A quantile regression approach to bank efficiency measurement

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1. Introduction

The estimation of bank efficiency, whether at the branch or at the institution level, is a topic that has attracted considerable attention in the literature (see Berger and Humphrey, 1997; Berger, 2007, Fethi and Pasiouras, 2010). Over the years a number of topics have been explored including the relationship of efficiency with ownership (Miller and Parkhe, 2002), regulations (Pasiouras, 2008), institutional development (Lensink et al., 2008), off-balance-sheet activities (Siems and Clark, 1997), risk (Berger and DeYoung, 1997), stock returns (Chu and Lim, 1998), mergers (Avkiran, 1999), and bank failure (Wheelock and Wilson, 2000) to name a few.

Despite the plethora of efficiency studies in the banking literature, there is no consensus on the preferred approach for the empirical estimation of the frontier (production, cost, profit etc.) of fully efficient firms. For example, Berger and Humphrey (1997) mention that 69 of the banking studies in their survey used nonparametric methods and 61 used parametric methods. In general, data envelopment analysis (DEA) is the most widely used non-parametric technique, and stochastic frontier analysis (SFA) is the most frequently employed parametric technique. Each approach has its advantages and disadvantages and as a result it has supporters and equally dedicated opponents. In general, the econometric approaches have the advantage of allowing for noise in the measurement of the efficiency but their disadvantages are the imposition of a particular production function form and the requirement of an assumption about the distribution of efficiency. In contrast, the main advantages of DEA are that: (i) it avoids the need for a priori specification of function forms, and (ii) it does not require any assumption to be made about the distribution of inefficiency. One the other hand, the shortcomings of DEA are that: (i) it assumes data to be free of measurement error, (ii) it is sensitive to outliers, (iii) having few observations and many inputs and/or outputs will result in many firms appearing on the frontier.

Lately, a third approach was proposed in the literature, namely Quantile regression analysis. This technique has been frequently employed in the econometrics literature; however, there are only a few studies in the context of efficiency estimation examining among others the efficiency of hotels (Bernini et al., 2004), nursing facilities (Knox et al., 2007), dairy farms (Chidmi et al., 2011), and check processing operations (Wheelock and Wilson, 2008). In the case of banking this techniques was applied only very recently, with a handful number of studies examining US (Wheelock and Wilson, 2009), German (Behr, 2010) and European banks (Koutsomanoli-Filippaki and Mamatzakis, 2011).

Quantile regression can be particular useful in the context of efficiency analysis. First, this approach is well-suited for efficiency estimations when there is considerable heterogeneity in the firm level data (Behr, 2010). More detailed, the estimation of conditional quantiles is more robust against outliers and it also provides the means to obtain different slope parameters describing the production of efficient firms rather than average firms. Furthermore, as discussed in Liu et al. (2008), quantile regression requires an assumption about the functional form of the production frontier (unlike DEA); however, it does not require the imposition of a particular form on the distribution of the inefficiency terms (unlike SFA). Additionally, quantile regression avoids the criticism against DEA of not allowing for random error.

The present Chapter aims to provide an overview of this promising alternative approach, along with an empirical application in a large international dataset, including 1,520 commercial banks operating in 73 countries, between 2000 and 2006. Apparently, with such a wide coverage our sample is quite heterogeneous both in terms of the countries' development as well as in terms of the banks' characteristics. Given the increasing number of cross-country studies, our approach provides an ideal setting for the application of quantile regression that can be particular useful in samples with large bank heterogeneity. The next section discusses the methodological framework of quantile regression. Then we present the empirical results. The concluding marks are discussed in the last section.

2. Methodology

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. Consequently, quantile regression was recently employed in various strands of the finance and banking literature, including banking risk and regulations (Klomp and de Haan, 2012), the herding behavior in stock markets (Chiang et al., 2012), capital structure (Fattouh et al., 2005), bankruptcy prediction (Li and Miu, 2010), ownership and profitability (Li et al., 2009), the relationship between stock price index and exchange rate (Tsai, 2012), and credit risk (Schechtman and Gaglianone, 2012).[1] In the context of our study, quantile analysis provides an ideal tool to examine bank efficiency heterogeneity, departing from conditional-mean models. More detailed, the quantile regression approach allows efficient or almost efficient banks to employ production relations that may differ strongly from the ones of average or low efficiency banks, and in a sense it provides the means for the proper comparison with truly "benchmark" banks that fall within the chosen quantile (Behr, 2010).

In detail, 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). Using standard formulation, the linear regression model takes the form:

$$y_{it} = x_{it}\beta_{\phi} + \varepsilon_{i\phi} \qquad (1)$$

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.

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:

[1] For a general discussion of quantile regression see Koenker and Hallock (2001).

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

which is solved via linear programming. Note that the median estimator, that is, quantile regression estimator for φ = 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.

For the estimation of efficiency 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, the DFA methodology assumes that the inefficiency of each bank remains constant across the sample period and that random error averages out over time.

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). Berger and Humphrey (1997) argue that 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. Therefore, under DFA a panel data is required and only panel estimates of efficiency over the entire time interval are available.[2]

[2] However, the rationality of the DFA assumptions depends on the length of period studied. 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

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

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

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

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

where all variables are expressed in natural logs.[3] 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[4]. 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, $\ln \hat{\varepsilon}_i$, 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:

(DeYoung, 1997). Following the empirical literature, the 7-year period of our sample reasonably balances these concerns.

[3] 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 $\alpha_{jk} = \alpha_{kj}$, $\forall i, j, k, m$.

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

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

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.

2.3. Data and specification of the frontier

We start the construction of our dataset by considering all the commercial banks in the Bankscope database. Once we exclude banks for which we do not have complete data for the period of our study, we end up with a sample of 1,520 commercial banks operating in 73 countries, between 2000 and 2006. This sample includes domestic and foreign banks as well as listed and unlisted banks. It is worth emphasizing that there exists certain degree of heterogeneity across banks as they operate in quite different environments in terms of regulations, institutional infrastructure, market characteristics, and overall development. Despite the bank heterogeneity , it is not uncommon for the recent bank efficiency literature to use such large international datasets (e.g. Lensink et al., 2008; Barth et al., 2010), making our setting ideal for testing the usefulness of a quantile approach. As discussed in the next section, to reveal potential differences across different levels of development, we combine information from the International Monetary Fund (IMF) and the European Bank for Reconstruction and Development (EBRD), and we classify banks in four groups according to the level of development of the country that they operate, namely major advanced countries, advanced countries, transition countries, and developing countries. Moreover to examine the impact of the aforementioned country-specific characteristics we use information from various sources such as the Worldwide Governance Indicators database, the World Bank database on Bank Regulation and Supervision, and the World Bank database on Financial Development and Structure and we perform second-stage regressions. These are results are discussed in detail in section 3.2.

There is a debate in the literature as for the selection of inputs and outputs, and in particular as for the appropriate treatment of deposits (Berger and Humphrey, 1997). Following Dietsch and Lozano-Vivas (2000), Maudos et al. (2002), Pasiouras et al. (2009), and others, we adopt the value added approach which suggests using deposits as outputs since they imply the creation of value added. Therefore, we use the following three outputs: loans (Y_1), other earning assets (*Y2*), and total deposits (*Y3*). Furthermore, consistent with numerous studies on bank efficiency we select the following three input prices: cost of borrowed funds (*P1*), calculated as the ratio of interest expenses to total deposits; cost of labour (*P2*), calculated by dividing the personnel expenses by total assets; and cost of physical capital (*P3*), calculated by dividing the expenditures on plant and equipment (i.e. overhead expenses net of personnel expenses) by fixed assets. Thus, our approach recognizes that deposits have both input and output characteristics, the first captured through the inclusion of the interest expense paid on deposits in the input prices vector, the second captured through the stock of deposits in the output vector.

Furthermore, we normalize the dependent variable and the three outputs by equity. Berger et al. (2000) point out that the normalization by equity capital controls for heteroskedasticity, reduces scale biases in estimation, it provides the grounds for a more economic interpretation, and it controls for financial leverage.

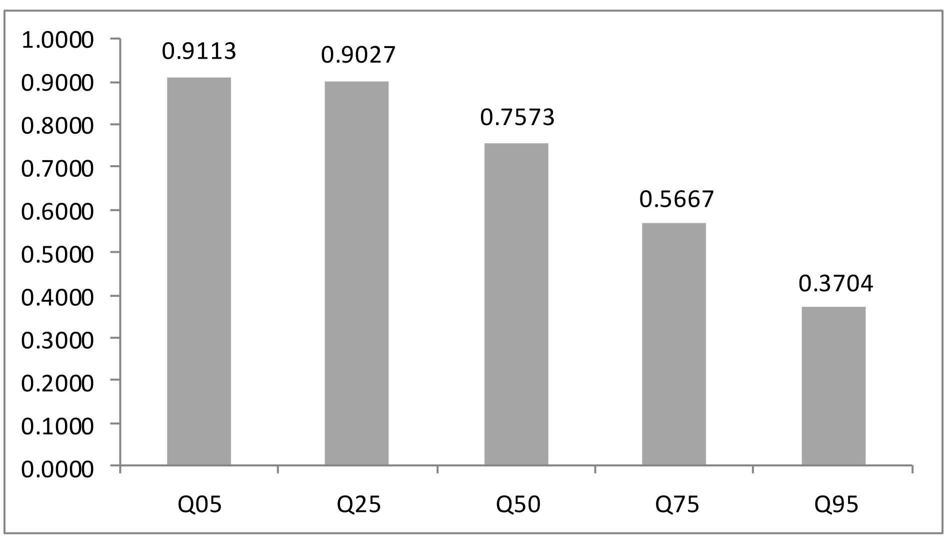
Additionally, to account for technological differences across different levels of a country's overall development, we use dummy variables to distinguish between major advanced, advanced, transition and developing countries (Lozano-Vivas and Pasiouras, 2010).

3. Empirical results

3.1 Cost efficiency estimates

We calculate cost efficiency scores for each bank in our sample using the Distribution-free approach and compare these scores across quantiles and across different levels of development. In order to cover as wide range of quantiles as possible, we run regressions for quantiles 0.05, 0.25, 0.75 and 0.95.

Figure 1 – Average cost efficiency scores by quantile

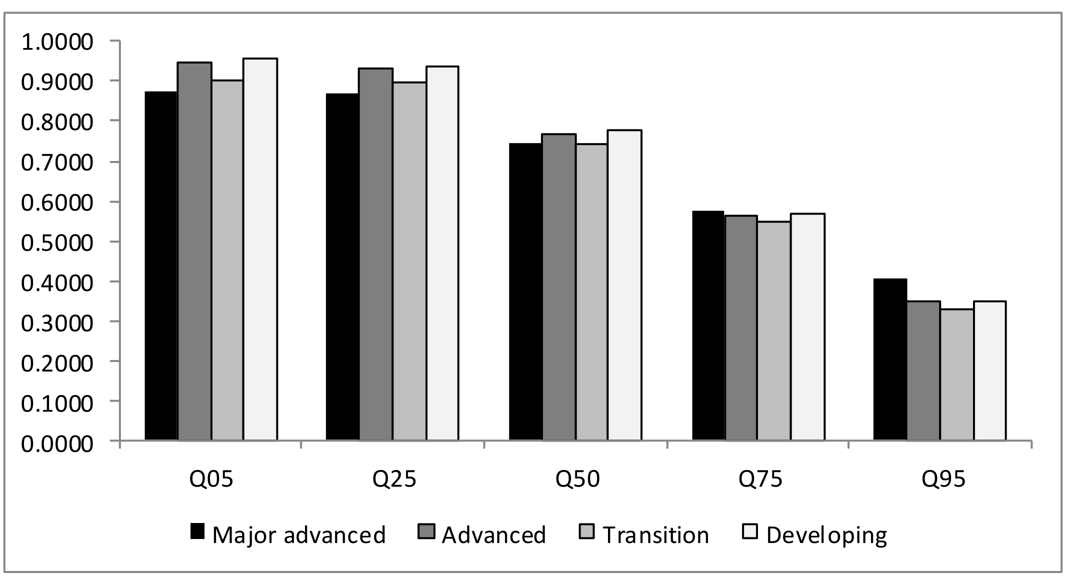


Source: Authors' estimations.

Figure 1 presents the average efficiency scores across quantiles. There are three interesting observations to be made. First, there is a remarkable variation across quantiles. More detailed the average efficiency score for the whole sample ranges from 0.3704 for quantile 0.95

to 0.9113 for quantile 0.05. Second, cost efficiency estimates across quantiles, and particularly in the tail of the distribution, differ substantially from the conditional mean (OLS) point estimate of efficiency, which is approximated by quantile 0.5 and equals 0.7573. Thus, quantile regression analysis provides a more comprehensive picture of the underlying range of disparities in cost efficiency than the classical estimation. Third, the average efficiency is monotonically decreasing as it follows a negative trend at higher order of quantiles. More detailed, cost efficiency is estimated at around 0.9113 for quantile 0.05, decreases to 0.9027 for quantile 0.25, dropping further to 0.7573 and 0.5667 for quantiles 0.50 and 0.75 respectively, while it reaches its minimum value at 0.3704 when the cost function is calculated at the 0.95 quantile. In general, these results confirm the ones of Koutsomanoli-Filippaki and Mamatzakis (2011) for European banks; however, the minimum cost efficiency in our case is considerably lower than the one recorded in their study.

Figure 2 – Average cost efficiency scores by country development level and quantiles



Source: Authors' estimations

Figure 2 presents a disaggregation of the estimated cost efficiencies by the level of a country's overall development (i.e. major advanced, advanced, etc.). First, this disaggregation confirms the aforementioned negative trend at higher order of quantiles, irrespective of the level of overall country development. Second, there appears to some variability in the underlying relationship between the level of a country's overall development and the cost efficiency of banks. More detailed, we observe that banks operating in major advanced countries appear to be less cost efficient when looking at the 0.05 and 0.25 quantiles, and more cost efficient when looking at the 0.75 and 0.95 quantiles. Additionally, the scores appear of similar magnitude when looking at the 0.50 quantile. This would imply that resolving into the classical OLS mean regression analysis would result to loss of valuable information regarding the bank performance across the world. Finally, the average cost efficiency of banks from major advanced countries is always higher than that of banks from all other categories the highest quantile, but the former becomes lower than that the latter at very low quantiles , i.e. Q5 and Q25. The differences in cost efficiency between advanced, transition and developing countries remain quite stable across quantiles, whilst they are not large in magnitude. It is worth noticing that countries in transition have a record of the lowest bank performance in our sample. This evidence suggests that reform efforts during transition could come at the expense of lowering bank cost efficiency, though once the country becomes advanced the benefits of these reforms translate into higher scores in cost efficiency.

Table 1 presents the spearman's rank correlation coefficients between the cost efficiency scores obtained across different quantiles. As expected, there are similarities and differences depending on whether we compare the rankings that are obtained from estimations at neighboring or distant quantiles.

Table 1 – Spearman's rank correlation coefficients

All sample	Q05	Q25	Q50	Q75	Q95
Q05	1.000				
Q25	0.908***	1.000			
Q50	0.692***	0.794***	1.000		
Q75	0.230***	0.356***	0.644***	1.000	
Q95	-0.217***	-0.088***	0.203***	0.580***	1.000
Major advanced countries	**Q05**	**Q25**	**Q50**	**Q75**	**Q95**
Q05	1.000				
Q25	0.920***	1.000			
Q50	0.661***	0.794***	1.000		
Q75	-0.013	0.147***	0.477***	1.000	
Q95	-0.567***	-0.417***	-0.045	0.574***	1.000
Advanced countries	**Q05**	**Q25**	**Q50**	**Q75**	**Q95**
Q05	1.000				
Q25	0.414***	1.000			
Q50	0.659***	0.348***	1.000		
Q75	0.581***	0.266***	0.800***	1.000	
Q95	0.464***	0.634***	0.620***	0.545***	1.000
Transition countries	**Q05**	**Q25**	**Q50**	**Q75**	**Q95**
Q05	1.000				
Q25	0.709***	1.000			
Q50	0.439***	0.744***	1.000		
Q75	0.172**	0.665***	0.699***	1.000	
Q95	-0.118*	0.514***	0.620***	0.907***	1.000
Developing countries	**Q05**	**Q25**	**Q50**	**Q75**	**Q95**
Q05	1.000				
Q25	0.948***	1.000			
Q50	0.862***	0.911***	1.000		
Q75	0.717***	0.791***	0.915***	1.000	
Q95	0.587***	0.697***	0.773***	0.848***	1.000

Notes: ***Statistically significant at the 1% level, **Statistically significant at the 5% level, *Statistically significant at the 10% level

For example, estimations at the 0.05 and 0.25 quantiles rank the banks in approximately the same way. Additionally, there are moderate correlations between estimations at the 0.50 quantile and the 0.75 quantile, as well as between the 0.75 quantile and the 0.95 quantile.

However, there are remarkable differences between estimations at the 0.05 and 0.95 quantile, as well as between the 0.25 and 0.95 quantiles, as it becomes evident by the negative coefficients. The correlations by level of development reveal the existence of differences across the group of countries. For example, the estimations for major advanced and transition countries are similar to the ones for the whole sample. Nonetheless, in the case of developing countries we observe that not only the correlation coefficients tend to be higher but there is also a moderate positive correlation between estimations at 0.05 and 0.95 quantiles. In the case of advanced countries, the correlations are similar to the ones of developing countries, although lower in magnitude.

3.2 Determinants of cost efficiency

To shed more light into our analysis we also perform second-stage regressions, where cost efficiency scores derived at different quantiles are regressed on a set of environmental variables. Following recent studies by, among others, Pasiouras (2008), Pasiouras et al. (2009), Lozano-Vivas and Pasiouras (2010) we account for regulatory conditions using four indices that control for capital requirements (CAPRQ), private monitoring (PRMONIT), supervisory power (SPOWER), and activity restrictions (ACTRS). To capture the macroeconomic conditions we use the inflation rate (INFL) and real GDP growth (GDPGR). To account for industry conditions we use the ratio of bank claims to the private sector over GDP (CLAIMS), and concentration in the banking sector (CONC). Finally, to control for the institutional development (INSTDEV) we use the average of six indicators measuring voice and accountability, political stability, government effectiveness, regulatory quality, rule of law, and control of corruption (see e.g. Lensink et al., 2008). Further information about these variables is provided in Appendix I.

The results in Table 2 reveal various interesting findings. First, the 0.75 and 0.95 quantiles appear to be of significance for the direction of the impact of various environmental variables on cost efficiency. Moreover, the positive impact of CAPRQ on cost efficiency that is reported at the 0.05 and 0.25 quantiles is reversed at the 0.75 and 0.95 quantiles. This change in the sign of CAPRQ has important implications as it shows that capital requirements have a positive influence on the more efficient banks and a negative impact on the less efficient banks. Thus, either the most efficient banks are capable of turning the regulatory burden imposed by higher capital requirements to their benefit or supervisors distinguish between efficient and inefficient banks. The latter would be in line with the results of DeYoung et al. (2001) who conclude in their US study that "…*regulators impose greater discipline and higher distress costs on inefficient banks than on efficient banks*" (p. 275). The impact of the institutional development also differs across quantiles, being positive for the more efficient banks and negative for the less efficient banks.

In contrast, GDPGR, CLAIMS and CONC exercise a negative influence on the efficiency of banks in the case of the 0.05 and 0.50 quantiles and a positive impact in the case of the 0.75 and 0.95 quantiles. The negative impact of GDP growth is in line with the findings of Maudos (2002) who argue that under expansive demand conditions, banks feel less pressured to control their costs and are therefore, less cost efficient. However, our results illustrate that there is a turning point after which banks are cautious and they take advantage of the growth in the economy so that they will operate more efficiently. The similar picture that emerges in the case of concentration could explain why the results in the literature, as for the impact of concentration on efficiency, are mixed.[5] Overall our findings indicate that an OLS analysis, which is close to the median quantile (0.5), would be misleading, as it would report an insignificant coefficient for capital requirements (CAPRQ) and institutional development (INSTDEV), and it would also ignore that the impact of environmental factors can vary across different levels of efficiency.

Table 2 – 2nd stage regressions

	Q05	Q25	Q50	Q75	Q95
CAPRQ	0.0006**	0.0004*	0.0000	-0.0004*	-0.0008**
	(0.026)	(0.084)	(0.889)	(0.060)	(0.022)
OFFPR	-0.0000	-0.0001	-0.0002	-0.0001	-0.0000
	(0.868)	(0.626)	(0.105)	(0.512)	(0.965)
PRMONIT	-0.0003	-0.0002	-0.0003	-0.0002	0.0001
	(0.565)	(0.639)	(0.375)	(0.572)	(0.915)
ACTRS	-0.0004	-0.0007	-0.0007	-0.0012	-0.0010
	(0.694)	(0.482)	(0.257)	(0.134)	(0.438)
INFL	0.0001*	0.0001	0.0001	-0.0000	-0.0000
	(0.087)	(0.136)	(0.518)	(0.891)	(0.580)
GDPGR	-0.0005***	-0.0004***	-0.0002**	0.0001	0.0004***
	(0.000)	(0.000)	(0.025)	(0.176)	(0.006)
CLAIMS	-0.0256***	-0.0204***	-0.0051***	0.0120***	0.0316***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
CONC	-0.0379***	-0.0296***	-0.0108***	0.0080***	0.0232***
	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)
INSTDEV	0.0130***	0.0089***	0.0012	-0.0055***	-0.0107***
	(0.000)	(0.000)	(0.480)	(0.008)	(0.002)
Constant	0.9378***	0.9267***	0.7716***	0.5662***	0.3514***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: ***Statistically significant at the 1% level, **Statistically significant at the 5% level, *Statistically significant at the 10% level; p-values in parentheses; Results obtained from fixed effects estimations with the dependent variable being the cost efficiency at different quantiles; Variables are defined in Appendix I

[5] For example, Fries and Taci (2005) find that there is no significant association between concentration and cost efficiency, Grigorian and Manole (2006) report a positive association, and Maudos et al. (2002) find a negative association.

4. Conclusions

This Chapter presents an application of quantile regression analysis in estimating the cost efficiency of 1,520 commercial banks operating in 73 countries during 2000-2006. This approach allows us to estimate banks' cost function for various quantiles of the conditional distribution and to examine the tail behaviours of that distribution. In further analysis we also examine whether and how the impact of environmental factors differs across the various quantiles of efficiency. The employed methodological framework is of particular importance in light of the heterogeneity in bank efficiency across various countries.

The results can be summarized as follows. First, there is a remarkable variation of efficiency across quantiles. Second, the efficiency estimates across quantiles, and particularly in the tail of the distribution, differ substantially from the conditional mean (OLS) point estimate of efficiency (i.e. quantile 0.5). Third, the average efficiency is monotonically decreasing. We confirm this negative trend at higher order of quantiles for all levels of overall country development (i.e. major advanced, advanced, transition, developing countries). Fourth, there appears to be some variability regarding the underlying relationship between the level of a country's overall development and bank cost efficiency. Fifth, the results of spearman's rank correlation coefficients show that there exist variability in the ranking of banks depending on whether we compare estimations from neighboring or distant quantiles. In this case, the results differ among different levels of overall country development. Sixth, the estimations of the second stage regressions illustrate that there is turning point as for the direction of the impact of various variables on cost efficiency. Furthermore, our findings indicate that an OLS analysis, which is close to the median quantile (0.5), would be misleading. Overall, we conclude that quantile regressions by permitting the estimation of various quantile functions of the underlying conditional distribution provide a more comprehensive picture of the underlying relationships.

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