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

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Abstract

This paper examines the impact of bank concentration on bank financial distress using a balanced panel of commercial banks belonging to EU 25 over the sample period running from 2003 to 2007. Financial distress is proxied by the observations falling below a given threshold of the empirical distribution of a risk adjusted indicator of bank performance: the Shareholder Value ratio. We employ a panel probit regression estimated by GMM in order to obtain consistent and efficient estimates following the suggestion of Bertschek and Lechner (1998). Our findings suggest, after controlling for a number of enviroment variables, a positive effect of bank concentration on financial distress.

Keywords*: EVA, Banking, Panel Probit, GMM*

JEL codes*: C33, C35, G21, G32*

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1. Introduction

Given the recent wave of consolidation in the European banking system (see Figure 1 reporting recent data on the incresing importance of M&A) there is an increasing concern on the impact of bank concentration on the stability of the overal 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.

Our contribution to the literature is threefold. First, we analyse the impact of bank concentration on financial distress focussing on both quoted and non-quoted European banks by using an indicator of shareholder value: the Shareholder Value Ratio. This indicator is obtained as the ratio of a bank Economic Value Added, EVA, to the shareholders' invested capital. In particular, our proxy of distress is retrieved by concentrating on the worst outcomes of the Shareholder Value Ratio, that is, by using a binary variables taking value equal to one, when we observe values of the Shareholder Value Ratio falling below the median value, or below the lowest tertile, or below the worst quartile. We motivate our focus on the Shareholder Value ratio, given that 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. Greenspan (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 whether banks are healthy and sound since they 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 evidence that profitable banks may not be as well financially sound. For our research purpose, shareholder value measures are superior to profit measures since these include both the bank economic profits and the opportunity cost of capital that is influenced by its risk-taking. The measure of bank shareholder value added we use is the Economic Value Added (EVA) since this can be calculated for both listed and non listed banks.

Second, we use a balanced panel of 180 large banks observed over four years for the 2003-2007 sample period within the EU 25 region. The number of studies dealing with the EU 25 banking system is limited (to our knowledge, only the study of Uhde, 2008, concentrates on EU, using the z score as a proxy of distress), few of these also consider non-quoted banks and none considered a so recent time period at the onset of the sub-prime crisis.

The third contribution of our study is from an econometric methodological point of view. Specifically, the panel probit regression model with non spherical disturbances we use is not estimated by Maximum Likelihood, ML (see Butler and Moffitt, 1982, Hajivassilou, 1993, among the others). We use, instead, GMM, following the suggestions of Bertschek and Lechner (1998). The use of ML would require the evaluation of multiple dimensional integrals of an order equal to the time series dimension and this might be a computationally intensive task which might imply lack of convergence of the algorithm employed and lack of achievement of global concavity. Estimation by GMM allows the implementation of an algorithm more feasible than ML in retrieving a consistent and efficient parameters estimator while allowing for non spherical disturbances. Although GMM is less efficient than Full Information Maximum Likelihood (given that the coefficients entering the covariance matrix of residuals are treated as nuisance parameters), the design of optimal instruments, along the lines of Newey (1993), can minimise the loss efficiency in the GMM estimator, while preserving consistency.

Our empirical finding suggest that there is a positive effect of bank concentration (proxied by either the Herfindal-Hirschman index, or by the index based upon the assets share of the five largest banks, C5) on financial distress, and this supports the view of of Boyd and De Nicolo' (2005).

The paper is organised as follows. Section 2 and 3 provide a literature review on the effect of bank consolidation on the oveall 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 (see 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 a 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. Finally, among those studies supporting the "concentration-stability" view there is the panel data analysis of Jimenez et al. (2007). The authors (using a rich dataset of Spanish banks) do not find a significant effect of bank concentration (proxied by either the market share of the first five commercial lenders in each province, denoted as C5, or by the Herfindal-Hirschman index, HHI) on bank systemic risk (which is proxied by non performing loans ratios). However,

when using the Lener index to proxy market power, there is evidence of a negative relationship between loan market power and bank risk

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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 evidence that more competitive banking markets are less prone to systemic crises and that systemic crises take longer to develop within a competitive environment. Uhde (2008))

applies panel data analysis to bank balance sheet data from banks across the EU-25 for the period of 1997-2005. The author uses the z-score as a proxy of banking stability and they find that market concentration has a negative impact on banks' financial soundness. 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: Panel probit regression

3.1 Definition of distress

In order to define distress, we focus on the Shareholder Value Ratio (i.e. the ratio between Economic Value Added and the shareholders capital invested at time t-1). We measure shareholder value focussing on the EVA since various empirical studies (e.g. 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. In particular, given our interest in financial distress, we consider the observations falling below a given threshold of the Shareholder Value Ratio. For robustness, the threshold values used are either the median value, or the lowest tertile, or the lowest quartile for the empirical probability distribution of EVA.

3.2 Model set up

Given a balanced panel with N cross sectional units observed over T period, the endogenous binary response observed for the ith bank at time period t is modelled as:

$$y_{it} = \begin{cases} 1 & \text{if } y_{it}^* - c \leq 0 \\ 0 & \text{if } y_{it}^* - c > 0 \end{cases} \tag{1}$$

The threshold c is set equal to the inverse of the Gaussian *cdf* for the chosen percentile[1]. Furthermore, the latent variable y_{it}^* driving the endogenous binary responses y_{it} is given by:

$$y_{it}^* = \beta' x_{it} + \varepsilon_{it} \tag{2}$$

where x_{it} is a k dimensional vector of explanatory variables observed for the ith bank at time period t. The residuals $u_i = (u_{1i},...,u_{Ti})'$ are assumed to be jointly normally distributed with mean zero and covariance matrix (not diagonal) Σ and to be independent of the explanatory variables. Therefore, the residuals are uncorrelated over different banks but they are correlated over time for the same bank. As pointed by Bertschek and Lechner (1998) one of the main diagonal element (the residual variance in the first period in our study) is set to unity for identification of β.

3.3 GMM estimation

The use of Maximum Likelihood, ML, would imply the joint estimation of the parameter vector β and of the off-diagonal elements of the residuals covariance matrix, Σ, and the evaluation of a T dimensional integral via simulation (see Hajivassiliou, 1993). This, would, then, be a computationally intensive task and lack of global concavity might be a problem as well (see Bertscheck and Lechner, 1998). Butler-Moffit (1982) propose a parsimonious way of modelling Σ, by using a one factor model specification underlying the correlation structure. However, as pointed by Bertschek and Lechner (1998) there is no proof available regarding the consistency of the estimator when the true correlation structure is not driven by a single common factor. The use of a GMM avoids the evaluation multiple dimensional integrals and also, by treating the off-diagonal elements of Σ as nuisance parameters, reduces the computational intensity of the estimation method, simplifying the convergence of the algorithm employed and the achievement of global concavity. Although, the lack of explicit modelling of the residual covariance structure leads to a loss of efficiency relative to Full Information Maximum Likelihood, the minimisation of this efficiency loss has to be

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[1] The threshold c in equation (1) is the intercept of a probit regression. Therefore, we estimate the slope coefficients by calibrating on the chosen relative frequency of observing EVA in distress.

achieved choosing optimal instruments when implementing the GMM algorithm. In particular, GMM involves solving the quadratic programming problem[2]:

$$\min_{\beta} g_N(\beta) g_N(\beta)'$$ (3)

where $g_N(\beta)$ is a $k \times 1$ vector of unconditional moment restrictions, and it is given by:

$$g_N(\beta) = \frac{1}{N} \sum_{i=1}^{N} A(X_i) M(X_i; \beta) = \begin{bmatrix} 0 \\ ... \\ 0 \end{bmatrix}$$ (4)

where the $T \times 1$ matrix of probit regression residuals is:

$$M(X_i; \beta) = \begin{bmatrix} y_{1i} - \Phi(x_{1i}\beta) \\ ...... \\ y_{Ti} - \Phi(x_{Ti}\beta) \end{bmatrix}$$ (5)

The total number of unconditional moments described by (4) is equal to number of parameters entering in β (and it is equal to k) and it is obtained by taking the sample average over the cross sectional dimension N of the conditional moment restrictions described by the addends entering the sum in (4). The conditional moments are orthogonally restrictions between the residuals of the probit regression at a given time period and (a function of) the explanatory variables at all time periods. The probit regression residuals are defined as a difference between the observed binary indicator of distress y_{ti} and the conditional predictive probability of observing distress given by the cumulative Gaussian cdf $\Phi(.)$. The instruments matrix $A(X_i)$ is $k \times T$, and as Chamberlain (1987) and Newey (1990) have shown, the optimal design of instruments is given by:

$$A^*(X_i) = D(X_i)'\Omega(X_i)^{-1}$$ (6)

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[2] The solution of the quadratic problem given by (3) is obtained by employing a Sequential Quadratic Programming algorithm embedded in the *sqpsolve* Gauss routine.

where the generic element d_{ti} of the gradient of moment conditions $D(X_i)$ is given by:

$$d_{ti} = -\Phi_{ti}(.)x_{ti} \tag{7}$$

and the generic element ω_{tsi} of the (conditional) covariance matrix of the residuals $\Omega(X_i)$ is:

$$\Omega(X_i) = \begin{bmatrix} \Phi_{ti}(1-\Phi_{ti}) & if & t=s \\ \Phi_{tsi}^{(2)} - \Phi_{ti}\Phi_{si} & if & t \neq s \end{bmatrix} \tag{8}$$

As pointed by Bertschek-Lechner (1998), the estimation of the optimal GMM-estimator is still difficult, because it depends on the unknown correlation coefficients of Ω, through the terms $\Phi_{tsi}^{(2)}$. The latter gives the bivariate cumulative Gaussian *cdf* and it depends on the unknwon correlation coefficients capturing the correlation among the latent variables *y**. Then, Bertschek-Lechner (1998) suggest various ways of modelling $\Omega(X_i)$ in a way such that the coefficients influencing the off-diagonal elements of $\Omega(X_i)$ are treated as nuisance parameters. The three different estimators are as follows:

3.3.1 The first method (see Bertschek-Lechner, 1998) gives consistent, but inefficient estimates of β given the ignorance of possible nonzero off-diagonal elements in $\Omega(X_i)$, that is:

$$\Omega(X_i) = \begin{bmatrix} \Phi_{ti}(1-\Phi_{ti}) & if & t=s \\ 0 & if & t \neq s \end{bmatrix} \tag{9}$$

3.3.2 The GMM algorithm based upon equation (8) is the benchmark model providing first step estimates used in the following two most efficient estimator whithin the class of GMM. In particular, in order to increase efficiency when dealing with small samples by avoiding the use of a a large number of instruments, therefore avoiding using an high dimensional matrix *A(.)*, one device relies on the assumption of equi-intertemporal residual correlation. This involves the use of random effects for the generic time period *t* in the probit regression.

Furthermore, by assuming a small variance of the random effects (equal to σ_c^2) relative to the total variance of the errors, we get:

$$\Omega(X_i) = \begin{bmatrix} \Phi_{ti}(1-\Phi_{ti}) + \sigma_c^2 \Phi_{ti} & if & t = s \\ \sigma_c^2 \Phi_{ti} \Phi_{si} & if & t \neq s \end{bmatrix} \quad (10)$$

Therefore the only coefficient additional to those entering in β is σ_c^2 and this parameter can be consistently be estimated by running the following OLS regression:

$$(y_{ti} - \tilde{\Phi}_{ti})(y_{si} - \tilde{\Phi}_{si}) = \sigma_c^2 \, \tilde{\Phi}_{ti} \, \tilde{\Phi}_{si} + error \qquad t, s = 1,...,T \quad t \neq s \qquad (11)$$

where $\tilde{\Phi}(.)$ is based upon a first step consistent estimation of β. Betschek and Lechner (1998) show through Montecarlo simulation, that among the GMM parametric estimators of $\Omega(X_i)$, the one based upon modelling the covariance matrix of residuals through (9) is the most efficient[3].

3.3.3 The final GMM algorithm is based upon $\tilde{\beta}$, that is on a first step consistent estimation of β, and the following model for the covariance matrix of residuals (conditional on X_i):

$$\Omega(X_i) = \sum_{j=1}^{N} w_{ij} M(X_j; \tilde{\beta}) M(X_j; \tilde{\beta})' \qquad (12)$$

where $M(X_j; \tilde{\beta})$ is the T dimensional vector of probit regression residuals given by (5) and the weights w_{ij} are positive for the k nearest neigbours, $j \leq k$, and equal to zero for $j > k$. As shown by Betschek and Lecnher, the GMM algorithm based upon the non parameteric estimation of $\Omega(X_i)$, hence independent of the additional coefficient ρ, and described by equation (12), turns out to be the most efficient among various GMM estimators (both parametric and non parametric) considered by the authors. In particular, the non parameteric algorithm is based upon unform weights, that is $w_{ij} = 1/k$, and k is chosen

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[3] The estimator based on (9) is more efficient than the sequential estimator proposed by Chamberlain (1983). See Bertscheck and Lechner (1998) for details.

by following the suggestions of Newey (1993), that is by minimising the cross validation function:

$$CV(k) = tr\left[Q\sum_{i=1}^{N}\tilde{R}(x_i)\tilde{\Omega}(x_i)\tilde{R}(x_i)'\right]$$ (13)

defining $\tilde{\Omega}(x_i)$ and $A^*(x_i)$, the residual covariance matrix and the instrument matrix evaluated at $\tilde{\beta}$, which is a first step, consistent estimate of β, then the matrix $\tilde{R}(x_i)$ entering in equation (13) is:

$$\tilde{R}(x_i) = \left\{A^*(x_i)\left[M(z_i;\tilde{\beta})M(z_i;\tilde{\beta})'-\tilde{\Omega}(x_i)\right]\right\}\tilde{\Omega}(x_i)^{-1}$$ (14)

3.3.4 Finally, Σ which is the covariance matrix of the parameters estimates β, corresponding to the one of the efficient estimator described above is given by:

$$\frac{1}{N}\sum_{i=1}^{N}\left[D(X_i)'\Omega(X_i)^{-1}D(X_i)\right]^{-1}$$ (15)

4 Data and variables

Our dataset has 720 bank-year observations for 180 commercial banks (within EU 25) for the four years sample period running from 2003 to 2007. As described in section 3.1 financial distress is measured by focussing on the worst outcomes of the Shareholder Value Ratio (i.e. the ratio between Economic Value Added and the shareholders capital invested at time t-1). EVA is calculated 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 shareholders' 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 is 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[4].

The explanatory variable of interest in our study are proxies of bank concentration. For this purpose we use the Herfindal-Hirschman index, HHI, obtained taking the sum of the squared values of market shares (in terms of assets) for each country and in a given time period. As robustness check, we also use the concentration ratio of top five banks, C5, that is the sum of the (asset) market shares of the five biggest banks in a country and in a given period as a measure of bank consolidation.

As proposed by various studies (e.g. Salas and Saurina 2003, Maudos and De Guevara 2004, Yildirim and Philippatos 2007, Brissimis et al., 2008), we also use two bank specific control variables: the income diversification ratio, and the asset size**.** As found by Lepetit et al., (2008), the income diversification plays an important role in influencing bank performance and risk in European banking so that this is likely to influence banks' distress. Following the aforementioned authors, we measure bank income diversification as the net non-interest income to net operating income ratio (ID). The other variable is the bank size (measured by the log of bank total assets). The asset size has two important implication for the banking stability

Finally, in order to proxy the current economic climate we use the log of GDP per capita: the country prosperity (i.e. GDP per-capita) is used by various previous studies (e.g. Dietsch and

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[4] 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 calculation. For further details, see Uyemura et al. (1996), Koeller et al. (2005) and Fiordelisi and Molyneux (2006).

Lozano-Vives 2000, Carvallo and Kasman 2005, Maudos and de Guevara 2007) dealing with bank performance.

From Table 1 of descriptive statistics, by comparing the minima and maxima of each covariates with the corresponding standard deviation, we can observe a degree of asymmetry for the bank specific control variables, ID and SIZE, and also for the two proxies of bank concentration, HHI and C5, higher than the one corresponding to a proxy of the current economic climate (e.g., the log of GDP per capita).

5 Findings

Before commenting the empirical findings, we briefly mention the values of a couple of parameters useful in the construction of the SS GMM estimator and of the k nearest neighbours GMM estimator described in section 3. As for the former, the parameter σ_c^2 retrieved from the OLS regression given by equation (11) is equal to 0.314, 0.612, 0.683 for the definition of distress given by the 50%, 33% and 25% worst outcomes of the Shareholder Value Ratio, respectively, and when the proxy of bank concentration is measured by the Herfindal-Hirschman index. Furthermore, the value obtained for σ_c^2 is equal 0.305, 0.629, 0.729 for the definition of distress given by the 50%, 33% and 25% worst outcomes of the Shareholder Value Ratio, respectively, and when the proxy of bank concentration is measured by C5. As for the latter, the *k* parameter, used for the constructions of weights w_{ij} entering in equation (12), has been obtained by minimising the cross validation function given by (13) searching over the grid ranging from 1 to 180 (which is the cross sectional dimension in our panel). The optimal values for *k* are 101, 108, 138 for the definition of distress given by the 50%, 33% and 25% worst outcomes of the Shareholder Value Ratio, respectively, and when the proxy of bank concentration is measured by C5. Finally, the optimal values for k are 132, 170, 171 for the definition of distress given by the 50%, 33% and 25% worst outcomes of the Shareholder Value Ratio, respectively, and when the proxy of bank concentration is measured by HHI.

We now turn our focus on the panel model estimation through GMM. From Tables 2 to 4, there is evidence of an increase in the probability of observing Shareholder Value Ratio in distress, the higher is the degree of bank concentration (either measured through HHI or

through C5). This result is supporting the "competition stability" view of Boyd and De Nicolo' (2005) and it is line with empirical findings of Boyd et al. (2006) as well as of De Nicoló and Loukoianova (2007) and of Shaeck et al. (2006). In particular, our findings complement those characterizing the EU-25 region provided by Uhde (2008) who uses the z score as a proxy of distress. The negative impact of bank concentration on financial soundness can be explained by recognising that, as the industry concentration increase, commercial banks have less competitive pressures and use their enhanced market power to create value for shareholders, by pushing the bank risk profile.

Second, we find that, when the degree of income diversication increase there is an increase in the likelihood of observe EVA in distress. In order to interpret this results, we note that the banking business model has certainly changed over the last decade: major international banks (especially in the U.S.) have changed from a buy and hold business model (i.e. banks grant customer loans and hold them in their balance-sheets) to an originate-to-distribute business model (i.e. loans are firstly originated and securitised by banks, so these are often sold on to other intermediaries and the revenues used for granting new loans). The traditional buy and hold business model require banks to carefully monitor the portfolio quality and results in the intermediation margin; conversely, the originate-to-distribute model results in a high level of leverage and in lower incentives for banks to monitor the loan portfolio quality giving the opportunity to display good performance, despite the risk of operations. While it is also possible to posit the bank adopting the originate-to-distribute model may be able to make profits following good business practise (e.g. working efficiently and/or effecting good risk management), the estimated positive link between bank income diversification and our distress variable seems to support that view that the originate-to-distribute raised model moral hazard in business operations by encouraging carelessness in risk-taking. As such, this empirical result suggests that it is not only an increase in loan risk triggered by the traditional commercial lending activity of commercial banks, but also a shift toward other businesses (such as investment banking) which is behind the higher likelihood of worst outcomes for the risk adjusted performance measure proxied by the Shareholder Value ratio.

Furthermore, from Tables 2-4, the positive impact of bank size on systemic distress (at the European banking level) can be reconciled with the findings associated with ID, given that the bigger is the bank (in terms of total assets) the higher is the degree of specialisation in activties different from traditional commercial lending. This result has two important policy implications for the banking supervisors. First, this empirical findings is consistent with a

"Too Big to Fail policy" (i.e. regulators would avoid the largest and most powerful banks to let fail in order to prevent the panic in financial markets). This regulatory policy raises the issue of moral hazard in business operations since it encourage carelessness in risk-taking since governments would pick up the pieces in the default event. The estimated positive impact of bank size on systemic distress provide evidence that banks expected regulators adopted a "Too Big to Fail policy", as concretely happened over the 2008 bank crises. The estimated positive impact of bank size on systemic distress also provide some support the traditional Structure Conduct Performance hypothesis (i.e. larger banks would have would have a stronger market power and so may set more favourable interest rate spreads).

Moreover, as expected, we find that an improved state of the macroeconomy, proxied by the log of GDP per capita pushes down the risk profile of the bank (on average).

Finally, in line with Bertschek-Lechner (1998), we can observe that the coefficient standard errors associated with the pooled probit GMM estimator ignoring residual autocorrelation are biased downwards. In particular, this occurs when the parameters standard errors for the pooled probit GMM estimator are compared with those coresponding to the most efficient estimators (e.g. those based upon the residuals covariance matrix modelled either through equation 10, or ethrough quation 12).

6. Conclusions

This paper assesses the impact of the bank consolidation process on financial distress using a balanced panel of 180 banks (within the EU-25 region) observed (at annual frequency) over the 2003-2007 sample period. We proxy distress by concentrating on the worst outcomes (e.g. either those below the median value or those below the lowest tertile, or the lowest quartile) of a measure of risk-adjusted bank performance, i.e., the Shareholder value ratio. We used a panel probit regression for the empirical analysis allowing for non spherical disturbances and we estimate the parameters of interest using GMM. In particular, we follow the suggestions of Bertscheck and Lechner (1998), by treating the parameters entering the covariance matrix of the residuals as nuisance parameters. This avoids using a computationally intensive estimation method (based upon the evaluation of multi dimensional integrals of an order equal to the time series dimension) which would, instead, occur when using ML. We look at a number of estimators efficient whithin the class of GMM and, in particular, at what Bertscheck and Lechner (1998) find the most efficient

GMM estimator, based upon a non parametric estimation of the instrument matrix, as proposed by Newey (1993). After controlling for bank specific variables, such as a proxy of asset size and one for income diversification, we find that an increase in bank concentration (measured through HHI or C5) increases the likelihood of observing banks in distress. Our findings support the "competition-stability" view of Boyd and De Nicolo' (2005), suggesting that, as the industry concentration increase, commercial banks have less competitive pressures and use their enhanced market power to create value for shareholders, by pushing the bank risk profile. Our results seems also to support the view that the banking business model change (from a buy and hold model to an originate-to-distribute business model) raised model moral hazard in business operations by encouraging carelessness in risk-taking. Furthermore, the estimated positive impact of bank size on systemic distress provide evidence that banks assumed regulators adopted a "Too Big to Fail policy", as concretely happened over the 2008 bank crises.

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Table 1: Descriptive statistics of variables used to empirically assess the impact of bank concentration on financial distress in European Banking between 2003 and 2007

	HHI	C5	ID	Log(SIZE)	Log(GDP/head)
Mean	0.096	0.522	0.197	16.187	10.119
Std Dev	0.068	0.187	0.095	2.202	0.342
Min	0.017	0.216	0.000	11.015	9.034
Max	0.403	0.986	0.750	21.637	10.643

Table 2: The impact of bank concentration on financial distress in European Banking between 2003 and 2007: the Panel Probit regression (the dependent variable is EVA in distress, defined by the 50% worst outcomes)

regressors	Pooled GMM	SS GMM	GMM : k nearest neigbours	regressors	Pooled GMM	SS GMM	GMM: k nearest neigbours
HHI	3.244 (0.291)	3.476 (1.022)	3.244 (1.003)	**C5**	1.230 (0.083)	1.570 (0.306)	1.230 (0.280)
ID	2.674 (0.173)	2.628 (0.592)	2.674 (0.496)	**ID**	2.524 (0.168)	2.745 (0.566)	2.523 (0.477)
SIZE	0.029 (0.007)	0.030 (0.027)	0.029 (0.024)	**SIZE**	0.023 (0.007)	0.039 (0.027)	0.020 (0.024)
GDP/head	-0.132 (0.012)	-0.132 (0.047)	-0.132 (0.042)	**GDP/head**	-0.155 (0.012)	-0.202 (0.049)	-0.152 (0.043)
Minimised objective function	0.000000	0.000000	0.00032		0.000000	0.000000	0.00032

Note: the standard errors are obtained by taking the square root of the main diagonal elements of the covariance matrix of parameter estimates given by equation (15).

Table 3: The impact of bank concentration on financial distress in European Banking between 2003 and 2007: the Panel Probit regression (the depandent variable is the EVA in distress defined by 33% worst outcomes)

| regressors	Pooled GMM	SS GMM	GMM : k nearest neigbours	regressors	Pooled GMM	SS GMM	GMM: k nearest neigbours
HHI	1.761 (0.356)	2.50 (1.316)	1.684 (1.272)	**C5**	0.712 (0.112)	1.008 (0.403)	0.681 (0.390)
ID	3.456 (0.222)	3.563 (0.820)	3.272 (0.697)	**ID**	3.365 (0.219)	3.529 (0.804)	3.181 (0.682)
SIZE	0.097 (0.010)	0.096 (0.037)	0.086 (0.035)	**SIZE**	0.0950 (0.010)	0.098 (0.037)	0.086 (0.035)
GDP/head	-0.238 (0.016)	-0.243 (0.061)	-0.212 (0.057)	**GDP/head**	-0.255 (0.016)	-0.277 (0.063)	-0.232 (0.060)
Minimised objective function	0.00000	0.00000	0.002932	**Minimised objective function**	0.00000	0.00000	0.00145

Note: the standard errors are obtained by taking the square root of the main diagonal elements of the covariance matrix of parameter estimates given by equation (15).

Table 4: The impact of bank concentration on financial distress in European Banking between 2003 and 2007: the Panel Probit regression (the depandent variable is EVA in distress defined by 25% worst outcomes)

regressors	Pooled GMM	SS GMM	GMM : k nearest neigbours	regressors	Pooled GMM	SS GMM	GMM: k nearest neigbours
HHI	2.603 (0.415)	3.158 (1.717)	2.363 (1.699)	**C5**	0.770 (0.132)	1.083 (0.516)	0.686 (0.475)
ID	3.081 (0.261)	3.585 (1.027)	2.719 (0.794)	**ID**	3.006 (0.262)	3.611 (1.017)	2.619 (0.791)
SIZE	0.120 (0.012)	0.114 (0.047)	0.107 (0.044)	**SIZE**	0.116 (0.012)	0.118 (0.048)	0.103 (0.044)
GDP/head	-0.273 (0.019)	-0.272 (0.080)	-0.237 (0.069)	**GDP/head**	-0.283 (0.020)	-0.308 (0.084)	-0.244 (0.072)
Minimised objective function	0.000000	0.000000	0.00032	**Minimised objective function**	0.000000	0.000000	0.00032

Note: the standard errors are obtained by taking the square root of the main diagonal elements of the covariance matrix of parameter estimates given by equation (15).

Figure 1 - Number and value of M&A transactions between bank s in Europe*
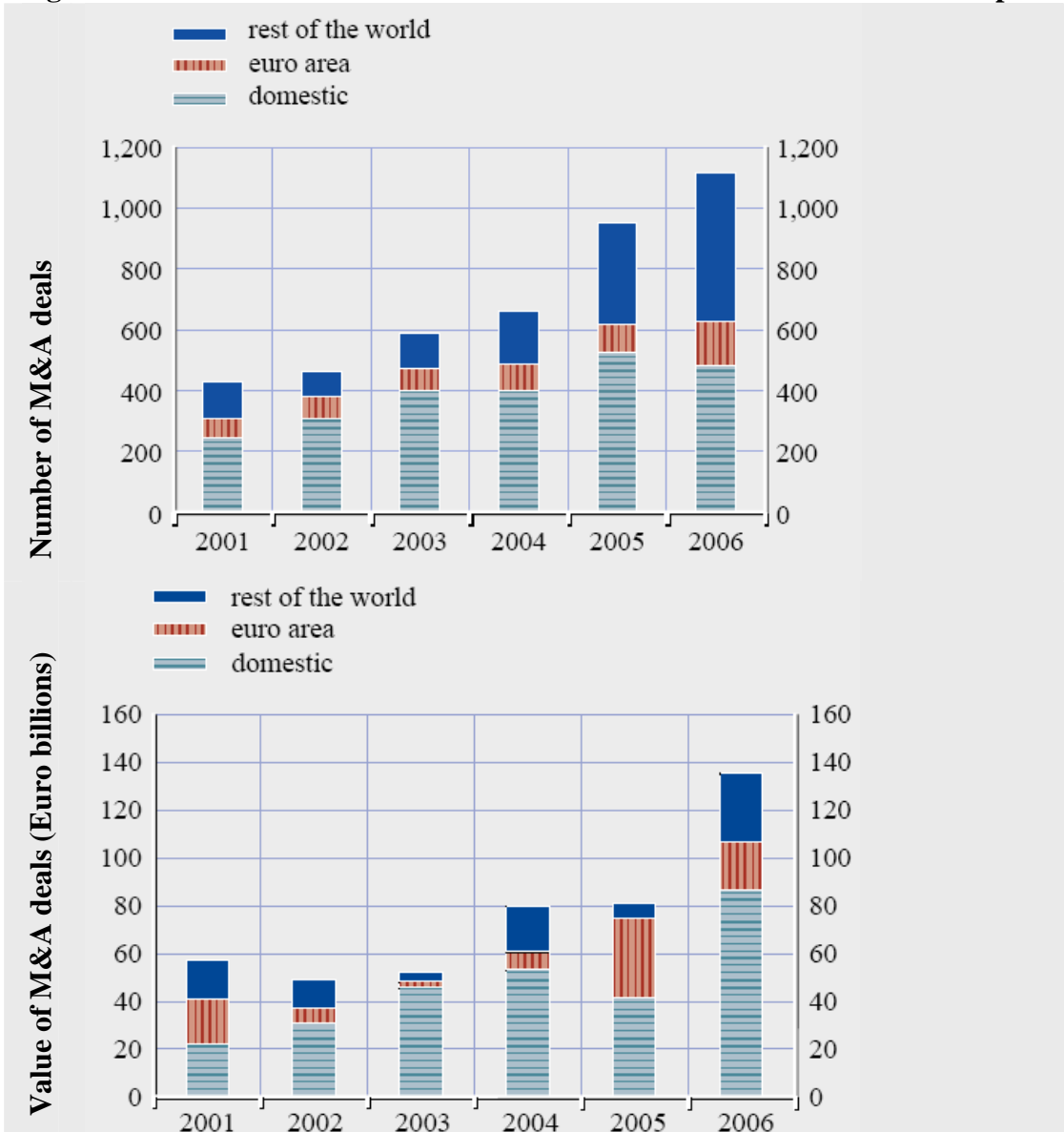
(*)All completed M&A where a bank is the acquirer.

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

Figure 2 – EVA calculation tailored for banking

$$\psi_{t-1,t} = \pi_{t-1,t} - k \bullet K_{t-1}\ ^{(1)}$$

where:

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

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

Legend:
ψ is the Economic Value Added
π is the "economic measure" of the bank net operating profits
π_{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)[5]: 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)

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[5]. 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.