship between bank competition (proxied by either the market share of the first five commercial lenders in each province, denoted as C5, or by HHI, or by the Lerner index) and banking systemic risk (which is proxied by non performing loans ratios). The authors (op. cit.), in their panel data analysis, do not find evidence of a possible U-shaped relationship between bank competition and stability as argued Martínez-Miera and Repullo (2007), that is, as the number of banks increases, the probability of bank default first declines but increases beyond a certain point<sup>2</sup>.

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<sup>2</sup> Martínez-Miera and Repullo (2007) acknowledge, in their model, an increase in defaults when interest rates increase

The study of Boyd and De Nicoló (2005) challenges the concentration-stability view showing that an increased bank concentration could result in higher interest rates charged on business loans, and this would raise the credit risk of borrowers due to moral hazard. The increase in firm bankruptcies could then spill into greater bank instability. Furthermore, advocates of the “concentration-fragility” observe that policymakers are more concerned about bank failures when there are only a few banks. Hence, banks in concentrated systems will tend to be considered “too important to fail” and this will trigger a moral hazard problem boosting bank risk-taking incentives (e.g., Mishkin, 1999). The competition-stability view finds empirical support from the studies of Boyd et al. (2006) as well as De Nicoló and Loukoianova (2007) which both use as a proxy of bank financial soundness the z-score. More specifically, Boyd et al. (2006) examine, first, a cross section of around 2,500 small, rural banks operating in the US, and then they apply panel data analysis to a sample of about 2,700 banks from 134 countries, excluding Western countries (considering either country or firm fixed effects in order to control unobserved heterogeneity). De Nicoló and Loukoianova (2007) apply panel data analysis to a sample of more than 10,000 bank-year observations for 133 non-industrialized countries during the 1993-2004 period. Among the most important findings, there is evidence of a positive and significant relationship between bank concentration and bank risk of failure. This relationship is particularly strong when bank ownership is taken into account, especially in the case of state-owned banks with sizeable market shares. The study of Schaeck et al. (2006) provides further empirical support to the competition-stability view. The authors (op. cit.) examine the impact of market structures on systemic stability for 38 countries and 28 systemic banking crises over the 1980-2003 sample period. The authors focus is on the impact of a proxy of bank competition, the Panzar and Ross H-Statistics (e.g. a proxy of bank competition) on systemic banking crises. The crisis events are detected using the Demirgüç-Kunt and Detragiache (2005) dating scheme based upon a number of criteria, such as emergency measures taken by the national government, the ratio of non performing loans to assets exceeding 10%, etc. Using both duration a logit regression fitted to a pooled dataset, the authors (op. cit.) find

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(due to an gigher degree of banking concentration). However, the authors observe that, at the same time, there is a margin effect that generates more revenue for the bank coming from those nondefaulted borrowers that pay a higher interest rate

evidence that more competitive banking markets are less prone to systemic crises and that systemic crises take longer to develop within a competitive environment. Finally, the study of Berger et al. (2008), using a panel study fitted to a dataset 8235 banks in 23 developed countries, show that banks with a higher degree of market power increase loan risk (proxied by non performing loans). However, the empirical findings of Berger et al. (2008) suggest that the increase in loan risk may be offset in part by higher equity capital ratios, given that banks with a higher degree of market power are shown to have less overall risk exposure (proxied by the z-score).

### **3 Econometric methodology: multivariate probit**

#### **3.1 Definition of distress**

First, we consider as a threshold, the 5 percentile of the EVA empirical probability distribution for a specific country. This threshold is obtained after sorting all the banks EVA observations (for different time periods) in a given country. If we observe a switch of the bank EVA, between time  $t-1$  and  $t$ , into the bottom 5 percentile of the EVA probability distribution (for the specific country), then we observe distress.

#### **3.2 Model set up**

Given a total of  $M$  countries (with  $M = 6$  in our study), let  $Y = (y_1, y_2, \dots, y_M)'$  be the  $M$  dimensional vector of binary endogenous variables (e.g. scoring 1 when EVA is observed to be in distress, according to the criterion specified above). We assume that the latent variables driving the endogenous responses  $Y$  have a multivariate Gaussian distribution. In particular, the stochastic process for the latent variable for the  $m^{\text{th}}$  country is given by:

$$y_{imt}^* = \beta_1 x_{mt} + \varepsilon_{imt} \quad (1)$$

where  $x_{mt}$  is the observation for the HHI for country  $m$  and for time  $t$ , while  $\varepsilon_{imt}$  is an idiosyncratic disturbance (specific to bank  $i$ ).

For the purpose of robustness, we also consider the following model specification:

$$y_{imt}^* = \beta_1 x_{mt} + \beta_2 (Dummy^* x_{mt}) + \varepsilon_{imt} \quad (1')$$

where  $Dummy^* x_{mt}$  is a slope dummy which is meant to capture the deviation from the average impact effect of bank concentration due to a specific group (say, for instance, commercial banks). More specifically, we consider four models of type (1') which differ according to the group dummy variable picking the observations of commercial banks, or of savings, or of cooperative, or, finally, of listed banks.

Given the use of a single explanatory variable (e.g., a proxy of bank concentration), in order to control for an omitted variable bias, we allow the shocks  $\varepsilon$  be contemporaneously correlated across countries. More specifically, the shocks  $\varepsilon$  follow a multivariate Gaussian process with mean zero, and with a covariance matrix  $\Sigma$  (not diagonal), and with elements normalised to unity along the main diagonal. We impose a common factor structure in order to model the covariance matrix  $\Sigma$ . Therefore the generic off-diagonal element of  $\Sigma$ ,  $\sigma_{mn}$  is given by  $\lambda_m \lambda_n$ , with the  $\lambda$ 's being the loadings factor coefficients for countries  $m$  and  $n$ . The endogenous binary response observed for the  $i^{th}$  bank in the  $m^{th}$  country at time period  $t$  is modelled as:

$$y_{imt} = \begin{cases} 1 & \text{if } y_{imt}^* - c_m \leq 0 \\ 0 & \text{if } y_{imt}^* - c_m > 0 \end{cases} \quad (2)$$

In light of equation (2), the components entering the vector of latent variable  $y^*$  can be interpreted as proxy of financial soundness. Once the index of financial soundness for a specific bank  $i$ , in country  $m$ , at time  $t$ , is below a threshold  $c_m$ , then we observe financial distress for that specific bank.

### 3.3 GMM estimation

Given that our focus is on studying the migration into distress for EVA within six European countries, if we used a ML estimation method, then we should specify the log-

likelihood taking account all the possible combination of joint probabilities (which are in a number of  $6^6$ ). More specifically, the probability of, say, the worst outcome corresponds to the joint probability of distress in all six countries and, in this case the multivariate cdf would be given by:

$$\Pr ob(y_1 = 1; y_2 = 1; \dots; y_M = 1) = \int_{-\infty}^0 \int_{-\infty}^0 \dots \int_{-\infty}^0 \varphi(z_1, z_2, \dots, z_M, \Sigma) dw_1 dw_2 \dots dw_M \quad (3)$$

where  $\varphi$  is a multivariate Gaussian density function (M dimensional). As one can observe, the model specification we are interested requires the computationally intensive solution of higher order dimensional integrals. One possible method would rely on the assumption of a common factor underlying the contemporaneous correlation among the innovations. By conditioning on the common factor, the endogenous responses  $y$  are independent, this would simplify the computation of the the conditional probability of observing  $m$  countries in distress. Then, the unconditional probability for a specific scenario, say the one defined for eq. (3), is a definite integral which can be approximated through Gauss-Hermite quadrature.<sup>3</sup> However, we argue that the combination of EM and Fisher scoring algorithms suggested by Bock and Gibbons (1996) in order to maximise the log-likelihood would be very computationally intensive, given the high number of positive definite integrals for the unconditional joint probabilities regarding distress in a m-fold of countries. Even though our method still relies on a common factor structure (as anticipated in section 3.2), we suggest the use of a less computationally intensive method based upon GMM. This method involves solving the quadratic programming problem:

$$\min_{\beta, \lambda} \bar{M}' W \bar{M} \quad (4)$$

where  $\bar{M}$  is an  $L \times 1$  vector of unconditional moment restrictions and  $W$  is a  $L \times L$  weight coefficients matrix. The unconditional moment conditions are sample means of conditional moments. The first set of (conditional) moments restrictions is the one

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<sup>3</sup> See Bock and Lieberman, 1970 and Bock and Aitkin, 1981 for a first implementation of this method regarding only factor modelling of multivariate probit

suggested by Bertschek and Lechner, (1998), relying upon orthogonality restrictions between explanatory variables and residuals from probit regression, that is:

$$x_{imt} [I_{imt}(\cdot) - NORM(c_m - \beta' x_{imt})] \quad (5)$$

where the first term entering the expression in square brackets of equation (5) is an indicator function taking value 1 if, for the  $i^{\text{th}}$  bank in country  $m$ , at period  $t$ , a migration into financial distress (from the previous period) is observed, and taking value 0, otherwise. The second term entering the expression in square brackets of equation (5) is given by the structural form marginal probability [obtained through a univariate Gaussian Cumulative Distribution Function (cdf), defined by  $NORM$ ], conditional upon a specific observation for the explanatory variable  $x$  (HHI) in country  $m$  and at a specific time period  $t$ . The total number of conditional moments given by (5) is equal to the overall sample size in a given country. Given the unbalanced panel under investigation (see Table 1) the total number of conditional moments in (5) varies across countries. Moreover, the total number of unconditional moments, obtained by averaging out all the observations in each country, is equal to  $M$ . Given an  $M+1$  number of unknown coefficients to be estimated, we introduce a second set of unconditional moment conditions which helps to over-identify the model. In particular, the second set of restrictions is given by focussing on unconditional joint probabilities, that is, on the distance:

$$jpd_{m,n}^{rf} - BIVNORM[c_m, c_n, \rho_{mn}] \quad (6)$$

The first term in (6) is  $jpd_{ij}^{rf}$  is the reduced form (pairwise) joint probability of migration into distress in two countries, obtained by using a time average estimator suggested, in the context of default migration, by Gagliardini and Gourieroux (2005):

$$jpd^{rf} = \frac{1}{T-1} \sum_{t=2}^T \pi_{mt} \pi_{nt} \quad (7)$$

where  $T$  is the number of time series observations (9 years in our study) and the  $\pi$ 's are marginal probability of migration into distress given by dividing  $D_t$ , which is the number banks, not in distress in the previous period, which have migrated into distress in the current period, to  $N_{t-1}$ , which is the total number of banks not in distress in the previous period. The second term in (6) is the joint bivariate cumulative standardised Gaussian distribution, which depends on threshold parameters  $c_m$  and  $c_n$ , and on the (pairwise) correlation coefficient between the shocks  $\varepsilon$ . Given equation (1) specifying the stochastic process underlying the latent variable  $y^*$  and the factor structure underlying the correlation parameters for the binary endogenous responses, the coefficient  $\rho_{mn}$  is given by  $\beta^2 + \lambda_m \lambda_n$ . The total number of moment restrictions given by (7) is  $M(M-1)/2 + M$ , which is equal to 21 for the model specification without dummy (and it is equal to 27 for the model specification with a dummy variable). This gives a total of 14 and 19 over-identifying restrictions to be tested for the model specification with and without dummy, respectively. We set the weight coefficient matrix  $W$  to the identity matrix, and the solution of the quadratic problem given (4) is obtained by employing a Sequential Quadratic Programming algorithm embedded in the *sqpolve* Gauss routine. Contrary to Bertschek and Lechner, (1998), who focus only on the conditional first moments, we estimate jointly the coefficients entering both the conditional first moments and the unconditional second moments for the binary endogenous responses, that is the  $\beta$  and  $\lambda$  coefficients, with the factor loadings varying across countries. The (unconditional) threshold parameters  $c$  entering both the marginal and joint probabilities (see eq. 5 and 6) are obtained by calibrating the estimation of the coefficients  $\beta$  and  $\lambda$  on the relative frequency of migration into distress, that is by taking the inverse of the standardised Gaussian cdf with respect to the country sample mean (across a given number of observations per country) of the indicator of migration into distress  $I(\cdot)$  entering eq. (5).

### 3.4 Inference

The covariance matrix of the parameters estimates is given by:

$$(G'G)^{-1}(G'VG)(G'G)^{-1} \quad (8)$$

where the elements of the matrix  $G$  are first derivatives of the sample mean values of the conditional moments (e.g. the terms entering the objective function to be minimised),

$$G = \left[ \frac{\partial \bar{M}(\beta, \lambda)}{\partial \beta'}, \frac{\partial \bar{M}(\beta, \lambda)}{\partial \lambda'} \right], \text{ evaluated at the point estimates of the coefficients } \beta \text{ and } \lambda.$$

Furthermore, the matrix  $V$  is the variance-covariance matrix of the conditional moments,  $V = \text{Var}[M(\beta, \lambda)]$ .

## 4 Data and empirical analysis

### 4.1 Data

Our dataset has 18,159 year observations for the 1997-2005 sample period (annual frequency) for six European countries: Austria, Belgium, France, Germany, Italy, and Spain. Table 1 show that the sample is dominated by German banks, especially in terms of savings and cooperative banks. As described in section 3.1 financial distress is measured by focussing on the worst 5% realisation of bank EVA. EVA was calculated for each bank in the sample between period  $t-1$  and  $t$  following the procedure adopted by previous studies (e.g. Uyemura et al., 1996, Fiordelisi 2007) by computing the difference  $\psi_{t-1,t} = \pi_{t-1,t} - k \bullet K_{t-1}$ , where  $\pi_{t-1,t}$  is the “economic measure” of the bank net operating profits,  $K$  is capital invested,  $k$  is the estimated cost of capital invested (as shown in figure 2). In order to minimise heteroscedasticity and scale effects in our model, we standardise EVA by capital invested so that this ratio expresses the shareholder value created for any euro of capital invested by shareholders in the bank. Regarding capital invested and its cost, various studies (Resti and Sironi, 2007 among the others) suggest measuring the bank’s capital invested (and, consequently, the capital charge) focussing on equity capital. The

estimation of the cost of equity capital is challenging in banking since most of the banks are non-quoted in any stock exchange market. As such, we estimate the shareholders' expected rate of return using the following procedure: 1) for quoted banks, we use follow a standard procedure applying a two-factor model using both market and interest rate risk factors (following Unal and Kane 1988); 2) for non-quoted banks, we use the mean of the cost of equity capital for comparable domestic quoted banks (in terms of total assets). Our estimation procedure is consistent to some recent papers that assume that the cost of equity in banking as constant (e.g. Stoughton and Zechner 2007) since the banking regulation constrain in the same way the leverage of banks. Finally, net operating profits and capital invested are calculated by undertaking various adjustments specific for banks to move the book values closer to their economic values. These adjustments concern: 1) loan loss provisions and loan loss reserves; 2) restructuring charges; 3) security accounting; 4) general risk reserves; 5) R&D expenses and 6) operating lease expenses<sup>4</sup>.

#### **4.2 Empirical analysis**

According to the definition of distress given above, the relative frequency of migration into distress are given in Table 3. The countries showing the smallest relative frequency is Spain, which is equal to zero for most of the years. Austria, France, Germany and Italy share similar values (averaging around 2%). Finally Belgium is the country exhibiting, in given years (more precisely, during 2002 and 2005) the largest values for the relative frequency of migration into distress.

The values for the unconditional pairwise joint probabilities of migration are given in Table 4. These probabilities can give insights about the systemic risk within each country and within the overall region of countries under investigation. According to the descriptive statistics in Table 4, Belgium seems to be the country with associated the highest degree of systemic risk. In particular, the highest joint probability of migration into a distress for any pair of banks within the same country are for Belgium, and this

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<sup>4</sup> Various adjustments have been made to face accounting distortions concerning loan loss provisions and loan loss reserves; general risk reserves; R&D expenses and operating lease expenses. Appendix B reports the accounting adjustments made to move the book values closer to their economic values in the  $EVA_{bkg}$  calculation. For further details, see Uyemura et al. (1996), Koeller et al. (2005) and Fiordelisi and Molyneux (2006).

value is equal to 0.8%. Furthermore, the highest values for the joint probabilities of migration into a distress for any pair of banks in two different countries are observed for the following pairs: Belgium-Austria (with joint probability equal to 0.2%), in Belgium and Italy (with joint probability equal to 0.2%), Belgium-France (with joint probability equal to 0.1%). Finally Spain is the country showing the smallest degree of system distress, given the values equal to zero for the unconditional probabilities.

The explanatory variable, proxy of bank concentration is the HHI. The latter is computed by taking the ratio of a given bank assets (book value) in a specific country and in a given time period to the total sum of assets for that specific country and for that given time period. From Table 2, we can observe that Belgium is the country showing the highest degree of bank concentration, according to the HHI, ranging from a minimum of 0.2001 (in year 1997) to 0.5755 (in year 2002). Overall, the descriptive statistics in Table 2 show a tendency towards an increase (over the 1997-2005 period) in the degree of bank concentration.

We now turn our focus on the panel model estimation through GMM. From table 5, and in particular, from the column labelled Model 1, we can observe (on average) a negative and statistically significant impact effect of bank concentration on the event of migration of EVA into distress: this support the “competition-stability” view of Boyd and De Nicolo’ (2005) showing that an industry concentration increase (so more market power is given to banks) is likely to increase the financial distress, i.e. a switch from two consecutive period (t-1; t) into the bottom 5 percentile of the EVA. However, from Table 5, and, especially from columns labelled Model 3 and 4 (where we assess the impact effect of slope dummies), the negative average effect holds only when we concentrate on the observations related to cooperative and savings banks, which constitute the majority of sample observations. Therefore, as for the results associated either with the model without dummy or with a slope dummy capturing the concentration effect peculiar either to savings or cooperative banks, they are supporting the concentration-stability view of Boyd and De Nicolo’ (2005). From Table 5 and from column 2, we can observe a statistically significant and positive effect (relative to the average) of bank concentration associated either with commercial or with listed banks. This finding is supporting the “competition-stability” view of Allen and Gale (2000 and 2004). In summary, once we

take into account the classification of banks into different ownership categories, we find that while the aforementioned relationship is negative (relative to the average) for savings and cooperative banks; in case of commercial and listed banks, we observe a positive effect (relative to the average) of bank concentration on financial distress. As such, the competition-stability view of Boyd and De Nicolo' (2005) is confirmed for cooperative and savings banks, while the competition-fragility view is supported for commercial and listed banks (consistently with Berger et al., 2008 results). These contrasting results can be explained by the different institutional aims of these banks (i.e. cooperative and savings bank tend to maximise the stakeholder value; commercial and listed banks aim to create shareholder value). In case of cooperative and savings banks, we find that an industry concentration increase (so more market power is given to banks) is likely to increase the probability of switch from two consecutive period (t-1; t) into the bottom 5 percentile of the Economic Value Added (EVA): as such, cooperative and savings banks exploit their larger market power to provide gains to all stakeholders. Conversely, as the industry concentration increase (so more market power is given to banks), commercial and listed banks have less competitive pressures and use their enhanced market power to create value for shareholders. As such, our study provide evidence that the bank ownership structure has an impact on the banking sector stability.

Looking at the various contries, the loading factor coefficient corresponding to Belgium has the highest (and statically signicant) positive value, while the loading factor coefficient associated with Spain is the only negative and statistically significant. The results for the  $\lambda$  parameters hold throughout the different models under investigation and suggest, in line with what documented in Table 3 and 4, that the major and minor sources of systemic risk Belgium and Spain, respectively.

Finally, it is customary to use the J statistics for testing the over-identifying restrictions. This statistics has a  $\chi^2$  distribution with the number of degress of freedom equal to the number of overidentifying restrictions (which are equal to 20 in case of the model without dummy, and they are equal to 27 in case of the model with dummy). From Table 5 (last row) we can observe that given that the value of the minimised objective function is equal to zero, then we do not reject the set of overidentifying restrictions imposed.

## 6. Conclusions

This paper assesses the impact of the bank consolidation process on financial distress using a large sample 18,159 observations for the 1997-2005 sample period (annual frequency) for six European countries: Austria, Belgium, France, Germany, Italy, and Spain. We are interested in the analysis of migration into distress, defined as a move from two consecutive periods  $(t-1, t)$  into the bottom 5 percentile of the EVA empirical distribution in a given country. While the existing literature on the impact of bank concentration on systemic stability controlled for the impact of observable common factors (such as GDP growth), in this paper we control for the omitted variable bias by imposing a common factor to correlation structure of the binary response indicators of migration into distress. As a consequence, contrary to the previous studies based upon a single equation limited dependent variable regression, our study uses a multivariate probit model. We also extend previous literature by explicitly investigating the role played by commercial, cooperative, savings and listed banks on the average impact of bank consolidation on financial distress. A final contribution of our study to the existing literature deals with the estimation method. In particular, while the implementation of an ML approach is computationally intensive when modelling joint probabilities in systems of more than two binary endogenous variables, we use a GMM type of analysis. Therefore, our approach is similar to Bertschek and Lechner, (1998). More specifically, while Bertschek and Lechner, (1998) focus only on moment conditions based upon marginal probabilities, we also take into account moment conditions based upon joint probabilities.

Our findings show that, on average, the impact of bank concentration on financial distress is negative, therefore supporting the competition-stability view of Boyd and De Nicolo' (2005), i.e. an industry concentration increase (so more market power is given to banks) is likely to increase the financial distress. However, our sample comprises different type of banks (i.e. commercial, cooperative and savings banks) and the sample is dominated by cooperative banks observations. Once we take into account the classification of banks into different ownership categories, we find that while the aforementioned relationship is negative (relative to the average) for savings and cooperative banks (supporting the "competition-stability" view); in case of commercial and listed banks we observe a

positive effect (relative to the average) of bank concentration on financial distress (supporting the “competition-fragility” view). These contrasting results can be explained by the different institutional aims of these banks (i.e. stakeholder vs. shareholder value creation). Indeed, the stated objective of cooperative and savings banks is not maximization of profits, but rather maximization of stakeholder value (e.g. consumer surplus in case of cooperative banks). This leaves cooperative and savings banks with relatively low average profits in normal years. However, in weaker years, cooperative banks are able to extract some of the consumer surplus, thereby mitigating the negative influence on returns (see the empirical findings of Hesse and Cihak, 2007, regarding this issue). Therefore, an higher degree of market power given to cooperative and savings banks allows providing further gains to all stakeholders, hence reinforcing the mitigating effect of stress on bank profitability, during weak periods. Conversely, as the industry concentration increase, commercial and listed banks have less competitive pressures and use their enhanced market power to create value for shareholders, via an increase in loan risk as suggested by Boyd and De Nicolo’ (2005). As such, these results have significant policy implications for academics, practitioners and, especially, regulators.

## References

- Abate, J.A., Grant, J.L., Stewart III, B.G. (2004). "The EVA Style of Investing." *The Journal of Portfolio Management*, 30, 61--73.
- Adsera, X., Vinolas, P. (2003). "FEVA: "A Financial and Economic Approach to Valuation". *Financial Analysts Journal* 59, 80--88.
- Allen, F. and Gale D. (2004) "Competition and Systemic Stability", *Journal of Money, Credit and Banking*, 36:3, 453-480.
- Beck T., Demirgüç-Kunt, A., Levine R. "2006. Bank Concentration, Competition, and Crises: First Results". *Journal of Banking and Finance*, 30:5, 1581-1603.
- Bertschek, I. and Lechner, M. (1998): "Convenient Estimators for the Panel Probit Model", *Journal of Econometrics*, 87, 329-371.
- Berger, A.N., Kappler, L. F. And Turk-Arriss, R. (2008): "Bank competition and Financial Stability", *World Bank* working paper 4696.
- Bock R.D. and M. Lieberman (1970) "Fitting a response model for  $n$  dichotomously scored items", *Psychometrika*, 35, pp 179-197
- Bock R.D. and R.D. Aitken (1981) "Marginal Maximum Likelihood Estimation of Item Parameters: an application to the EM algorithm", *Psychometrika*, 46, pp 443-459
- Bock R.D. and R.D. Gibbons (1996) "High dimensional Multivariate Probit", *Biometrics*, 52, pp. 1183-1194.
- Bordo, M., Redish, A., Rockoff, H. (1995): "A comparison of the United States and Canadian Banking Systems in the Twentieth Century: Stability vs. Efficiency", in: Bordo, M., Sylla, R. (Eds.), *Anglo-American Financial Systems: Institutions and Markets in the Twentieth Century*. Irwin Professional Publishers, New York, pp. 11-40.
- Boyd, J., De Nicolò, G. and Jalal, A.M (2006): "Bank Risk-Taking and Competition Revisited: New Theory and New Evidence, *IMF Working Paper* No. 06/297
- Boyd, John H., and Gianni De Nicolò, (2005), "The Theory of Bank Risk Taking and Competition Revisited," *Journal of Finance*, Vol. 60, Issue 3, pp. 1329-343.
- Carletti, E., Hartmann, P., (2003): "Competition and Financial Stability: What's Special about Banking?, In *Monetary History, Exchange Rates and Financial Markets: Essays in Honour of Charles Goodhart*", Vol. 2, edited by P. Mizen, Cheltenham, UK: Edward Elgar
- De Nicoló, G. and Loukoianova, E. (2007): "Bank Ownership, Market Structure and Risk, *IMF Working Paper* No. 07/215
- Demirgüç-Kunt, A. and Detragiache, E. (2005): "Cross-Country Empirical Studies of Systemic Bank Distress: A Survey," *IMF Working Paper* 05/96 (Washington: International Monetary Fund).
- Demsetz, R., Saldenber, M.R., Strahan, P.E., (1996): "Banks with something to lose: The disciplinary role of franchise value". *Federal Reserve Bank of New York Economic Policy Review*, 2, 1-14

- European Central Bank, 2007b. Financial Stability Review, December
- Ferguson R., Rentzler J., Yu, S., (2005), “Does Economic Value Added (EVA) improve stock performance or profitability?”. *Journal of Applied Finance*, 15, 101-113.
- Ferguson R., Rentzler J., Yu, S., (2006), “Trading Strategy on EVA® and MVA: Are They Reliable Indicators of Future Stock Performance?”. *Journal of Investing*, 15, 88-94
- Ferguson, R., Leistikow, D. (1998) “Search for the Best Financial Performance Measure: Basics are Better”. *Financial Analysts Journal* 54(1), 81--86.
- Fiordelisi, F. Molyneux, P.(2006): *Shareholder Value in Banking*. Palgrave Macmillan, London
- Fiordelisi, F., (2007), “Shareholder value-efficiency in banking”, *Journal of Banking and Finance*, 31, 2151–2171
- Gagliardini, P. and C. Gourieroux (2005): Migration correlation, definition and efficient estimation, *Journal of Banking and Finance*, 29, pp. 865-894,
- Gibbons, R.D. and V. Wilcox Gok, (1998) “Health Service utilisation and insurance coverage: a Multivariate Probit analysis”, *Journal of American Statistical Association*, 93, 441, pp. 63-72.
- Jimenez, G., J. Lopez and J. Saurina, (2007): “How does competition impact bank risk taking?”, working paper, Banco de Espana..
- Hausmann, J.A. and Wise, A (1978), “A conditional probit model for qualitative choice: discrete decisions recognizing interdependence and heterogeneous references, *Econometrica*, 46, 403-426.
- Heimeshoff, U. and Uhde A. (2008): “Consolidation in Banking and Financial Stability in Europe”, *mimeo*
- Hesse, H. and M. Cihak (2007): “Cooperative banks and Financial Stability”, *IMF working paper*, 07/2.
- Hoggarth, G., Milne, A., Wood, G. (1998): “Alternative Routes to Banking Stability: A Comparison of UK and German Banking Systems”. Bank of England Systemic Stability Review 5, 55-68.
- Keeley, M., (1990): “Deposit Insurance, Risk and Market Power in Banking”, *American Economic Review*, 80, 1183-1200
- Koller, T., Goedhart, M., Wessels, D. ( 2005): *Valuation: Measuring and Managing the Value of Companies*. John Wiley & Sons, Fourth edition, New Jersey, U.S.
- Machuga, S.M., Preiffer, R.J., Verma, K. (2002): “Economic Value Added, Future Accounting Earnings, and Financial Analysts’ Earnings Per Share Forecasts”. *Review of Quantitative Finance and Accounting*, 18, 59--73.
- Marcus, A.J., (1984): “Deregulation and bank financial policy”, *Journal of Banking and Finance*, 8, 557-565
- Martínez-Miera, D. and R. Repullo, 2007. “Does competition reduce the risk of bank failure?”, unpublished manuscript, CEMFI.

- Mishkin, F.S. (1999): "Financial Consolidation: Dangers and Opportunities". *Journal of Banking and Finance*, 23, 675-691.
- Resti A., Sironi, A. (2007): "Risk management and shareholder value in banking", John Wiley & Sons, Chichester, U.K.
- Saurina, J.S., Jimenez, G. and Lopez, J. (2007): "How Does Competition Impact Bank Risk Taking?" Federal Reserve Bank of San Francisco Working Paper 2007-23
- Schaeck K., Cihak, M., Wolfe, S. (2006): "Are More Competitive Banking Systems More Stable?" *IMF Working Paper* No. 06/143, Washington D.C.
- Stoughton, N. M., Zechner, J. (2007): "Optimal capital allocation using RAROC and EVA". *Journal of Financial Intermediation*, 16, 312-342.
- Unal, H., Kane, E., (1988): "Two Approaches to Assessing the Interest Rate Sensitivity of Depository Institution Equity Returns". *Research in Finance*, 7, 113-137.
- Uyemura, D.G., Kantor, G.C., Pettit, J.M. (1996): "EVA for banks: value creation, risk management and profitability measurement". *Journal of Applied Corporate Finance*, 9, 94--105

**Table 1: Sample size per group**

|         | Commercial banks | Cooperative Banks | Savings banks | Listed banks | Total |
|---------|------------------|-------------------|---------------|--------------|-------|
| Austria | 159              | 359               | 474           | 32           | 992   |
| Belgium | 75               | 47                | 45            | 5            | 167   |
| France  | 563              | 520               | 201           | 76           | 1284  |
| Germany | 776              | 6827              | 4234          | 110          | 11837 |
| Italy   | 375              | 2800              | 319           | 53           | 3494  |
| Spain   | 170              | 65                | 150           | 39           | 385   |

**Table 2: The Herfindahl-Hirschman Index in the European Banking**

|      | Austria | Belgium | France | Germany | Italy  | Spain  |
|------|---------|---------|--------|---------|--------|--------|
| 1997 | 0.0697  | 0.2001  | 0.0823 | 0.0378  | 0.0336 | 0.0447 |
| 1998 | 0.0685  | 0.2253  | 0.0790 | 0.0445  | 0.0349 | 0.0480 |
| 1999 | 0.0554  | 0.0475  | 0.0923 | 0.0476  | 0.0359 | 0.0694 |
| 2000 | 0.0590  | 0.1532  | 0.1138 | 0.0779  | 0.1011 | 0.0546 |
| 2001 | 0.0736  | 0.1463  | 0.1088 | 0.0784  | 0.0650 | 0.0546 |
| 2002 | 0.0722  | 0.5755  | 0.0890 | 0.0737  | 0.1055 | 0.0546 |
| 2003 | 0.0891  | 0.4698  | 0.0930 | 0.0755  | 0.1004 | 0.0546 |
| 2004 | 0.0827  | 0.4694  | 0.0997 | 0.0814  | 0.0447 | 0.0546 |
| 2005 | 0.0974  | 0.4773  | 0.1161 | 0.1263  | 0.0428 | 0.0546 |

**Table 3: Relative frequency of migration into distress**

|      | Austria | Belgium | France | Germany | Italy  | Spain  |
|------|---------|---------|--------|---------|--------|--------|
| 1998 | 0.0181  | 0.0000  | 0.0055 | 0.0068  | 0.0141 | 0.0000 |
| 1999 | 0.0000  | 0.0000  | 0.0056 | 0.0063  | 0.0270 | 0.0000 |
| 2000 | 0.0267  | 0.0000  | 0.0123 | 0.0553  | 0.0130 | 0.0094 |
| 2001 | 0.0149  | 0.0000  | 0.0655 | 0.0193  | 0.0243 | 0.0000 |
| 2002 | 0.0521  | 0.2142  | 0.0215 | 0.0148  | 0.0585 | 0.0000 |
| 2003 | 0.0167  | 0.0000  | 0.0070 | 0.0411  | 0.0234 | 0.0000 |
| 2004 | 0.0088  | 0.0000  | 0.0071 | 0.0359  | 0.0145 | 0.0000 |
| 2005 | 0.0326  | 0.1052  | 0.0340 | 0.0230  | 0.0161 | 0.0000 |

Note: The entries of this table are computing by numbering, in each period and for each country, the migration into distress events, and dividing this number by total number of observations in a given country and for a specific period

**Table 4: Unconditional (pairwise) joint probability of migration into distress**

|         | Austria | Belgium | France | Germany | Italy  | Spain  |
|---------|---------|---------|--------|---------|--------|--------|
| Austria | 0.0007  | 0.0020  | 0.0005 | 0.0006  | 0.0006 | 0.0000 |
| Belgium | -       | 0.0080  | 0.0011 | 0.0007  | 0.0019 | 0.0000 |
| France  | -       | -       | 0.0008 | 0.0005  | 0.0005 | 0.0000 |
| Germany | -       | -       | -      | 0.0009  | 0.0005 | 0.0000 |
| Italy   | -       | -       | -      | -       | 0.0008 | 0.0000 |
| Spain   | -       | -       | -      | -       | -      | 0.0000 |

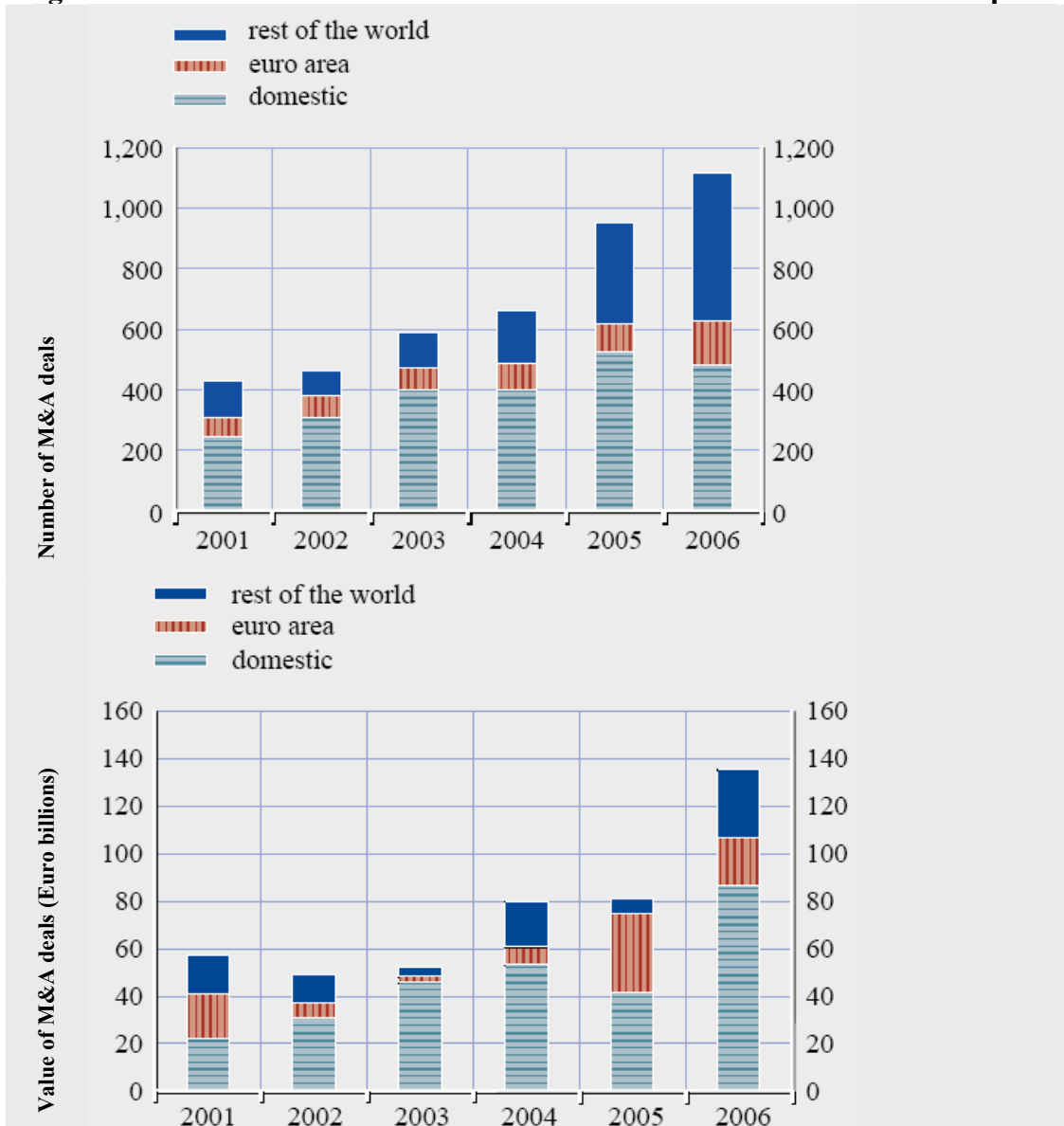
Note: The entries of this table are computing by using eq. (7), that is by using a time average estimator suggested, in the context of default migration, by Gagliardini and Gourieroux (2005).

**Table 5: Estimation results**

|                                     | <b>Model 1:<br/>All banks</b> | <b>Model 2:<br/>Commercial banks</b> | <b>Model 3:<br/>Cooperative banks</b> | <b>Model 4:<br/>Savings banks</b> | <b>Model 5:<br/>Listed banks</b> |
|-------------------------------------|-------------------------------|--------------------------------------|---------------------------------------|-----------------------------------|----------------------------------|
| $\Lambda_1$                         | 0.3148<br>(0.1812)            | 0.3115<br>(0.1810)                   | 0.3122<br>(0.1804)                    | 0.3120<br>(0.1807)                | 0.3109<br>(0.1816)               |
| $\Lambda_2$                         | 0.7029<br>(0.2107)            | 0.7122<br>(0.2112)                   | 0.7130<br>(0.2110)                    | 0.7123<br>(0.2112)                | 0.7128<br>(0.2111)               |
| $\Lambda_3$                         | 0.2207<br>(0.1338)            | 0.1985<br>(0.1377)                   | 0.2143<br>(0.1339)                    | 0.2074<br>(0.1357)                | 0.1739<br>(0.1543)               |
| $\Lambda_4$                         | -0.05077<br>(0.1674)          | -0.0611<br>(0.1660)                  | -0.0519<br>(0.1671)                   | -0.0573<br>(0.1689)               | -0.0667<br>(0.1772)              |
| $\Lambda_5$                         | 0.2823<br>(0.2205)            | 0.2810<br>(0.2198)                   | 0.2816<br>(0.2192)                    | 0.2814<br>(0.2195)                | 0.2804<br>(0.2204)               |
| $\Lambda_6$                         | -0.3419<br>(0.0670)           | -0.3322<br>(0.0619)                  | -0.3402<br>(0.0662)                   | -0.3384<br>(0.0642)               | -0.3365<br>(0.0627)              |
| $B_1$                               | -0.6520<br>(0.2843)           | -1.0418<br>(0.0095)                  | -0.5401<br>(0.0011)                   | -0.3878<br>(0.0073)               | -0.7201<br>(0.0073)              |
| $B_2$                               |                               | 1.1671<br>(0.0304)                   | -0.3030<br>(0.0036)                   | -0.9332<br>(0.0172)               | 2.2371<br>(0.8464)               |
| <b>Minimised objective function</b> | 0.000000                      | 0.000000                             | 0.000000                              | 0.000000                          | 0.000000                         |

**Note:** In the column labelled Model 1, we report the results for the model without dummy. In the columns labelled Model 2-Model 5, we report the results associated with the model with a dummy picking either the observations of commercial banks, or of savings, or of cooperative, or, finally, of listed banks. Standard errors are reported in brackets.

**Figure 1 - Number and value of M&A transactions between banks in Europe\***



(\*)All completed M&A where a bank is the acquirer.

Source: ECB (2007, p. 237) quoting Bureau van Dijk (ZEPHYR database) as data-source

## Figure 2 – EVA calculation tailored for banking

$$\Psi_{t-1,t} = \pi_{t-1,t} - k \bullet K_{t-1} \quad (1)$$

where:

$$\pi_{t-1,t} = \pi_{acc} + \text{R\&D Expenses} + \text{Training expenses} + \text{Operating Lease Expenses} + \text{Loan loss provisions} - \text{Net charge-off} + \text{General risk provisions} - \text{Net charge-off}$$

$$K_{t-1} = \text{Book value of equity} + \text{Capitalised R\&D expenses}^{(2)} + \text{Capitalised training expenses}^{(2)} - \text{Proxy for amortised R\&D expenses}^{(3)} - \text{Proxy for amortised training expenses}^{(3)} + \text{Proxy for the present value of expected lease commitments over time}^{(4)} - \text{Proxy for amortised operating lease commitments}^{(4)} + \text{Net Loan loss reserve} + \text{General Risk Reserve}$$

### Legend:

$\Psi$  is the Economic Value Added

$\pi$  is the “economic measure” of the bank net operating profits

$\pi_{acc}$  is the “accounting” net operating profits

$K$  is the capital invested

$k$  is the estimated cost of capital invested,

R&D is “Research and Development”

$i$  and  $t$  subscripts denote the cross-section and the time dimensions, respectively

### Notes:

- (1) Capital invested cannot be simply measured using total assets and the cost of invested capital is not estimated as the Weighted Average Cost of Capital (WACC). Since financial intermediation is the core business for banks, debts should be considered as a productive input in banking rather than a financing source (as for other companies). As such, interest expenses represent the cost for acquiring this input and, consequently, should be considered as an operating cost rather than a financial cost (as for other companies). As a consequence, if the capital charge is calculated following a standard procedure (i.e. applying WACC on total assets), EVA will be biased since it will double count the charge on debt. As such, the charge on debt should be firstly subtracted from NOPAT (the capital charge is calculated on the overall capital – i.e. equity and debt - invested in the bank and, consequently, it includes the charge on debt) and, secondly, it would be subtracted from operating proceeds in calculating NOPAT: interest expenses (i.e. the charge on debt capital) are in fact subtracted from operating revenues. In the case of banks, it seems reasonable to calculate the capital invested (and, consequently, the capital charge) focussing on equity capital (among others, Di Antonio 2002, Resti and Sironi 2007)<sup>5</sup>: as such, we measure the capital invested in the bank as the book value of total equity and the cost of capital as the cost of equity. The cost of equity is estimated following procedure: 1) for quoted banks, we use follow a standard procedure applying a two-factor model using both market and interest rate risk factors (following Unal and Kane 1988); and 2) for non-quoted banks, we use the mean of the cost of equity capital for comparable domestic quoted banks (in terms of total assets).
- (2) Capitalised R&D expenses and capitalised training expenses are obtained summing annual R&E expenses and training expenses, respectively, over a period of five years (e.g. Stewart, 1991 suggests that five years is the average useful life of R&D expenses).
- (3) The proxies for amortised R&D expenses and amortised training expenses are obtained as the mean of the R&D expenses over the 1996-2005 period.
- (4) Since data availability does not allow us to evaluate the present value of expected lease commitments over time, the present value of expected future lease commitments capitalised is assumed to be equal to the overall amount of operating leases expenses over for a five years period. The amount annually amortised is close to the amount of R&D expenses divided by 3 years (assuming a straight-line amortisation process).

Source: adjusted by Fiordelisi (2007, p.2169)

<sup>5</sup> Otherwise, it would be necessary to distinguish between borrowed funds assigned to finance banking operations and those representing a productive input. Since our dataset do enable us to make this differentiation, we prefer to focus only on equity capital.