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Risk in the EU banking industry and efficiency under quantile analysis

July 2009

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Abstract

This study estimates cost efficiency under a quantile regression framework. Our purpose is to investigate whether cost efficiency differs across quantiles of the conditional distribution. Efficiency scores are derived using the distribution-free approach. Results show that for higher conditional distributions, efficiency scores are lower. In a second stage analysis, we examine the relationship between risk, measured as distance to default and efficiency. Cross section regressions show that the higher the risk the lower the level of efficiency. The magnitude and the significance of the coefficient of the distance to default increases for conditional distributions associated with lower levels of efficiency.

JEL Classification: G21; L25

Keywords: Cost efficiency; Quantile regression; Distribution-free approach; Distance to default.

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1. Introduction

The efficiency of the European banking industry has attracted particular research attention, as is documented by its long tradition in the literature (i.e., Allen and Rai (1996), Lozano-Vivas et al., 2001, De Guevara and Maudos, 2002, Maudos et al., 2002, Vander Vennet, 2002, and Casu and Molyneux, 2003). A large number of studies on bank efficiency has emerged as a result of rapid changes in the structure of the European financial services industry in response to major advances in regulation and technology and to the implementation of the EU Single Market and the Monetary Union. These developments have created a more competitive financial sector throughout Europe and have spurred research interest in the banking systems of the European Union. Indeed, in light of the increased competition under the Single Market for financial services, the ability of EU credit institutions to compete and survive in an increasingly integrated European financial landscape has become even more important. This has been convincingly highlighted by the recent financial crisis, as the emergence of an increasingly integrated financial market in the EU has increased contagion risks, thereby jeopardizing financial stability (De Larosiere Report, 2009). Moreover, the different structures and past legacies of the European countries create additional challenges in terms of real convergence in a unified European banking market. At the same time, the dominant role played by banks in the provision of financial services in the European economies makes the performance of the banking system crucial for economic development and for the sound functioning of the industrial sectors, as an improvement of bank performance would lead to a better allocation of financial resources, and therefore to an increase of investment that favors growth (Molyneux et al., 1996).

The importance of efficiency measures as instruments for the analysis of bank performance becomes explicit, partly because efficiency scores provide an accurate evaluation of the performance of individual banks, but also of the financial industry as a whole, and partly because of the information that efficiency scores entail regarding the cost of financial intermediation and the overall stability of financial markets. Several studies have investigated efficiency in the European banking industry, and particularly focused on cross-country comparisons, using either parametric (i.e., Allen and Rai, 1996; Altunbas et al., 2001; Bikker, 2002; Carbo et al., 2002; De Guevara and Maudos, 2002; Maudos et al., 2002; Vander Vennet, 2002) or non-parametric approaches (i.e., Lozano-Vivas et al., 2001; 2002; Casu and Molyneux, 2003) or both (Weill, 2004). Overall, one of the main findings of most of these studies is the existence of significant efficiency differences across EU countries.

However, despite the plethora of studies investigating efficiency in the European banking industry, this paper departs from previous literature in several ways. First, we use, for the first time, quantile regression analysis to estimate banks' cost function. This type of analysis, proposed by Koenker and Bassett (1978), allows us to derive different parameter estimates of the cost function for various quantiles of the conditional distribution and as a result different efficiency scores. In particular, the quantile regression relaxes one of the fundamental conditions of the OLS and permits estimating various quantile functions, examining in particular the tail behaviours of that distribution.[1] Therefore, quantile regression is capable of providing a complete statistical analysis of the underlying diversity of stochastic relationships among stochastic variables by supplementing the estimation of conditional mean functions with an entire family of conditional quantile functions.

[1] In general, each quantile regression characterizes a particular, centre or tail, point of a conditional distribution. This approach estimates also the median (0.5^{th} quantile) function as a special case, which approximates the mean function of the conditional distribution of banks' cost.

Secondly, we investigate the relationship between cost efficiency and risk across different quantiles. This interaction has become particularly important, in light also of recent adverse events in global financial markets. In particular, the on-going financial crisis has indentified several shortcomings in the functioning of the global financial system and specifically, significant incentive misalignments that have greatly contributed, on the micro level, to the current financial turmoil (Caprio et al. 2008). In essence, these misaligned incentive structures have contributed to an understatement of true risk, generating mispricing of credit instruments. In light of this, the quantile regression analysis allows us to examine whether the underlying relationship between risk and performance changes across quantiles. This is an issue of particular importance as the recent crisis has demonstrated that the tales of the distribution, i.e. representing higher risk, may hold the key of understanding what have been malfunctioned in the banking industry.

Moreover, we measure risk using banks' distance to default (DD thereafter) (see Merton, 1974), which is considered to be a more comprehensive indicator of risk than the commonly used index-number proxies based on accounting data. To empirically estimate cost efficiency, we follow Berger (1993) and employ the Distribution-free approach (DFA thereafter). Apart from risk, in a second stage analysis, we also investigate the relationship between efficiency and other bank specific and macroeconomic variables.

Overall, we employ the quantile regression methodology to address a number of questions regarding cost efficiency and risk in the European banking system and discuss their policy implications. What is the level of cost efficiency across countries under different quantiles? Is there a general trend that can describe the evolution of efficiency scores when estimated for different quantiles? What is the relationship between efficiency and risk and how does this relationship evolve across quantiles? What is the relationship between efficiency and various banking variables and does quantile estimation affect these interactions?

A first glimpse at the results shows efficiency scores exhibiting marked diversity across quantiles that would go unnoticed in the classical efficiency estimations. In particular, we find that in higher quantiles average cost efficiency is lower compared to that of lower quantiles. In addition, our analysis regarding the relationship between risk and efficiency suggests that there is a positive relationship between efficiency and banks' distance to default, especially in the case of lower conditional distributions. Moreover, the second-stage regression analysis reveals that the interaction between efficiency and various banking and macroeconomic variables varies substantially across quantiles. Two notable examples are the relationship between cost efficiency and bank concentration and the relationship between efficiency and credit risk.

The rest of the paper is organized as follows. Section 2 presents the methodology, while Section 3 provides the description of the data. Section 4 discusses the empirical results, while conclusions are drawn in Section 5.

2. Methodology

2.1 Quantile regression

Quantile regression is a statistical technique intended to estimate, and perform inference about, conditional quantile functions. This analysis is particularly useful when the conditional distribution does not have a standard shape, such as an asymmetric, fat-tailed, or truncated distribution.[2] In the context of our study, quantile analysis provides an ideal tool to examine evidence on bank efficiency heterogeneity, departing from conditional-mean models.

Moreover, let y be a random variable with the distribution function F_Y and Φ be a real number between zero and one. The Φ^{th} quantile of F_Y we denote as $q_Y(\Phi)$ and is derived as the solution to $F_y = \Phi$, that is

$$q_Y(\Phi) := F_Y^{-1}(\Phi) = \inf \{ y : F_Y(y) \geq \Phi \}$$

This simply implies that $100\Phi^{th}\%$ $(100(1-\Phi)\%)$ of the probability mass of Y is below (above) $q_Y(\Phi)$.

As in the case of the least squares estimator the Φ^{th} quantile of F_Y is derived by minimizing an objective function with respect to q, i.e.,

$$\phi \int_{y>q} |y-q| dF_Y(y) + (1-\Phi) \int_{y<q} |y-q| dF_Y(y)$$

$$= \phi \int_{y>q} (y-q) dF_Y(y) - (1-\Phi) \int_{y<q} (y-q) dF_Y(y).$$

Note that the first order condition of this minimisation problem gives the Φ^{th} quantile of F_Y as

$$0 = -\phi \int_{y>q} dF_Y(y) + (1-\Phi) \int_{y<q} dF_Y(y)$$

[2] Quantile regression has recently gained attention in the financial literature, and particularly in the field of empirical finance. For example, Taylor (1999) provides quantile estimates for the distribution of multi-period returns, whilst Basset and Chen (2001) use quantile regression index models to characterise the diversity of mutual fund investment styles. For excellent reviews of the literature, see Koenker (2000) and Koenker and Hallock (2001).

$$= -\Phi\left[1 - F_Y(y)\right] + (1-\Phi)F_Y(y)$$

$$= -\Phi + F_Y(y)$$

Now, when Y has the conditional distribution $F_{Y/X}(y)$, with Φ^{th} quintile be $Q_{Y/X}(\Phi) := F_{Y/X}^{-1}(\Phi)$. $Q_{Y/X}(\Phi)$ is a function of X and solves

$$\min_q \left[\Phi \int_{y>q} |y-q|\,dF_{Y/X}(y) + (1-\Phi)\int_{y<q} |y-q|\,dF_{Y/X}(y)\right]$$

The conditional medina is thus $Q_{Y/X}(0.5)$ of $F_{Y/X}$. Now, taking $Q_{Y/X}(\Phi)$ is a linear function *X'β* with unknown parameter β then the above min is equivalent to

$$\min_\beta \left[\Phi \int_{y>X'\beta} |y-X'\beta|\,dF_{Y/X}(y) + (1-\Phi)\int_{y<X'\beta} |y-X'\beta|\,dF_{Y/X}(y)\right]$$

The solution gives β^{Φ} which is the Φ^{th} conditional quantile $Q_{Y/X}(\Phi) = X'\beta_{\Phi}$.

Given the above, a quantile regression involves the estimation of conditional quantile functions, i.e., models in which quantiles of the conditional distribution of the dependent variable are expressed as functions of observed covariates (Koenker and

Hallock, 2000). Briefly stating standard formulation, the linear regression model takes the form:

$$y_{it} = x_{it}\beta_{\phi} + \varepsilon_{i\phi} \tag{1}$$

where $\varphi \in (0, 1)$, x_i is a $K \times 1$ vector of regressors, $x_i\,\beta_\varphi$ denotes the φ^{th} sample quantile of y (conditional on vector x_i), and $\varepsilon_{i\varphi}$ is a random error whose conditional quantile distribution equals zero.

In general, the objective function for efficient estimation of β corresponding to the φ^{th} quantile of the dependent variable (y) can be expressed by the following minimization problem:

$$\min_{\beta} \frac{1}{n}\left\{ \sum_{i: y_i \geq x_i\beta} \phi \left| y_i - x_i\beta \right| + \sum_{i: y_i \leq x_i\beta} (1-\phi)\left| y_i - x_i\beta \right| \right\} \tag{2}$$

which is solved via linear programming. Note that the median estimator, that is, quantile regression estimator for $\varphi = 0.5$, is similar to the least-squares estimator for Gaussian linear models, except that it minimizes the sum of absolute residuals rather than the sum of squared residuals.

2.2 Estimating cost efficiency

A number of different approaches have been proposed in the literature for the estimation of bank efficiency, each of which has its individual strengths and weaknesses (see Berger and Humphrey 1997 for a review). In this study we opt for a parametric methodology and employ the Distribution-free approach (DFA), developed by Berger (1993), who follows Schmidt and Sickless (1984). This approach is a particularly attractive technique due to its flexibility as it does not impose *a-priori* any specific shape on the distribution of efficiency (DeYoung, 1997). Instead of that, the

DFA methodology assumes that the inefficiency of each financial institution remains constant across the sample period and that random error averages out over time.[3]

By averaging the residuals to estimate bank-specific efficiency, DFA estimates how well a bank tends to do relative to its competitors over a range of conditions over time, rather than its relative efficiency at any one point in time (DeYoung, 1997). This is useful in the banking sector, since relative efficiencies among different banks may shift somewhat over time because of changes in management, technical change, regulatory reform, the interest rate cycle, and other environmental influences.[4] However, the rationality of the DFA assumptions depends on the length of period studied.[5] Empirical investigation (i.e., DeYoung, 1997; Mester, 2003) into the number of years that may be needed to strike a balance between the benefits from having an additional observation to help average the random error and the costs associated with adding extra information, which increases the likelihood that the efficiency in the extra year might drift further away from its long term level shows that a six year period reasonably balances these concerns.

For the estimation of the Distribution-free approach we opt for the translog cost function[6], which gives us the following specification:

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[3] In detail, the formal procedure used to carry out the separation between inefficiency and the random error can be described in three steps. First, a consecutive series of annual cost functions are estimated for a given set of banks and some predetermined number of years. Secondly, based on this estimated function, the difference between the observed cost and the predicted cost is calculated for each bank, and for each period. Finally, for each bank, the persistent components observed during the sample period are identified and for each bank, the resulting time series of estimated residuals is averaged across time so as to separate cost inefficiency from the annual random errors.

[4] According to Berger and Humphrey (1997) the DFA approach gives a better indication of a bank's longer-term performance by averaging over a number of conditions, than any of the other methods, which rely on a bank's performance under a single set of circumstances. Therefore, under DFA a panel data is required and only panel estimates of efficiency over the entire time interval are available.

[5] Choosing a too short period, may leave large amounts of random error in the averaged residuals, in which case random error would be attributed to inefficiency. On the other hand, if too long a period is chosen, the firm's average efficiency might not be constant over the time period because of changes in environmental conditions making it less meaningful (DeYoung, 1997).

[6] The translog functional form has been widely employed in the efficiency literature. Berger and Mester (1997) have compared the translog to the more flexible Fourier Flexible Form (FFF) and found

$$\ln C_i = \alpha_0 + \sum_i a_i \ln P_i + \sum_i \beta_i \ln Y_i + ½ \sum_i \sum_j a_{ij} \ln P_i \ln Pj + ½ \sum_i \sum_j \beta_{ij} \ln Y_i \ln Y_j$$

$$+ \sum_i \sum_j \delta_{ij} \ln P_i \ln Y_j + \sum_i \varphi_i \ln N_i + ½ \sum_i \sum_j \phi_{ij} \ln N_i \ln N_j + \sum_i \sum_j \xi_{ij} \ln P_i \ln N_j$$

$$+ \sum_i \sum_j \zeta_{ij} \ln Y_i \ln N_j + kD_i + \ln v_i + \ln u_i \qquad (3)$$

where all variables are expressed in natural logs.[7] C_{it} denotes observed total cost for bank i, P_i is a vector of input prices Y_j is a vector of bank outputs, and N is a vector of fixed netputs[8]. Moreover, because structural conditions in banking and general macroeconomic conditions may generate differences in banking efficiency from country to country, we also include country effects in the estimation of the cost frontier. Note that u_i is the bank specific efficiency factor and v_i is the random error term. All elements of Equation (3) are allowed to vary across time with the exception of u_i, which remains constant for each bank by assumption. In the estimation, the $\ln v_i$ and $\ln u_i$ terms are treated as a composite error term, i.e., $\ln \hat{\varepsilon}_i = \ln \hat{v}_i + \ln \hat{u}_i$. Once estimated the residuals, $\ln \varepsilon_i$, are averaged across T years for each bank i. The averaged residuals are estimates of the X-efficiency terms, $\ln u_i$, because the random error terms, $\ln v_i$, tend to cancel each other out in the averaging. Thus, bank's i efficiency is defined as:

$$EFF_i = \frac{\exp[\hat{f}(p_i y_i)\exp[(\ln \hat{u}_{\min})]}{\exp[([\hat{f}(p_i y_i)\exp[(\ln \hat{u}_i)} = \exp[(\ln \hat{u}_{\min} - \ln \hat{u}_i)] \qquad (4)$$

where $\ln \hat{u}_i$ is the residual vector after having averaged over time and $\ln \hat{u}_{\min}$ is the most efficient bank in the sample.

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that despite the latter's added flexibility, the difference in results between these methods appears to be very small.

[7] To ensure that the estimated cost frontier is well behaved, standard homogeneity and symmetry restrictions are imposed: $\sum_i a_i = 1$, $\sum_i a_{ij} = 0$, $\sum_i \delta_{ij} = 0$, $\sum_i \xi_{ij} = 0$, $\alpha_{im} = \alpha_{mi}$ and $\alpha_{jk} = \alpha_{kj}$, $\forall i, j, k, m$.

[8] Fixed netputs are quasi-fixed quantities of either inputs or outputs that affect variable costs.

3. Data description

Our data comprises of all listed banks over the period 2000 to 2005 in fourteen European Union Member States, namely: Austria, Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden and the UK. Balance-sheet and income statement data were obtained from the Bankscope database, while for the estimation of bank default risk, stock price data were obtained from the combination of Datastream, Bloomberg and Bankscope databases. After reviewing the data for reporting errors and other inconsistencies, we obtain a balanced panel dataset of 690 observations, which includes a total of 115 different banks. The number of banks varies widely across countries, ranging from 3 in Luxembourg to 34 in Denmark.

For the definition of bank inputs and outputs, we follow the intermediation approach proposed by Sealey and Lindley (1977.[9] The output vector includes loans (defined as total loans net of provisions) and other earning assets, while total cost is defined as the sum of overheads (personnel and administrative expenses), interest, fee, and commission expenses. Regarding input prices, the price of labour is proxied by the ratio of personnel expenses to total assets, while the price of deposits is defined as the ratio of interest expenses to total funds. We also specify physical capital and equity as fixed netputs. The treatment of physical capital as a fixed input is relatively standard in efficiency estimation (Berger and Mester, 1997)[10], while the level of

[9] A variety of approaches have been proposed in the literature for the definition of bank inputs and outputs; yet, there is little agreement among economists as what unequivocally constitutes an acceptable definition, mainly as a result of the nature and functions of financial intermediaries. See Berger and Humphrey (1992) for a review of the various methods used to define inputs and outputs in financial services.

[10] Physical capital is considered as fixed netput, and not as input, partly due to the difficulty in calculating a reliable input price for fixed assets in the absence of data on the market value of real estate and premises.

equity is included so as to account for both the risk-based capital requirements and the risk-return trade-off that bank owners face (Färe et al., 2004). Apart from this, a bank's capital directly affects costs by providing an alternative to deposits as a funding source for loans (see Berger and Mester, 1997).

The methodology for the computation of bank default risk is presented in the Appendix (*Appendix A*). The annual equity volatility for each bank is estimated based on the daily returns, derived as the standard deviation of the moving average of daily equity returns times $\sqrt{261}$. All liabilities are assumed to be due in one year, T=1, while as the risk free interest rate we take the twelve months interbank rate, except for Greece, for which we opt for the six month interbank rate due to data availability. Liabilities are derived from Bankscope Fitch IBCA and include the total amount of deposits, money market funding, bonds, and subordinated debt.

(Please insert Table 1 about here)

Table 1 provides descriptive statistics of the main variables used in this study by country and for the overall sample over the period 2000-2005. Overall, there are considerable variations across countries in relation to cost, outputs quantities and input prices, as well as differences regarding the size of the country-specific control variables.

4. Empirical results

4.1 Cost efficiency under a quantile regression analysis

The estimated parameters of the translog cost function for quantiles 0.05, 0.25, 0.5, 0.75 and 0.95, are presented in Appendix B. These estimates have been obtained using simultaneous quantile regression analysis. The advantage of this method is the estimation of the entire variance-covariance matrix, which allows us to test the hypothesis of whether the coefficients between different quantiles are equal.[11] Table 2 presents the test results for the various quantiles. All tests show that coefficients are statistically different from each other between all quantiles, confirming the validity of our analysis.

(Please insert Table 2 about here)

Next, we calculate cost efficiency scores for each bank in our sample using the Distribution-free approach and compare these scores across quantiles and across countries. Figure 1 presents the average efficiency scores by country across quantiles (0.05 to 0.95).

(Please insert Figure 1 about here)

Overall, we observe a marked variability between the average efficiency scores across quantiles, suggesting that previous research on efficiency, which is based on the approximation of the mean function of the conditional distribution, delivers an incomplete notion of the efficiency dispersion across banks. In particular, the average efficiency score for the whole sample ranges from 0.68 for quantile 0.95 to 0.88 for quantile 0.05. More importantly, cost efficiency estimates across quantiles, and particularly in the tail of the distribution, differ substantially from the conditional mean (OLS) point estimate of efficiency, as it is approximated by quantile 0.5. This suggests that the quantile regression analysis clearly provides a more comprehensive picture of the underlying range of disparities in cost efficiency that the classical estimation would have missed.

Moreover, note that a distinct common pattern emerges across quantiles. In particular, we observe that average efficiency follows a negative trend at higher order

[11] Coefficient standard errors were obtained by bootstrapping with 100 sample replications.

of quantiles, indicating the existence of monotonically decreasing quantile efficiency. In particular, cost efficiency is estimated at around 0.88 for quantile 0.05, drops to 0.85 for quantile 0.25, declines further to 0.78 and 0.71 for quantiles 0.50 and 0.75 respectively, while it reaches its minimum value at 0.68 when the cost function is calculated at the 0.95 quantile. Nevertheless, this observed pattern between average efficiency and quantile conditional distributions is less clear in the cases of Germany and the UK. In particular, the average cost efficiency for German banks drops from 0.85 for quantile 0.05 to 0.68 for quantile 0.75, but rises to 0.74 when the cost function is estimated at the 0.95 quantile. Similarly, in the case of the UK, average cost efficiency drops from 0.89 at quantile 0.05 to 0.68 at quantile 0.75, while it remains stable when the cost function is estimated at the 0.95 quantile. Overall, efficiency scores exhibit however a negative trend at higher quantiles for the majority of countries, that is, average efficiency decreases for the upper tail of the distribution.

(Please insert Table 3 about here)

To shed more light into our analysis, Table 3 presents the estimated cost efficiency scores for each bank in our sample across different quantiles. Overall, Table 3 reveals a similar picture to the one of Figure 1, and confirms our previous finding of a negative trend of efficiency scores across higher quantiles. In particular, for the vast majority of banks in our sample, efficiency scores decrease as the cost function is estimated at higher quantiles. Yet, there are some notable exceptions, concerning mostly German and British banks. Note, for example, DAB Bank, Deutsche Bank, HSBC Trinkaus & Burkhardt AG, Irish Life & Permanent Plc, LBB Holding AG, Man Group Plc and Oldenburgische Landesbank (OLB), which present the most notable exceptions. Moreover, Dexia, Fortis, Irish Life & Permanent Plc, KBC Groupe SA and Oesterreichische Volksbanken AG report a cost efficiency score that is higher in quantile 0.95 compared to quantile 0.75. In the case of IKB Deutsche Industriebank AG cost efficiency is higher in the upper tail of the distribution, quantile 0.75, compared to quantile 0.5. These findings may be of some interest in the aftermath of the recent credit crisis as Dexia and Fortis were among the banks that came close to default, whereas IKB closed hedge funds in 2007 as a result of the experienced large losses linked to the downturn in the U.S. mortgage market. Given that for these banks the classical estimations underestimate their underlying inefficiency scores, quantile analysis appropriately identifies the true disparity of efficiency scores across conditional distributions, which in turn would be of crucial importance for the performance, and ultimately for the survival of banks.

4.2 Cost efficiency and risk

The previous section has showed that the disparity of efficiency scores across conditional distributions would prove critical for appropriately assessing the performance of financial institutions. In this section, we go a step further and examine the relationship between cost efficiency and risk, as measured by the distance to default, focusing mainly on the evolution of this interaction across quantiles. The link between efficiency and risk has long been at the centre of academic research (see for example, Berger and DeYoung, 1997; Mester, 1996; Hughes, 1999; Hughes et al., 2001; Altunbas et al., 2000), while the current financial crisis has further highlighted the shortcomings and inadequacies of risk management models based on Basel II and has stressed the need to re-appraise the relationship between risk and performance.

Figure 2 shows in scatter plot the relationship between the estimated average cost efficiency scores for all banks in our sample and four categories of DD scores. These categories are defined according to the median value of the estimated distance-to-default as follows: the first category includes the riskiest banks in the sample, with estimated DD scores ranging from 0 to 6, while the second riskier group of banks has DD scores ranging from 6 to 8. The majority of financial institutions in our sample belongs to the next two categories, with DD scores ranging from 8 to 10.34 and from 10.35 to 13 respectively. Lastly, the least risky banks in our sample are grouped in the fifth category that have distance-to-default scores higher than 13.[12] Overall, and despite some extreme cases, Figure 2 shows that the relationship between DD scores and the average efficiency across countries remains relatively stable for low values of the distance to default, whereas for higher values of the distance to default a slight positive trend can be observed. This picture might imply that average quantile efficiency could be positively linked to the distance to default. However, given that efficiency scores in Figure 2 present average scores across banks, this heavy averaging could blur the view of the exact nature of the underlying relationships.

To sharpen the picture, Figure 3 presents efficiency scores under different quantiles plotted against the distance to default categories defined above. At a first glimpse, an interesting finding is that for each category of DD scores, average efficiency levels derived under different quantiles exhibit a clear trend. In detail, the average cost efficiency at quantile 0.05 is always higher that average cost efficiency at quantile 0.25 for all clusters of DD scores. Note that in the case of conditional distributions for low DD scores, that range between 0 to 6, the average cost efficiency score derived under quantile 0.95 is higher than the average efficiency score of quantile 0.75. In other words, at the upper tails of the distribution and for low values of distance-to-default (high default risk), cost efficiency does not follow the negative trend observed in the case of higher DD scores and lower quantiles.

[12] We identify the five groups of banks based on the histogram of the distance to default scores reported in Appendix C. The median value of the distance to default is calculated at 10.34.

(Please insert Figures 2 and 3 about here)

Nevertheless, the most striking finding derived from Figure 3 is that the relationship between efficiency and distance-to-default differs not only across the various quantiles, but also across different levels of default risk. In particular, in both tails of the distribution of banks' distance-to-default (banks with the highest and the lowest default risk), we observe a clear positive relationship between cost efficiency and distance-to-default across all quantiles. That is, cost efficiency increases for higher scores of distance-to-default, or in other words for lower levels of risk and this positive relationship is particularly apparent in the case of the riskiest and the safest banks in our sample.

On the other hand, the relationship between cost efficiency and distance-to-default for banks that have DD scores that lay around the median of the distribution is less clear and differs across quantiles. In particular, for banks with DD scores around the median in our sample we observe a negative relationship between cost efficiency and banks' distance-to-default for quantiles 0.05, 0.25 and 0.95. This is however less clear in the case of quantiles 0.50 and 0.75, as the relationship between cost efficiency and distance-to-default changes trend for banks with DD scores around the median. Overall, our results suggest that while there is some indication of a positive relationship between cost efficiency and the distance to default for most quantiles and for most classifications of DD scores, in the case of the 0.5 and 0.75 quantile distributions and for values of the distance to default from 8.01 to 10.34, cost efficiency seems to follow a different path. Thus, more analysis is warranted so as to draw more definite conclusions on this issue.

To this end, we regress banks' distance to default on cost efficiency derived at different quantiles. Results are presented in Table 4.[13] Despite the fact that only a small part of the variation in cost efficiency is explained by the distance to default, we can observe a clear positive relationship between the two variables that increases in magnitude and significance for higher quantiles, suggesting that a higher level of efficiency is associated with a higher distance to default and thus with lower risk. More specifically, whereas for low order quantiles the coefficient of DD is not significant, for quantiles 0.75 and 0.95 this coefficient becomes highly statistically significant and also increases in magnitude.

(Please insert Table 4 about here)

This finding suggests that an OLS analysis, which is close to the median quantile (0.5), would be misleading, as it would report an insignificant coefficient for the distance to default. On the other hand, quantile regressions by permitting the estimation of various quantile functions of the underlying conditional distribution provide us with a more complete picture of the underlying relationships. This is evident in the present empirical application, where the distance to default appears to assert a significant and higher in magnitude impact on efficiency for the 0.75 and 0.95 quantiles. Moreover, as we have showed in the previous section, cost efficiency on average decreases for higher order quantiles (at 0.75 and 0.95) compared to lower order quantiles. Thus, the positive coefficient of the distance-to-default variable may suggest that risk asserts a higher impact on banks with low cost efficiency, or alternatively phrased, banks in quantiles 0.75 and 0.95 are more responsive to risk than banks placed in quantiles 0.05, 0.25 and 0.5.

[13] We also include country dummies in the regressions (not shown). Results are available upon request.

4.3 Second-stage regressions

As part of a sensitivity analysis we also perform second-stage regressions, where cost efficiency scores derived at different quantiles are regressed on a set of macroeconomic and bank variables. In particular, apart from bank's distance to default, the following variables are included in our estimations: the capitalization ratio (E/A) the ratio of loan loss provisions to loans (LLP/L) to control for credit risk, the liquidity ratio the return on equity ratio (ROE) that captures bank profitability, the logarithm of total assets (TA) to control for bank size, the ratios of loan to assets (LO/A) and deposits to assets (DEP/A) that capture banks' product mix, GDP per capita (GDPpc) and inflation (INFL) to control for the macroeconomic environment, the five-firm concentration ratio (CR_5) that captures market structure, two measures of density, the deposits per square kilometre (DEPDEN) and the branches per square kilometre variables (BRADEN), the intermediation ratio (INTER) that measures financial development, the interest spread (INTSPR) that captures competition and the asset share of foreign owned banks (ASFOB). The second stage regressions were estimated using OLS estimators, where the standard errors were calculated using White's (1980) correction for heteroscedasticity. Table 5 reports the results of the estimation.[14] Overall, several of the coefficients are significant and are in line with our expectations.

(Please insert table 5 about here)

On the whole, our previous results regarding the relationship between efficiency and default risk are confirmed. In particular, the sign of the DD coefficient

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[14] In order to check for potential multicollinearity correlations among the independent variables, we calculated variance inflation factors (VIFs) for all independent variables specified. Our reported results are as follows: VIF: DD (=1.56); E/A (= 2.59); LLP/L (=1.94); ROE (=1.82); TA (=3.66); LO/A (=1.66); DEP/A (=1.62); GDPpc (=5.49); INFL (=3.03); CR5 (=1.97); BRADEN (=2.71); DEPDEN (=3.58); INTER (=5.51); INTSPR (=2.66); ASFOB (=5.84); Mean VIF is calculated at 2.93 and indicates no multicollinearity problem.

is positive across all quantiles, which implies that the higher the distance to default, the higher the level of efficiency. Nevertheless, this relationship becomes statistically significant only for quantiles 0.75 and 0.95, which is consistent with the results presented in Table 4.

In addition, several interesting results emerge. For instance, we observe that the least efficient banks, or in other words banks in quantile 0.95, have on average lower loan loss provisions and a lower ratio of loans to assets. Also banks in quantile 0.95 operate in more concentrated markets and face increased interest spreads. A similar (though not identical) picture emerges for the 0.75 quantile. In this case, one can additionally mention the observed negative relationships between efficiency and the capitalization and liquidity ratios, as well as the deposit ratio. Cost efficiency is also found to be negatively related to the level of financial development (see Grigorian and Manole, 2002; Kasman and Yildirim, 2006) and positively related to the inflation rate. An interesting finding is that the negative relationship between cost efficiency and market concentration that is reported at 0.95 quantile is reversed at 0.75 quantile. In particular, for banks in quantile 0.75 a higher level of bank concentration asserts a positive impact on cost efficiency, which indicates that competitive outcomes are possible even in concentrated systems (Baumol, 1982). This finding suggests that the relationship between concentration and efficiency is not a straightforward one, as already suggested by the literature (see for example Casu and Girardone, 2006) and also that different interactions may exist across different quantiles and particularly across the most and the least efficient banks in one market.

A similarly mixed picture emerges in the case of the loan loss provisions ratio, which is reported to assert a positive impact on efficiency at quantiles 0.05, 0.25 and 0.50 and a negative one in the case of quantile 0.95. This indicates that the '*skimping*' hypothesis of Berger and DeYoung (1997) could describe more accurately the behaviour of the worst performing banks, while on the other hand, the relationship between cost efficiency and the loan loss provisions ratio for banks in higher quantiles may be better described by the *'bad management*' or the '*bad luck*' hypotheses. According to Berger and DeYoung (1997), the '*skimping*' hypothesis assumes that there is a trade-off between short-term costs and future loan performance problems, as banks that devote fewer resources to credit underwriting and loan monitoring may appear to be more cost efficient in the short-run. This hypothesis could provide some explanation on the positive relationship between efficiency and the loan loss provisions ratio. On the other hand, under the 'bad management' hypothesis of Berger and DeYoung (1997), loan quality is assumed to be endogenous in the quality of bank management, indicating that managers who are poor at dealing with day-to-day operations are also poor at managing their loan portfolio, suggesting a negative relationship between efficiency and the loan loss provisions ratio. This positive relationship could also be explained by the *'bad luck'* hypothesis, implying that an exogenous increase in non-performing loans may force even the most cost efficient banks to purchase additional inputs necessary to administer these problematic loans (Berger and DeYoung, 1997). Finally, best performing banks appear to have higher profitability, a higher fraction of loans in their portfolio, lower branch density and higher deposit density.

5. Conclusion

This paper investigates cost efficiency in the European banking industry over the period 2000-2005 using a quantile regression analysis. This type of analysis allows us to estimate banks' cost function for various quantiles of the conditional distribution and to examine in particular the tail behaviours of that distribution. This is relevant in light of the documented heterogeneity in bank efficiency across European countries.

We address several questions related to cost efficiency while we also incorporate risk in our analysis, in light also of the current re-appraisal of risk triggered by the global financial crisis. On the whole, we observe significant differences in the average efficiency across quantiles as well as across countries. Moreover, bank efficiency exhibits a steady negative trend across quantiles, suggesting that cost efficiency is higher for lower quantiles of the conditional distribution compared to higher ones. Also, our analysis suggests that the observed disparity of efficiency scores across conditional distributions is significant, which makes the quantile regression estimation a more comprehensive framework for assessing the performance of financial institutions compared to the classical estimation.

Regarding the relationship between cost efficiency and risk, our findings suggest that there is a positive relationship between efficiency and risk, in particular for higher quantiles. In detail, our results suggest that risk asserts a higher impact on banks with low cost efficiency, or in other words, banks in quantiles 0.75 and 0.95 are more responsive to risk than banks placed in quantiles 0.05, 0.25 and 0.5. Moreover, in a second-stage regression framework, we investigate the relationship between efficiency and various macroeconomic and banking variables. Our results indicate that interactions between efficiency and various control variables also vary significantly across quantiles. Two notable examples are the relationship between cost efficiency and concentration and the relationship between efficiency and credit risk.

Overall, researchers and policy makers can draw some useful lessons from this study. In particular, it has been clearly highlighted that due to the high degree of observed heterogeneity in the European banking industry, when examining bank performance it is important to supplement the estimation of conditional mean functions with an entire family of conditional quantile functions, so as to get a more comprehensive picture of efficiency scores. Otherwise, there is a danger of significantly overestimating banks' efficiency scores, especially for financial institutions that are placed at the lower tail of the distribution. In addition, our findings regarding the relationships between efficiency and default risk, concentration and credit risk suggest that the interaction between these variables may vary substantially across quantiles. In other words, the attitude of banks towards risk and their strategic decisions regarding risk management may well depend on their location in the conditional distribution of cost efficiency.

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Table 1: Descriptive statistics

Country	AT	BE	DK	FR	DE	GR	IE	IT	LU	NL	PT	ES	SE	UK	EU
Cost															
Cost (in % of total assets)	4.341	6.696	5.410	9.685	11.441	6.937	4.290	4.816	7.177	4.689	5.686	4.341	4.217	6.439	6.553
	(1.175)	*(3.681)*	*(1.212)*	*(14.033)*	*(17.683)*	*(1.889)*	*(1.691)*	*(1.076)*	*(2.509)*	*(1.484)*	*(0.757)*	*(1.289)*	*(1.133)*	*(4.308)*	*(8.152)*
Input prices															
Price of labour	0.913	0.768	2.002	4.594	3.883	2.098	1.007	1.473	1.417	1.059	1.176	1.061	0.787	2.067	2.206
	(0.264)	*(0.370)*	*(0.621)*	*(10.776)*	*(8.269)*	*(0.440)*	*(0.356)*	*(0.323)*	*(0.440)*	*(0.248)*	*(0.246)*	*(0.361)*	*(0.117)*	*(2.617)*	*(4.724)*
Price of deposits	4.535	8.353	2.480	3.721	8.058	3.440	3.697	3.365	6.155	3.725	4.923	3.334	4.917	6.786	4.363
	(2.462)	*(5.593)*	*(1.197)*	*(1.761)*	*(9.821)*	*(1.628)*	*(1.157)*	*(1.357)*	*(2.058)*	*(1.689)*	*(1.126)*	*(1.148)*	*(1.575)*	*(15.638)*	*(6.241)*
Outputs															
Loans (in % of total assets)	61.228	40.439	62.416	60.218	45.925	64.375	55.414	63.712	33.948	52.591	67.506	64.663	61.550	53.755	58.290
	(8.953)	*(4.563)*	*(9.902)*	*(21.940)*	*(28.270)*	*(10.020)*	*(13.882)*	*(9.929)*	*(26.035)*	*(22.167)*	*(4.841)*	*(12.189)*	*(8.914)*	*(19.436)*	*(17.780)*
Other earning assets (in % of total assets)	32.739	51.402	30.665	29.588	43.269	25.053	29.739	27.360	54.682	42.732	22.623	27.850	28.454	33.106	32.669
	(8.474)	*(5.390)*	*(9.891)*	*(17.015)*	*(21.695)*	*(9.504)*	*(8.277)*	*(9.470)*	*(23.998)*	*(22.814)*	*(5.674)*	*(10.320)*	*(8.639)*	*(9.341)*	*(14.712)*
Fixed netputs															
Equity (in % of total assets)	5.039	3.562	11.769	13.664	9.140	7.617	5.560	6.971	5.626	3.877	5.449	5.826	4.163	7.564	8.934
	(0.934)	*(1.015)*	*(3.839)*	*(18.100)*	*(15.325)*	*(2.497)*	*(1.266)*	*(2.039)*	*(1.110)*	*(1.340)*	*(0.556)*	*(0.983)*	*(0.554)*	*(6.517)*	*(8.963)*
Fixed assets (in % of total assets)	1.633	0.614	1.729	2.650	2.781	2.840	1.050	1.872	1.863	1.106	1.492	1.347	0.389	1.752	1.884
	(0.639)	*(0.345)*	*(0.862)*	*(5.044)*	*(6.541)*	*(1.554)*	*(0.375)*	*(1.203)*	*(0.926)*	*(0.320)*	*(0.605)*	*(0.551)*	*(0.242)*	*(2.266)*	*(3.015)*
Bank-specific control variables															
Distance-to-default (DD)	16.146	8.310	12.006	10.059	8.562	6.436	8.715	9.845	9.551	8.889	10.646	9.289	8.102	8.578	10.348
	(3.073)	*(2.830)*	*(2.742)*	*(2.908)*	*(4.286)*	*(1.513)*	*(2.087)*	*(2.430)*	*(2.498)*	*(2.589)*	*(2.224)*	*(2.762)*	*(2.945)*	*(2.592)*	*(3.521)*
Loan loss provision (in % of total loans)	0.711	0.249	1.054	0.396	1.261	0.968	0.159	0.716	0.811	0.199	0.593	0.632	0.128	0.491	0.775
	(0.199)	*(0.120)*	*(0.420)*	*(0.119)*	*(1.751)*	*(0.658)*	*(0.096)*	*(0.400)*	*(0.108)*	*(0.107)*	*(0.194)*	*(0.202)*	*(0.014)*	*(0.275)*	*(0.744)*
Liquidity ratio	1.722	0.685	3.117	1.279	1.435	4.118	1.398	0.779	2.706	1.159	2.544	2.086	1.005	2.130	2.015
	(0.865)	*(0.294)*	*(2.419)*	*(0.864)*	*(1.343)*	*(2.324)*	*(0.803)*	*(0.342)*	*(1.025)*	*(0.803)*	*(0.753)*	*(1.024)*	*(0.200)*	*(3.448)*	*(2.006)*
ROE	11.266	19.962	16.709	16.770	6.629	3.968	19.870	14.160	15.540	21.409	15.171	17.482	19.858	25.475	15.620
	(2.372)	*(3.180)*	*(3.312)*	*(7.691)*	*(7.696)*	*(5.066)*	*(3.714)*	*(7.102)*	*(3.596)*	*(3.019)*	*(3.326)*	*(4.131)*	*(2.243)*	*(6.943)*	*(7.343)*
logarithm of Total assets	16.106	19.709	13.241	15.941	16.493	14.524	18.095	16.503	15.930	17.435	17.066	17.631	18.885	18.400	15.822
	(1.438)	*(0.380)*	*(1.709)*	*(2.207)*	*(2.878)*	*(0.432)*	*(0.486)*	*(1.773)*	*(1.793)*	*(2.088)*	*(0.916)*	*(1.457)*	*(0.411)*	*(2.417)*	*(2.707)*
Country-specific control variables															
CR5	44.467	81.267	66.050	47.917	20.950	66.100	43.983	27.200	29.400	83.250	62.883	43.817	55.617	31.800	48.167
Interest spread	2.317	5.028	4.106	3.633	5.265	4.977	3.524	4.732	1.437	1.063	2.655	1.925	3.219	1.744	3.756
Intermediation ratio	129.215	79.837	284.811	124.936	124.153	71.309	140.639	149.253	61.120	133.893	130.087	106.980	224.519	117.502	174.123
Asset share of foreign owned banks	19.415	23.850	17.900	13.224	5.424	14.560	49.883	6.867	93.767	11.467	25.100	10.683	7.133	50.467	19.200
Branch density	0.053	0.179	0.051	0.047	0.139	0.025	0.013	0.100	0.106	0.108	0.059	0.079	0.005	0.058	0.072
Deposit density	2.615	11.982	2.439	2.095	6.811	1.105	2.277	2.455	83.677	13.525	1.523	1.592	0.283	7.954	5.228
GDP per capita	22467	21261	27993	21146	21545	10631	25358	17903	44815	22429	10182	13792	26004	23444	22902
Inflation	2.089	2.188	2.127	1.883	1.581	3.244	3.866	2.442	2.442	2.504	3.120	3.256	1.369	2.515	2.244

Note: The table presents mean values and standard deviations in *parentheses*. Total cost, outputs and fixed netputs are expressed as a percentage of total assets. The price of labour is defined as personnel expenses to total assets (in percent); the price of deposits is defined as interest expenses to total deposits (in percent). Distance-to-default is calculated by the methodology proposed by Merton (1974). The liquidity ratio is defined as cash and due from banks divided by total assets (in percent). ROE is defined as profit before tax to equity (in %). CR5 is defined as the sum of the market share of the five largest banks in terms of total assets. Interest spread is defined as the difference between the average lending rate and the deposit rate. The intermediation ratio is defined as the ratio of total loans to total deposits. Branch density is defined as branches per square kilometer, while deposit density is defined as Total deposits per square kilometer. **Sources**: Bankscope, Datastream, Bloomberg, World Development Indicators, ECB reports, Central bank reports.

Table 2: Post estimation linear hypotheses testing

H_0: Q_5= Q_{25}	H_0: Q_{25}= Q_{50}	H_0: Q_{50}= Q_{75}	H_0: Q_{75}= Q_{95}
Test whether: Translog cost function coefficients are equal between quantiles Q_5 and Q_{25} F (19, 653) = 15.78 Probability>F = 0.000	**Test whether**: Translog cost function coefficients are equal between quantiles Q_{25} and Q_{50} F (19, 653) = 24.62 Probability >F = 0.000	**Test whether:** Translog cost function coefficients are equal between quantiles Q_{50} and Q_{75} F (19, 653) = 6.23 Probability >F = 0.000	**Test whether:** Translog cost function coefficients are equal between quantiles Q_{75} and Q_{95} F (19, 653) = 13.19 Probability >F = 0.000

Note: The table presents F-tests for testing the hypothesis whether coefficients between different quantiles are equal. Quantiles have been estimated by simultaneous regression analysis. Standard errors were obtained by bootstrapping with 100 replications.

Table 3: Quantile cost efficiency scores across banks

	EFF Q5	EFF Q25	EFF Q50	EFF Q75	EFF Q95
ABN Amro Holding NV	0.9166	0.8514	0.7680	0.6644	0.5979
Alliance & Leicester Plc	0.8779	0.8195	0.7530	0.6785	0.6665
Allied Irish Banks plc	0.7779	0.7275	0.7751	0.7589	0.7029
Amagerbanken, Aktieselskab	0.8593	0.8148	0.7355	0.6448	0.6037
Arbuthnot Banking Group Plc	0.8204	0.8914	0.7901	0.7143	0.8464
Aspis Bank SA	0.8537	0.7931	0.7091	0.6609	0.5974
Baader Wertpapierhandelsbank AG	0.9728	0.9110	0.7800	0.6609	0.5974
Banca Ifis SpA	0.9647	0.8898	0.7934	0.7254	0.6732
Banca Lombarda e Piemontese SpA	0.9069	0.8941	0.8334	0.7313	0.6688
Banca popolare dell'Emilia Romagna	0.9346	0.8960	0.8059	0.6982	0.6713
Banca Popolare di Intra - Societa Cooperativa per Azioni	0.9256	0.9203	0.8426	0.7616	0.7324
Banca Popolare di Milano SCaRL	0.8599	0.8266	0.7731	0.6828	0.6979
Banca Popolare di Sondrio Societa Cooperativa per Azioni	0.8886	0.8521	0.7651	0.6709	0.6302
Banca Popolare di Spoleto SpA	0.8800	0.8498	0.7767	0.6882	0.7021
Banco Bilbao Vizcaya Argentaria SA	0.8280	0.8095	0.7666	0.6773	0.6244
Banco BPI SA	0.9153	0.8651	0.8067	0.7087	0.7072
Banco Desio - Banco di Desio e della Brianza SpA	0.8259	0.8376	0.8338	0.7491	0.7119
Banco di Sardegna SpA	0.9248	0.8806	0.8000	0.7005	0.6939
Banco Espirito Santo SA	0.8838	0.8387	0.7702	0.6795	0.6786
Banco Pastor SA	0.9711	0.8991	0.8199	0.7101	0.6635
BANIF SGPS SA	0.9058	0.8504	0.7633	0.6598	0.6232
Bank of Attica SA	0.9638	0.8895	0.7809	0.7346	0.7043
Bank of Ireland	0.8126	0.7471	0.8120	0.7997	0.6945
Bankinter SA	0.8955	0.8649	0.7738	0.6805	0.6420
Banque de Savoie	0.9717	0.9535	0.8882	0.7934	0.7326
Banque Degroof Luxembourg SA	0.7430	0.7051	0.7406	0.6678	0.6265
Banque Tarneaud	0.9312	0.8688	0.7747	0.6923	0.6565
Barclays Plc	0.8591	0.8806	0.7607	0.6609	0.5974
Bayerische Hypo-und Vereinsbank AG	0.8738	0.8836	0.8013	0.7184	0.8088
Berlin Hyp-Berlin-Hannoverschen Hypothekenbank AG	0.9208	0.8716	0.7571	0.6735	0.6297
BKS Bank AG	0.9198	0.8659	0.7911	0.7481	0.7454
Bonusbanken A/S	0.8852	0.8704	0.7758	0.6962	0.7344
Commerzbank AG	0.8915	0.8811	0.7713	0.6923	0.7893
Concord Effekten AG	0.9728	0.9110	0.7800	0.6609	0.5974
Credit Agricole de l'Ille-et-Vilaine	0.9163	0.8856	0.7753	0.6876	0.6305
Credit Agricole de Toulouse et du Midi Toulousain	0.9351	0.8960	0.7919	0.7106	0.6631
Credit Agricole du Morbihan	0.8288	0.8089	0.7246	0.6565	0.6109
Credit Agricole Loire Haute-Loire	0.8375	0.8135	0.7261	0.6599	0.6236
Credit Industriel et Commercial - CIC	0.8808	0.8136	0.7919	0.7239	0.6667
Credit Agricole Alpes Provence	0.9223	0.8929	0.7871	0.7074	0.6694
Credit Agricole Sud Rhene Alpes	0.8914	0.8499	0.7550	0.6778	0.6332
Credito Artigiano	0.8578	0.8190	0.7426	0.6538	0.6475
Credito Emiliano SpA	0.8515	0.8023	0.7417	0.6492	0.6483
Credito Valtellinese SCarl	0.8771	0.8453	0.7674	0.6671	0.6202
DAB Bank AG	0.4234	0.4286	0.3837	0.3921	0.5974
Danske Bank A/S	0.9592	1.0000	0.9450	0.8318	0.7025
Deutsche Bank AG	0.8957	0.8444	0.7691	0.7077	0.8986
Deutsche Hypothekenbank (Actien-Gesellschaft)	0.9728	0.9110	0.8468	0.8247	0.6780
Dexia	0.8496	0.8015	0.7524	0.8172	0.6190
DiBa Bank A/S	0.8800	0.8622	0.7879	0.7085	0.6950
Djurslands Bank A/S	0.9398	0.9057	0.8208	0.7204	0.6945
DVB Bank AG	0.8454	0.8198	0.7606	0.6949	0.7745
Erste Bank der Oesterreichischen Sparkassen AG	0.7775	0.7266	0.6845	0.6462	0.6065
Espirito Santo Financial Group S,A,	0.9728	0.9110	1.0000	1.0000	0.8662
FB Bank Copenhagen A/S-Forstaedernes Bank A/S	0.8056	0.7925	0.7251	0.6462	0.6293
Fionia Bank A/S	0.8888	0.8607	0.7693	0.6864	0.6672
Fortis	0.6427	0.5910	0.5822	0.6792	0.6383
General Bank of Greece SA	0.9728	0.9110	0.8082	0.7475	0.6503
Gronlandsbanken A/S-Bank of Greenland	0.8660	0.8526	0.7685	0.6863	0.7294
Gruppo Monte dei Paschi di Siena	0.9041	0.8692	0.8210	0.7157	0.6771
Hadsten Bank Aktieselskab	0.8654	0.8615	0.7665	0.6738	0.6546

HBOS Plc	0.8606	0.8813	0.7995	0.7031	0.6460
HSBC Holdings Plc	0.9517	0.9166	0.7996	0.7200	0.6665
HSBC Trinkaus & Burkhardt AG	0.9340	0.9137	0.8153	0.7979	1.0000
IKB Deutsche Industriebank AG	0.6534	0.6585	0.6785	0.6775	0.6648
Irish Life & Permanent Plc	0.7966	0.7438	0.8150	0.8412	0.7816
Jyske Bank A/S (Group)	0.9031	0.8821	0.8196	0.7224	0.6410
Kas Bank NV	0.9498	0.8906	0.7876	0.7168	0.6241
KBC Groupe SA	0.9728	0.9110	0.8028	0.8903	0.7870
Kreditbanken A/S	0.9725	0.9363	0.8513	0.7741	0.7810
LBB Holding AG-Landesbank Berlin Holding AG	0.8734	0.8500	0.7709	0.7130	0.8195
Lloyds TSB Group Plc	0.9641	0.9137	0.8252	0.7265	0.7129
Lokalbanken i Nordsjaelland	0.8880	0.8309	0.7508	0.6762	0.6225
Lollands Bank	0.9143	0.8903	0.8024	0.7286	0.7017
Man Group Plc	0.9728	0.9110	0.7812	0.7013	0.8211
Max Bank A/S	0.7985	0.7930	0.7220	0.6616	0.6427
Merkur-Bank KGaA	0.8492	0.8313	0.7503	0.6609	0.6473
Millennium bcp-Banco Comercial Portugues, SA	0.9390	0.8935	0.8000	0.6756	0.6415
Moens Bank A/S	0.9086	0.8839	0.8040	0.7196	0.7104
Morsoe Bank	0.9128	0.8932	0.7926	0.7081	0.6881
Natexis Banques Populaires	0.8433	0.7997	0.7581	0.6741	0.6225
Noerresundby Bank A/S	0.9539	0.9098	0.8268	0.7441	0.7286
Nordea Bank AB	0.9480	0.9088	0.7909	0.6969	0.6003
Nordfyns Bank	0.7629	0.7776	0.7174	0.6310	0.6164
Nordjyske Bank A/S	0.9565	0.8848	0.8136	0.7339	0.7101
Northern Rock Plc	0.8483	0.7976	0.7324	0.6377	0.5974
Oberbank AG	0.9036	0.8448	0.7704	0.7270	0.7033
Oesterreichische Volksbanken AG	0.7235	0.6829	0.6666	0.6719	0.6120
Oestjydsk Bank A/S	0.8454	0.8238	0.7159	0.6416	0.6321
Oldenburgische Landesbank - OLB	0.9580	0.9285	0.8132	0.7370	0.9503
Ringkjoebing Bank	0.9626	0.9253	0.8403	0.7551	0.7548
Ringkjoebing Landbobank	0.9503	0.9408	0.8579	0.7644	0.7602
Roskilde Bank	0.9088	0.8694	0.7802	0.6809	0.6361
Royal Bank of Scotland Group Plc (The)	0.8666	0.8302	0.7259	0.6587	0.5995
Salling Bank A/S	0.7789	0.7859	0.7165	0.6327	0.6122
San Paolo IMI	0.8553	0.8505	0.8003	0.6891	0.6548
Skandinaviska Enskilda Banken AB	0.9704	0.8780	0.7593	0.6617	0.6104
Skjern Bank	0.8943	0.8726	0.7714	0.6842	0.6457
Societe Generale	0.9508	0.8993	0.8448	0.7718	0.7015
Spar Nord Bank	0.8670	0.8275	0.7497	0.6590	0.6210
Sparbank Vest A/S	0.7604	0.7846	0.7749	0.6679	0.6329
Sparekassen Faaborg A/S	0.9623	0.9671	0.9173	0.8147	0.8117
Standard Chartered Plc	0.9215	0.8808	0.7881	0.6964	0.7113
Swedbank AB	0.9382	0.9023	0.7937	0.6992	0.6321
Sydbank A/S	0.8911	0.8433	0.7591	0.6657	0.6037
Toender Bank A/S	0.8823	0.8683	0.7630	0.6842	0.6550
Totalbanken A/S	0.8853	0.8504	0.7630	0.6837	0.6573
UniCredito Italiano SpA	0.8541	0.8287	0.7578	0.6628	0.6003
Union Financiere de France Banque	0.8223	0.7357	0.7351	0.6609	0.5974
Van Lanschot NV	0.9510	0.8897	0.7983	0.6897	0.6022
Vestjysk Bank A/S	0.8882	0.8498	0.7623	0.6678	0.6271
Vinderup Bank A/S	0.8686	0.8435	0.7389	0.6943	0.7141
Vorarlberger Landes-und Hypothekenbank AG	1.0000	0.9761	0.9871	0.9563	0.8400
Vorarlberger Volksbank	0.9056	0.8610	0.7935	0.7308	0.6844
Vordingborg Bank A/S	0.8230	0.8364	0.7730	0.6993	0.6900

Note: The table presents bank-specific efficiency scores under different quantiles (Q_5, Q_{25}, Q_{50}, Q_{75}, Q_{95}), as estimated by employing the DFA approach.

Table 4: Regression results: Cost efficiency and distance to default

	Q_5		Q_{25}		Q_{50}		Q_{75}		Q_{95}	
	Coef.	*St. Err.*	*Coef.*	*St. Err.*	*Coef.*	*St. Err.*	*Coef.*	*St. Err.*	*Coef.*	*St. Err.*
DD	0.005	*0.004*	0.005	*0.004*	0.005	*0.003*	0.007**	*0.003*	0.011***	*0.003*
constant	0.824***	*0.048*	0.808***	*0.044*	0.731***	*0.040*	0.614***	*0.037*	0.541	*0.043*
R-sq	0.129		0.160		0.177		0.259		0.271	

Note: The table presents coefficient estimates when regressing efficiency scores derived under different quantiles on distance-to-default. Dependent variable: cost efficiency under quantiles 0.05 (Q_5), 0.25 (Q_{25}), 0.5 (Q_{50}), 0.75 (Q_{75}) and 0.95 (Q_{95}). Robust standard errors are presented in *italics*. Country dummies are also included (not shown) *, **, ***, indicate significance level at 10%, 5% and 1%, respectively.

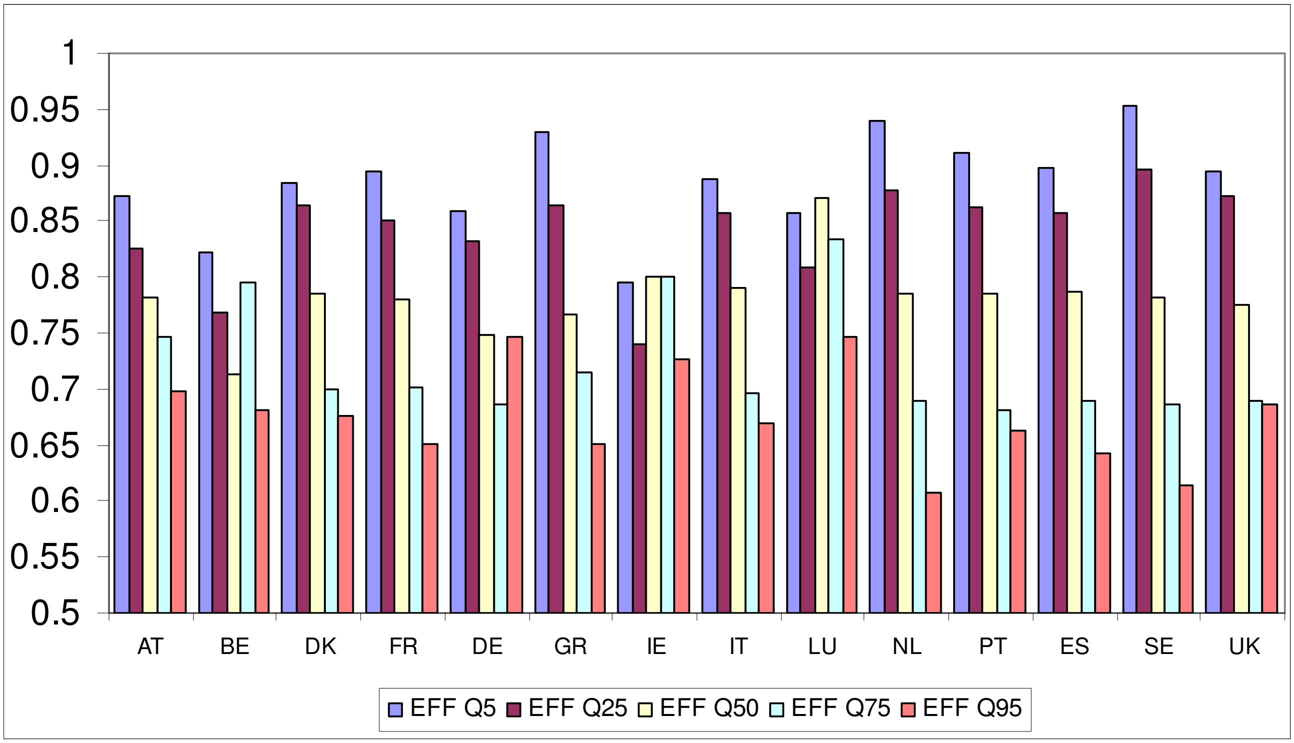
Table 5: Second-stage regressions

	Q_5	Q_{25}	Q_{50}	Q_{75}	Q_{95}
DD	0.0018	0.0006	0.0040	0.0075***	0.0088***
	0.0032	*0.0030*	*0.0025*	*0.0023*	*0.0029*
E/A	-0.0008	-0.0011	-0.0011	-0.0017*	-0.0010
	0.0013	*0.0012*	*0.0010*	*0.0009*	*0.0012*
LLP/L	0.0332**	0.0275**	0.0176*	0.0066	-0.0280**
	0.0132	*0.0125*	*0.0104*	*0.0096*	*0.0122*
ROE	0.0027**	0.0021*	0.0023**	0.0014	0.0002
	0.0013	*0.0012*	*0.0010*	*0.0009*	*0.0012*
LIQR	-0.0048	-0.0043	-0.0062*	-0.0053*	0.0017
	0.0040	*0.0038*	*0.0032*	*0.0029*	*0.0037*
TA	0.0025	0.0009	0.0022	0.0008	-0.0049
	0.0050	*0.0047*	*0.0039*	*0.0036*	*0.0046*
LO/A	0.0009*	0.0010*	0.0008*	0.0005	-0.0011**
	0.0006	*0.0005*	*0.0004*	*0.0004*	*0.0005*
DEP/A	-0.0009	-0.0007	-0.0013***	-0.0016***	0.0000
	0.0005	*0.0005*	*0.0004*	*0.0004*	*0.0005*
GDPpc	-0.00000674*	-0.0000076**	0.0000	0.00000624**	0.0000
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*
DEPDEN	0.0034**	0.0027*	0.0032***	0.0004	-0.0008
	0.0015	*0.0014*	*0.0012*	*0.0011*	*0.0014*
CR_5	0.0004	0.0000	-0.0001	0.0012***	-0.0010**
	0.0005	*0.0005*	*0.0004*	*0.0004*	*0.0005*
BRADEN	-0.606**	-0.3673	-0.5580**	-0.2213	0.3611
	0.3020	*0.2847*	*0.2364*	*0.2187*	*0.2789*
INTERM	0.0002	0.0004	0.0001	-0.0005***	0.0000
	0.0003	*0.0002*	*0.0002*	*0.0002*	*0.0002*
ASFOB	-0.0009	0.0000	-0.0011	-0.0002	0.0016
	0.0011	*0.0010*	*0.0009*	*0.0008*	*0.0010*
INTSP	-0.0042	-0.0070*	0.0052	0.0229***	0.0186**
	0.0098	*0.0092*	*0.0077*	*0.0071*	*0.0090*
INFL	-0.0320	-0.0421*	0.0207	0.0367**	-0.0030
	0.0250	*0.0236*	*0.0196*	*0.0181*	*0.0231*
constant	1.0140***	1.0206***	0.6980***	0.4422***	0.6876***
	0.1794	*0.1690*	*0.1404*	*0.1299*	*0.1656*
R^2	0.2143	0.2095	0.2991	0.4191	0.2892
F	1.67 (0.065)	1.62 (0.077)	2.61 (0.002)	4.42 (0.000)	2.49 (0.003)

Note: The table presents coefficient estimates when regressing efficiency scores derived under different quantiles on various banking and macroeconomic variables. Dependent variable: cost efficiency under quantiles 0.05 (Q_5), 0.25 (Q_{25}), 0.5 (Q_{50}), 0.75 (Q_{75}) and 0.95 (Q_{95}). Robust standard errors are presented in *italics*. *, **, ***, indicate significance level at 10%, 5% and 1%, respectively.

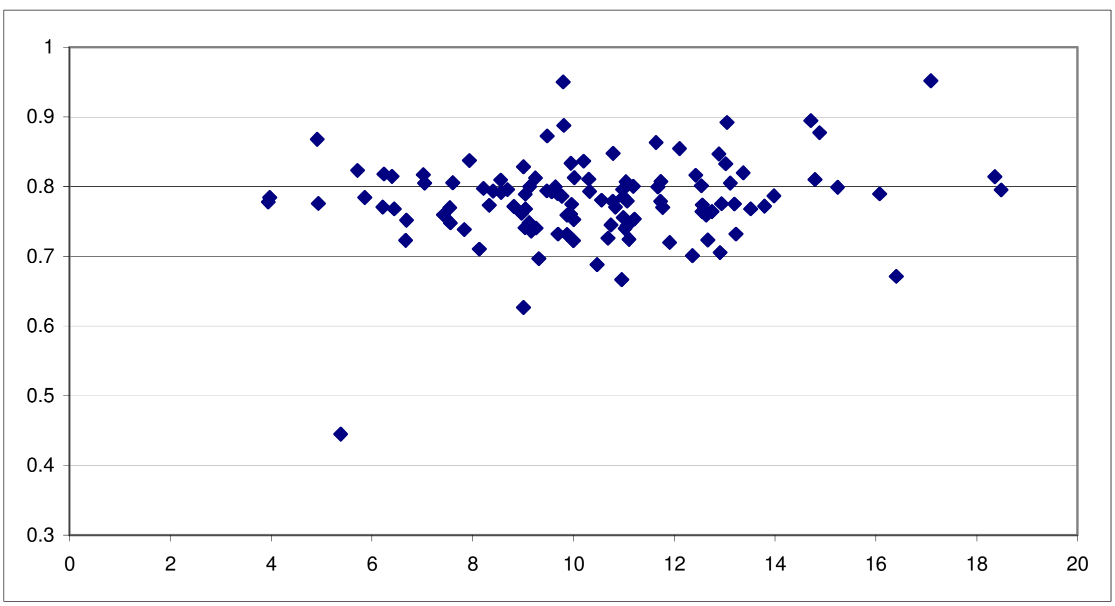
FIGURES

Figure 1: Quantile cost efficiency across countries



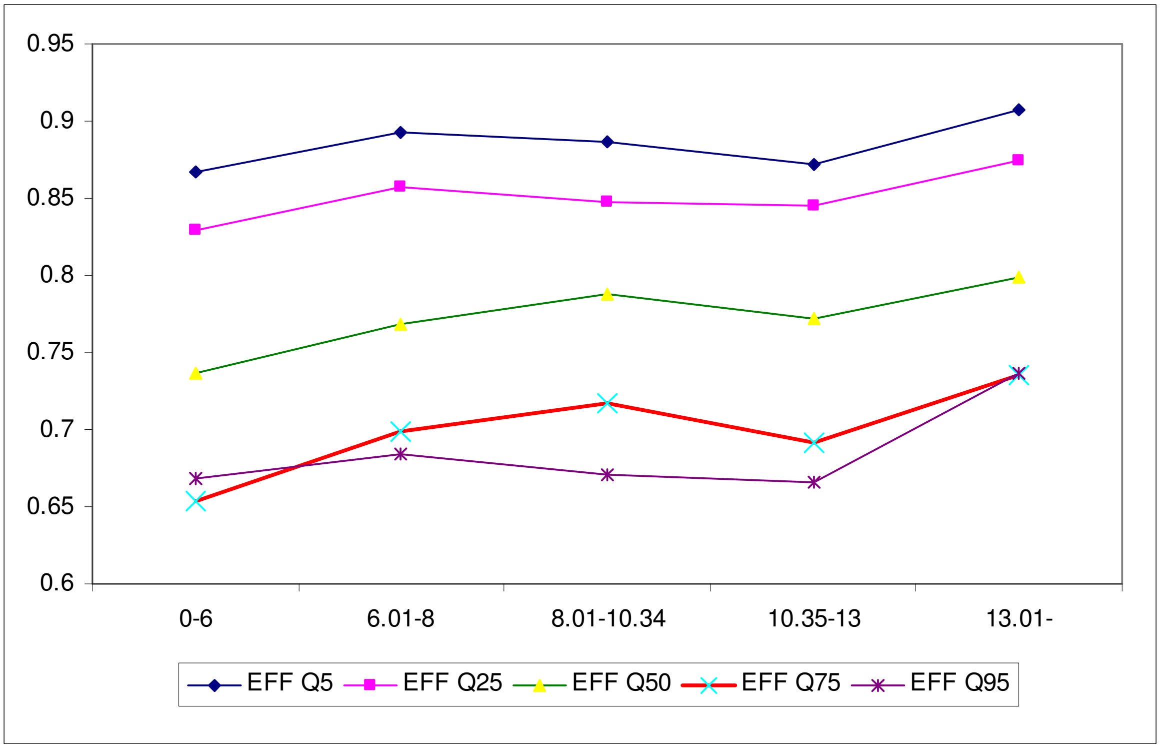
Note: The horizontal axis describes the range of different quantiles (0.05, 0.25, 0.5, 0.75 and 0.95) and the vertical axis the corresponding average cost efficiency by country, as measured in a scale from 0 to 1.

Figure 2: Average quantile cost efficiency and DD scores.



Note: The horizontal axis describes the range of the different DD scores and the vertical axis the corresponding total cost efficiency, as measured in a scale from 0 to 1.

Figure 3: Quantile cost efficiency scores across different scores of DD



Note: The horizontal axis presents the five categories of DD scores (defined based on the median of DD scores in our sample). The vertical axis presents cost efficiency scores, as measured in a scale from 0 to 1, derived under different quantiles (Q_5, Q_{25}, Q_{50}, Q_{75}, Q_{95}).

APPENDIX A

Deriving distance to default

In order to derive banks' distance to default, we employ the optimisation model of Merton (1974) of credit risk. The Merton model is based on the option pricing of Black and Scholes (1973) to estimate the market value of the bank assuming that the asset value follows a geometric Brownian motion with a drift. In some detail, the main components of the distance to default are: the market value of the bank's assets, the asset risks, which measure the uncertainty or risk, and lastly the leverage, which provides insights over the bank's contractual liabilities. Moreover, the market value of the bank's assets follows a stochastic process that is a geometric Brownian motion with a drift:

$$dMV_B = \mu MV_B dt + \sigma_B MV_B dz \qquad \text{(A1)}$$

where MV_B and dMV_B is the bank's asset value and change in the asset value respectively, μ, σ_B is the bank's asset value drift and volatility, while dz is a Wiener process. Here, we assume that the drift, as in the Merton model, can be approximated by the risk free interest rate.

The liabilities are both the bank's debt (D) and equity (E), thus the market value of equity (MV_E) is:

$$MV_E = MV_E N(d_1) - De^{-rT} N(d_2) \qquad \text{(A2)}$$

, where $d_1 = \frac{\ln(\frac{MV_B}{D}) + (r + \frac{\sigma_B^2}{2})}{\sigma_B \sqrt{T}}$, $d_2 = d_1 - \sigma_B \sqrt{T}$, with r being the risk free interest rate. Now, it can be shown that the volatility of equity and market value of bank are related as follows:

$$\sigma_E E_0 = N(d_1) \sigma_B B \qquad \text{(A3)}$$

From the above system of equations (A2) and (A3) we can solve for MV_B and σ_B, so as to derive the bank's distance to default, the measure of our risk, as:

$$DD = \frac{\ln(\frac{MV_B}{D_t}) + (\mu - \frac{\sigma_B^2}{2})t}{\sigma_B \sqrt{T}} \qquad \text{(A4)}$$

The DD essentially measures the number of standard deviations that the bank is away from default.

APPENDIX B

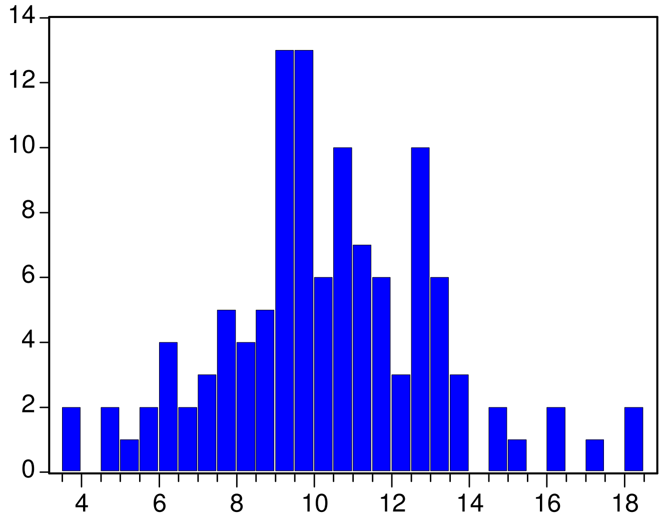
Table B1: Cost function estimates under different quantiles

	Q5		Q25		Q50		Q75		Q95	
lnC	***Coef.***	***t***	***Coef.***	***t***	***Coef.***	***t***	***Coef.***	***t***	***Coef.***	***t***
ln(p1)	0.269	1.610	-0.044	-0.240	-0.133	-0.830	-0.080	-0.340	0.003	0.010
ln(p2)	0.691	1.950	0.998	5.000	1.133	5.700	0.945	4.160	0.992	3.710
ln(y1)	0.603	4.950	0.726	4.340	0.678	4.220	0.557	4.120	0.759	2.880
ln(y2)	0.514	3.120	0.463	5.200	0.509	4.230	0.351	4.010	0.214	1.470
ln(n1)	0.038	0.120	-0.093	-0.530	-0.131	-0.570	0.025	0.130	0.062	0.200
ln(n2)	-0.131	-0.620	-0.024	-0.190	0.026	0.170	0.175	0.940	0.127	0.780
$\ln(p1^2)$	-0.025	-0.360	0.003	0.060	-0.017	-0.290	-0.008	-0.160	-0.044	-0.860
$\ln(y1^2)$	0.133	4.990	0.112	5.170	0.143	4.850	0.141	5.390	0.102	2.660
$\ln(y2^2)$	0.139	8.540	0.131	8.390	0.156	7.770	0.159	7.880	0.146	4.820
ln(y1)ln(y2)	-0.142	-5.980	-0.132	-6.940	-0.161	-6.570	-0.154	-6.440	-0.132	-3.790
$\ln(n1^2)$	-0.063	-0.970	0.009	0.220	0.048	0.880	0.051	1.310	0.039	0.760
$\ln(n2^2)$	-0.063	-1.250	0.002	0.050	0.041	1.020	0.046	1.780	0.033	0.850
ln(n1)ln(n2)	0.068	1.290	0.002	0.060	-0.036	-0.790	-0.049	-1.570	-0.034	-0.820
ln(y1)ln(p1)	-0.070	-1.790	-0.063	-2.220	-0.060	-1.460	-0.052	-1.480	-0.054	-1.390
ln(y2)ln(p1)	-0.054	-0.960	-0.027	-1.010	0.030	1.420	0.032	1.100	0.038	0.910
ln(n1)ln(p1)	0.085	1.180	0.006	0.130	-0.033	-0.880	-0.048	-1.030	0.011	0.160
ln(n2)ln(p1)	0.127	3.590	0.078	2.900	0.052	2.310	0.001	0.040	0.040	1.030
AT	-0.358	-3.350	-0.081	-1.450	-0.039	-0.700	0.003	0.070	0.045	1.080
BE	-0.028	-0.490	0.001	0.020	0.033	0.280	0.068	0.490	0.215	1.700
FR	0.001	0.020	0.099	4.640	0.096	4.290	0.094	3.780	0.155	2.660
DE	0.013	0.390	0.075	1.630	0.079	1.160	0.077	1.370	0.326	1.550
GR	0.038	0.790	0.073	1.540	0.123	3.070	0.151	4.650	0.200	4.750
IE	-0.548	-2.830	0.038	0.670	0.084	1.440	0.085	2.890	0.694	2.160
IT	-0.137	-2.900	-0.051	-2.020	-0.017	-0.520	0.005	0.240	0.077	1.960
LU	0.033	0.580	0.068	1.040	0.049	0.580	0.110	0.920	0.123	0.820
NT	0.011	0.320	0.047	1.480	0.073	1.370	0.082	2.150	0.213	2.860
PT	0.041	0.910	0.105	2.040	0.097	2.420	0.090	2.970	0.181	4.950
ES	-0.246	-2.430	-0.010	-0.190	0.011	0.320	0.052	1.300	0.150	3.510
SE	-0.063	-1.030	-0.024	-0.250	0.056	1.320	0.042	0.940	0.105	2.520
UK	0.054	0.740	0.133	3.970	0.148	3.550	0.186	6.020	0.358	6.830
constant	-2.918	-3.560	-3.163	-7.310	-3.144	-5.360	-2.821	-3.680	-3.235	-3.490
R^2	0.9461		0.9551		0.9573		0.9569		0.9442	

Note: Quantiles have been estimated by simultaneous regression analysis. Standard errors were obtained by bootstrapping with 100 replications. Standard homogeneity and symmetry restrictions are imposed, thus coefficients of interaction terms with lnp2 are excluded. The county dummy for Denmark is excluded so as to avoid perfect collinearity.

APPENDIX C

Table C1: Histogram of the distance to default (DD)



Series: DD
Observations 115

Mean	10.34812
Median	10.01611
Maximum	18.48779
Minimum	3.945530
Std. Dev.	2.800987
Skewness	0.282781
Kurtosis	3.478416
Jarque-Bera	2.629384
Probability	0.268557