Risk and efficiency in the Central and Eastern European banking industry under quantile analysis

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This paper estimates cost efficiency in the banking industry of 11 Central and Eastern European (CEE) countries over the period 1998–2005 using a quantile regression analysis. Our purpose is to investigate for the first time whether cost efficiency in CEE banks differs across quantiles of the conditional distribution. We employ stochastic frontier analysis across quantiles using the Distribution-Free Approach. The reported evidence demonstrates lower efficiency scores for higher conditional distributions. The paper goes further into a second-stage analysis to investigate how risk, measured by non-performing loans and loans loss provisions, affects bank efficiency across quantiles. This second-stage analysis finds that risk asserts a negative impact on cost efficiency, especially in high-order quantiles. Finally, the paper investigates the relationship between bank-specific '*z*' variables, such as structural reforms, bank concentration and profitability, and cost efficiency across quantiles.

Keywords: Applied finance, European financial markets, Financial econometrics, Parameter estimation techniques

JEL Classification: D2, D21, G2, G21, L2

1. Introduction

The Central and Eastern European (CEE) countries banks' market has been substantially transformed over recent years. Initial reforms in CEE countries towards a market-based economy set the cornerstone for accelerating the pace of liberalisation so as to achieve the goal of accession to the European Union (EU). For most CEE countries the process of accession to the EU was launched back in 1998 and paved the way that led to a successful participation in the EU on 1 May 2004. Eight CEE countries, namely the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia and Slovenia, became members of the EU in 2004, whereas Bulgaria and Romania joined later on 1 January 2007. In this paper we also include Croatia in our analysis, which has been granted the status of a candidate country and is currently in accession negotiations with the EU.

For most new EU member states, accession to the EU underlines a substantial catching up process that in turn has led to rapid financial development and high economic growth. This is certainly the case for the CEE countries. Within this context it is of importance to accurately measure the financial performance, and due to the weight of the banking industry in the CEE countries, to measure the bank performance. A study of bank performance in CEE countries would then allow us to disentangle its main determinants and would, in particular, provide an assessment of the importance of risk.

The importance of providing bank performance measurements for transition economies that are in the process of evolving both in terms of technology and product mix is well documented in the literature (Grigorian and Manole 2002, Green *et al*. 2004, Bonin *et al*. 2005, Fries and Taci 2005, Yildirim and Philippatos 2007). Moreover, numerous studies have investigated bank efficiency using stochastic frontier analysis in transition economies (Allen and Rai 1996, Lozano-Vivas *et al*. 2001, De Guevara and Maudos 2002, Maudos *et al*. 2002, Vander Vennet 2002, Casu and Molyneux 2003).

The present paper, although employing stochastic frontier analysis to estimate bank cost efficiency, contributes to the ongoing debate regarding bank

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efficiency and risk in several ways. First, we employ Stochastic Frontier Analysis, and in particular the Distribution-Free Approach, as in Berger (1993) to estimate bank efficiency scores across quantiles. To the best of our knowledge this type of analysis has not been applied for the CEE region. We follow the methodology proposed by Berger (1993) and Schmidt and Sickles (1984) and derive different parameter estimates of a translog cost function for various quantiles of the conditional distribution and as a result different cost efficiency scores. Next, we investigate the relationship between cost efficiency and risk across different quantiles using cross-section regressions.

The main advantage of quantile regression analysis is that it relaxes one of the main OLS hypotheses and permits the estimation of various quantile functions and the tail behaviour of the distribution.y To this end, quantile regression provides a detailed view of the underlying relations among stochastic variables by enhancing the estimation of conditional mean functions with the entire family of conditional quantile functions. This is of interest given the importance of risk for bank performance, as the recent financial crisis has highlighted. In addition, quantile analysis including the tails of the distribution provides new information on the interaction between risk and bank cost efficiency away from the classical media distribution. Lastly, we run cross-section regressions to examine the impact of '*z*' bank-specific variables on the cost efficiency of CEE countries across quantiles.

A first glimpse of the results reveals that bank efficiency scores show substantial variation across quantiles. This is new information that has gone unnoticed in the literature. Moreover, we find that, in high-order quantiles, the average cost efficiency is low. In addition, the second-stage cross-section analysis regarding the relationship between risk and efficiency suggests that the former asserts a negative impact on the latter, especially in high-order conditional distributions. Further analysis reveals that the interaction between efficiency and bank- specific '*z*' variables, such as structural reforms, bank concentration and profitability, also varies across quantiles.

The rest of the paper is organized as follows. Section 2 presents a literature review in relation to the CEE banking market, and section 3 provides the methodology. Section 4 reports a description of the data. Section 5 discusses the empirical results, and the conclusions are drawn in section 6.

2. Literature review on bank efficiency in the CEE region

Past studies (Grigorian and Manole 2002, Green *et al.* 2004, Bonin *et al.* 2005, Fries and Taci 2005, Yildirim and Philippatos 2007) rely on conditional mean regression analysis to examine bank cost efficiency. This paper departs from the related literature by employing quantile regression analysis to estimate bank cost efficiency. An obvious question emerges: Why is it of importance to study bank efficiency across quantiles and then subsequently the impact of risk on efficiency? Foremost, cost efficiency can be accurately used as a bank performance indicator as it is based on the underlying meaningful cost minimisation framework. In this respect, bank cost efficiency entails information regarding the cost of financial intermediation. However, due to substantial bank heterogeneity across countries in the CEE region, standard conditional mean regression analysis would result in a biased estimation of bank efficiency, and, in particular, it would overestimate efficiency scores. This overestimation, in turn, would provide a distorted account of bank performance. Quantile regression analysis resolves this issue by providing a framework that fully accounts for bank heterogeneity (Schmidt and Sickles 1984, Berger 1993).

The next question that emerges is: What is the appeal of the CEE region? This region is of interest due to the different pace of structural changes (Fries and Taci 2005, Yildirim and Philippatos 2007) that takes place in the financial markets, which, in turn, enhances the heterogeneity of banks' cost efficiency. This issue has not been studied to date for the CEE region, despite there being a number of studies that examine the impact of ownership, in particular in relation to the foreign share, on bank efficiency (Green *et al.* 2004, Bonin *et al.* 2005, Fries and Taci 2005, Kasman and Yildirim 2006, Yildirim and Philippatos 2007). On the other hand, Weill (2003, 2007) argues that there is indeed an efficiency gap between CEE and Western countries due to differences in managerial performance. Yildirm and Philippatos (2007), in a study for the CEE banking sectors, provided evidence that competition has a positive influence on bank cost efficiency, whereas it is associated negatively with profit efficiency. Alas, as is often the case in the empirical literature, the evidence is not unequivocal, as Brissimis *et al.* (2008) show that competition can improve profit efficiency. Grigorian and Manole (2002) use a different type of non-parametric analysis, namely data envelope analysis, to examine bank performance heterogeneity in transition countries.

This study presents for the first time an analysis of bank cost efficiency across quantiles in the CEE region and subsequently investigates the relationship between cost efficiency and risk. The interaction between risk and bank efficiency is not a new topic. For example, Berger and DeYoung (1997), in a comprehensive study, emphasize the importance of risk for bank efficiency, and suggest that there exist four underlying hypotheses, namely the 'bad management', the 'bad luck',

yNote that a centre or tail, a point of a conditional distribution, represents a specific quantile. The quantile regression also estimates the median (0.5 quantile) function. This is then the mean OLS function of the conditional distribution of bank cost reported in previous studies (Grigorian and Manole 2002, Green *et al*. 2004, Bonin *et al*. 2005, Fries and Taci 2005, Yildirim and Philippatos 2007).

the 'skimping' and the 'moral hazard' hypotheses. The 'bad management' hypothesis suggests that inefficient banks suffer from poor risk management and as a result the relationship between efficiency and risk is positive. Along these lines, the 'bad luck' hypothesis argues that exogenous negative shocks could result in hikes in bank risk and subsequently could increase bank inefficiency. However, the 'skimping' hypothesis follows a different line of reasoning, suggesting the existence of a trade-off between efficiency and risk in the short run. To this end, banks could perform efficiently in the short run at the expense of devoting fewer resources to manage their risks. Lastly, the 'moral hazard' hypothesis reports a negative relationship between bank capital and risk. Thus, managers in less capitalized banks could prefer higher levels of risk. Berger and DeYoung (1997), using Granger-causality techniques, argue that bank cost efficiency can be used as an indicator of non-performing loans in the US. Other studies, such as Williams (2004), advocate that 'bad management' is the dominant hypothesis in the EU. Podpiera and Weill (2008) show that the impact of non-performing loans on cost efficiency is negative for Czech banks with the causality running from cost inefficiency to non-performing loans.

In terms of measuring risk in banking, Berg *et al*. (1992) were the first to employ non-performing loans as an approximation to risk in a non-parametric study of the bank production function, whereas Hughes and Mester (1993) employed non-performing loans in parametric estimations. Other subsequent studies opted for equity capital as a control variable for risk (Altunbas *et al*. 2001, Maudos *et al*. 2002), while others incorporate loan loss provisions in their efficiency estimation (Altunbas *et al.* 2000). Mester (1996) and Hughes *et al*. (2001) argue that one needs to take into account the impact of risk on bank efficiency as the former negatively affects the latter. Pastor and Serrano (2005) and Yildirim and Philippatos (2007) went a step further by investigating whether certain risks are more common across banks. Kwan and Eisenbeis (1997) opted for a simultaneous equation framework to examine various links between bank risk, capitalization and operating efficiency. Their evidence suggests that underperforming banks are exposed to higher levels of risk. Altunbas *et al*. (2007), employing a similar methodology to Kwan and Eisenbeis (1997) for a sample of European banks, show no evidence of a positive relationship between inefficiency and risk-taking.

This paper complements these studies and in a second-stage analysis examines the impact of risk on bank efficiency across quantiles for the first time.

3. Methodology

3.1. Stochastic frontier analysis: the Distribution-Free Approach

We begin by estimating the cost efficiency for each bank of our sample across the different quantiles. To this end, we opt for a flexible translog cost function specification as in Berger and DeYoung (1997). A common assumption (Berger and DeYoung 1997, Yildirim and Philippatos 2007) refers to the underlying distribution of the efficiency term, that is the half normal distribution. In this study we relax this assumption and estimate cost efficiency using the Distribution-Free Approach (DFA) as developed by Schmidt and Sickles (1984) and Berger (1993). This approach is quite flexible as it does not impose *a priori* any specific shape on the distribution of efficiency. Moreover, the DFA relies on averaging regression residuals to estimate bank-specific efficiency and as a result it provides information regarding the performance of a specific bank relative to its competitors over a range of conditions over time (DeYoung 1997). This comparison is quite important as it offers a cost efficiency ranking of banks and also allows us to apply quantile regression analysis as it provides cost efficiency across banks and also across quantiles.[†] Note that the DFA crucially depends on the period studied.[‡] DeYoung (1997) and Mester (2003) argue that there is a trade-off between adding more years to effectively average out residuals and seeking the optimal number of years that would ensure a constant level of efficiency. Mester (2003) demonstrates that around six to eight years reasonably balance these concerns.

Bonin *et al*. (2005), Yildirim and Philippatos (2007) and Karas *et al*. (2010) use stochastic frontier analysis for transition economies. Following these studies we opted for stochastic frontier analysis to disentangle the inefficiency term from the residual. However, in this paper we opt for the DFA and employ the following translog cost function using panel data analysis:

$$
\begin{aligned}
\ln C_i = {} & \alpha_0 + \sum_i \alpha_i \ln P_i + \sum_i \beta_i \ln Y_i \\
& + \frac{1}{2}\sum_i \sum_j \alpha_{ij} \ln P_i \ln P_j + \frac{1}{2}\sum_i \sum_j \beta_{ij} \ln Y_i \ln Y_j \\
& + \sum_i \sum_j \delta_{ij} \ln P_i \ln Y_j + \varphi_i \ln N_i \\
& + \frac{1}{2}\sum_i \sum_j \varphi_{ij} \ln N_i \ln N_j + \sum_i \sum_j \theta_{ij} \ln P_i \ln N_j \\
& + \sum_i \sum_j \rho_{ij} \ln Y_i \ln N_j + \kappa D_i + \ln v_i + \ln u_i, \qquad (1)
\end{aligned}
$$

where all variables are expressed in natural logs.[§] C_i is the total cost of bank i over time,[¶] P_i is a vector

[†] Berger (1993) shows that the DFA approach is a better method of measuring bank performance as it is based on averaging over a number of conditions. Thus, the DFA approach averages bank efficiency across time.

[‡] The choice of time period is important as a short period could result in errors when averaging residuals, in which case random errors would be falsely attributed to inefficiency. A long period would solve the issue of random errors, but then it is hard to believe that bank efficiency remains constant over a long period of time (DeYoung 1997).

[§] To ensure that the estimated cost frontier is well behaved, standard homogeneity and symmetry restrictions are imposed: $\sum_i a_i = 1$, $\sum_i a_{ij} = 0$, $\sum_i \delta_{ij} = 0$, $\sum_i \theta_{ij} = 0$, $a_{ij} = a_{ji}$ and $\theta_{ij} = \theta_{ji}$.

[¶] For notational simplicity the sub-index for time, t, is dropped.

of input prices, Y_j is a vector of bank outputs, and N is a fixed netput.† Moreover, because bank-specific characteristics and economic conditions may cause bank efficiency to vary across countries, 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 variables in equation (1) are time varying except for u_i. Moreover, the $\ln v_i$ and $\ln u_i$ terms are composite error terms such that

$$\ln \hat{\varepsilon}_i = \ln \hat{v}_i + \ln \hat{u}_i \tag{2}$$

After estimating $\ln \hat{\varepsilon}_i$, we average over time for each bank i. The averaged residuals are estimates of the cost efficiency terms $\ln u_i$, as the random errors $\ln v_i$ tend to cancel each other out in the averaging. Then, bank's i efficiency is given by

$$EFF_i = \frac{\exp[\hat{f}(p_i y_i)]\exp[\ln \hat{u}_{\min}]}{\exp[\hat{f}(p_i y_i)]\exp[\ln \hat{u}_i]} = \exp[\ln \hat{u}_{\min} - \ln \hat{u}_i], \tag{3}$$

where $\ln \hat{u}_i$ is the average residual vector and $\ln \hat{u}_{\min}$ is the most efficient bank in the sample.

Note that we employ the DFA approach in three steps so as to estimate the cost efficiency for all CEE banks, but also crucially across the five identified quantiles. In the first step, a panel estimation of the translog cost function is applied over the sample period of eight years for each identified quantile, namely quantiles 0.05, 0.25, 0.5, 0.75 and 0.95. In the second step, based on the first-stage estimations, we estimate the difference between the observed cost and the predicted cost for each CEE bank and for each period. Then, for each CEE bank, the DFA is applied to average residuals over time for each CEE bank and for each period. Then, for each CEE bank, we classify persistent components observed in the sample and the DFA residuals are averaged over time for each CEE bank to provide cost efficiencies across quantiles. In the final step of the analysis, we employ quantile regressions using the DFA so as to estimate bank-specific cost inefficiencies. In doing so, for the first time we take into account bank cost efficiency heterogeneity, departing from the standard conditional-mean models as in Weill (2003, 2007), Green *et al*. (2004), Bonin *et al*. (2005), Fries and Taci (2005), Kasman and Yildirim (2006) and Yildirim and Philippatos (2007).‡

3.2. *Quantile regression*

Having derived the bank-specific cost efficiency using DFA we can proceed with the second-stage analysis, which is the quantile regression analysis. To briefly state the standard methodology, let CE be a random variable; in this study, CE is bank cost efficiency, with the distribution function F_{CE}, and θ is a real number between zero and one. The θth quantile of F_{CE} is denoted by $q_{CE}(\theta)$ and is derived as the solution to $F_{CE} = \theta$, that is

$$q_{CE}(\theta) := F_{CE}^{-1}(\theta) = \inf\{CE : F_{CE}(CE) \geq \theta\}. \tag{4}$$

This simply implies that 100θth% ($100(1-\theta)$%) of the probability mass of CE is below (above) $q_{CE}(\theta)$.

As in the case of the least-squares estimator, the θth quantile of F_{CE} is derived by minimizing an objective function with respect to q, i.e.

$$\begin{aligned}&\theta\int_{y\geq q}|CE-q|\,dF_{CE}(CE) + (1-\theta)\int_{y<q}|CE-q|\,dF_{CE}(CE)\\ &= \theta\int_{CE\geq q}(CE-q)\,dF_{CE}(CE) - (1-\theta)\int_{CE<q}(CE-q)\,dF_{CE}(CE).\end{aligned} \tag{5}$$

Note that the first-order condition of this minimisation problem gives the θth quantile of F_{CE} as

$$\begin{aligned}0 &= -\theta\int_{CE\geq q} dF_{CE}(CE) + (1-\theta)\int_{CE<q} dF_{CE}(CE)\\ &= -\theta[1-F_{CE}(CE)] + (1-\theta)F_{CE}(CE)\\ &= -\theta + F_{CE}(CE).\end{aligned} \tag{6}$$

Now when CE has the conditional distribution $F_{CE|X}(CE)$, the θth quintile will be $Q_{CE|X}(\theta) := F^{-1}_{CE|X}(\theta)$. $Q_{CE|X}(\theta)$ is a function of X and solves

$$\min_q \left\{\theta\int_{CE\geq q}|CE-q|\,dF_{CE|X}(CE) + (1-\theta)\int_{CE<q}|CE-q|\,dF_{CE|X}(CE)\right\}. \tag{7}$$

The conditional median is thus $Q_{CE|X}(0.5)$ of $F_{CE|X}$. Now taking $Q_{CE|X}(\theta)$ as a linear function $X'\beta$ with unknown parameter β, then the above min is equivalent to

$$\min_\beta \left\{\theta\int_{CE\geq X'\beta}|CE-X'\beta|\,dF_{CE|X}(CE) + (1-\theta)\int_{CE<X'\beta}|CE-X'\beta|\,dF_{CE|X}(CE)\right\}. \tag{8}$$

Solving this quantile gives β_θ, which is the θth conditional quantile.

Thus, the quantile regression model takes the form

$$CE_i = x_i\beta_\theta + \varepsilon_{i\theta}, \tag{9}$$

where $\theta \in (0, 1)$, x_i is a $K \times 1$ vector of regressors, $x_i\beta_\theta$ is the θth sample quantile of CE (conditional on vector x_i),

†In this paper we opt for the intermediation approach as in Berger and Humprey (1997). Specifically, banks are considered to act as mediators so as to receive deposits and provide loans and other earning assets using labor and fixed capital. This approach has been widely applied (Berger and Mester 1997, Weill 2003, Karas *et al*. 2010). We also use a fixed netput. Fixed netputs are quasi-fixed variables, both for inputs and outputs that affect variable costs. This implies that this is a short-run cost function.

‡Taylor (1999) employs quantile analysis in empirical finance to estimate the distribution of returns over time. Basset and Chen (2001) employ quantile regression analysis to examine the diversity of mutual fund investment styles (see also Koenker and Basset (1978), Koenker (2000) and Koenker and Hallock (2001)).

and "$_{i<1}$ denotes a random error with a zero conditional quantile distribution.

4. Banks in the CEE region and data description

Our sample is an unbalanced panel dataset of 1389 observations with a total of 188 different banks. We include in the data set commercial, savings and cooperative banks of 11 Central and Eastern European countries, namely Bulgaria, Croatia, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia, that are listed in the IBCA-Bankscope database over the period 1998 to 2005. In this paper we opt for the intermediation approach as proposed by Berger and Humprey (1997) and Sturm and Williams (2004). Thus, interest income and non-interest income are formed from financial capital and non-financial inputs. The price of financial capital is the interest paid on funds divided by total funds. The price of non-financial inputs is the ratio of operating (non-interest) expenses to assets.[y] We opt for two outputs: total loans and securities, and other earning assets. In addition, capitalization is measured by equity as a fixed netput (Hughes *et al.* 2001). This fixed netput is included as a quasi-fixed variable of the variable costs given that we are dealing with the short run. We define total cost as the sum of overheads (personnel and administrative expenses), interest, fees, and commission expenses. Country dummies are employed in the estimation of the cost stochastic frontier to include country-specific effects for the underlying technology that could result in efficiency variations across banks and across countries.

In a second-stage analysis we employ ‘z’ bank-specific variables. Specifically, we focus on the impact of risk on cost efficiency across quantiles. As risk we consider non-performing loans to control for differences in loan quality. We also use loans loss provisions to account for the credit risk (Fries and Taci 2005, Bonin *et al.* 2005). In addition, we use bank-specific variables such as the five-firm concentration ratio, capturing asset market concentration, and the EBRD index of banking reform, which allows for variation in banking reform and institutional developments across countries.[z]

Table 1 provides descriptive statistics for banks across countries. Clearly, there are variations across countries, especially with reference to total cost, outputs and input prices, suggesting that it is crucial to study bank efficiency across quantiles. The average cost to assets ratio is 8.33%, ranging from 5.75% in Latvia to 13.92% in Romania. The average value is much larger if compared with the average of old member states of the EU, indicating that CEE banks have room to improve their performance. The average interest income to assets ratio is 7.73%, fluctuating from 4.89 in Latvia to 12.89 in Romania. On the other hand, the average ratio of non-interest income is 1.68%, ranging from 1.05 in Slovakia to 2.68 in Romania. This suggests that interest income comprises the main source of banks’ revenues in CEE countries, and that non-interest income falls far below the EU average. Referring to input prices, the average price of financial capital takes a value of 5.01, ranging from 2.33 in Latvia to 8.06 in Romania. The average price of the non-financial input is 4.45, ranging from 2.85 in the Czech Republic to 6.79 in Romania.

Note that the capital ratio is quite high, at 13.49%, indicating that CEE banks have increased their credit, as depicted by the high lending growth rates, without weakening their capital position. This could imply that CEE banks, by demonstrating a high capital adequacy ratio, could signal their solvency and thereby they could be in a better position of attracting funds for their credit expansion (Fries and Taci 2002). Equity ratios exhibit substantial variation across countries, taking values from 9.66% in the Czech Republic to 19.35% in Romania. However, the observed high average ratio of non-performing loans (NPL) raises concerns over loan quality and thus risk. High NPL ratios could be explained by the burden of bad loans most CEE banks inherited from the past. Note though that there is not a ‘*one size fits all*’ case, as the NPL to loans ratio shows considerable variation across countries, ranging from 1.19 in Estonia to 18.50 in Poland. In addition, NPL ratios should be treated with caution due to the lack of a standard reporting practice across countries. Regarding concentration, CEE banks are characterized by a high degree of concentration as reported by the CR_5. On average, the largest five banks hold 61.19% of total banking sector assets, ranging from 49.99% in Poland to 98.84% in Estonia. Lastly, to account for progress in banking reform we opt for the transition reform indicator of the European Bank for Reconstruction and Development (EBRD).[x] Based on

[y] Data availability issues meant that, as a proxy for personnel expenses, we employ a broad measure for the price of non-financial inputs (labor and physical capital). Moreover, we employ the ratio of operating (i.e. non-interest) expenses to assets as in Hasan and Marton (2003), Fries and Taci (2005) and Bonin *et al.* (2005). Hasan and Marton (2003) suggest that administrative expenses are indirect employees’ benefits, and therefore non-interest expenses can be used instead of employee benefits.

[z] Market concentration could reduce efficiency, as enhancing market power for some banks could result in higher costs as a result of slack. Alternatively, market concentration could be a sign of consolidation and thus increase efficiency as only the more efficient banks would survive. Thus, market contestability could lead to greater efficiency (Demsetz 1973, Baumol 1982, Casu and Girardone 2006). We expect that the EBRD index should assert a positive impact on efficiency, as reforms impose capital adequacy requirements and other prudential constraints on risk taking, which enhance efficiency (Fries and Taci 2005). Lastly, the relationship between cost efficiency and non-performing loans is expected to be negative based on the ‘*bad management*’ hypothesis proposed by Berger and DeYoung (1997).

[x] This indicator denotes an index of liberalization and institutional reform in banking with a scale from 1 to 4. The low scale of the index takes the value of 1, meaning little progress. A high score of 4 means a level of reform according to the institutional standards and norms of a market economy in line with the Basle Committee’s Core Principles on Effective Banking Supervision and Regulation.

Table 1. Basic characteristics of CEE banks across countries.

	C/A	y_1/A	y_2/A	p_1	p_2	n_1/A	CR_5	EBRD	NPL
Bulgaria	7.25	6.40	1.71	2.97	5.38	17.58	53.13	3.23	7.44
	(2.90)	(2.59)	(0.95)	(3.29)	(2.42)	(12.53	(3.65)	(0.36)	(4.34)
Croatia	7.53	7.32	1.84	4.65	4.39	14.91	60.97	3.51	12.78
	(2.70)	(2.31)	(1.63)	(2.99)	(2.23)	(9.94)	(3.46)	(0.41)	(4.69)
Czech Rep.	6.24	5.36	1.20	4.51	2.85	9.66	65.21	3.59	16.40
	(4.91)	(3.29)	(0.97)	(5.06)	(2.02)	(9.89)	(0.73)	(0.24)	(14.51)
Estonia	6.97	5.86	1.56	3.34	4.34	12.50	98.84	3.74	1.19
	(3.17)	(2.01)	(0.50)	(1.68)	(2.25)	(9.09)	(0.34)	(0.19)	(1.14)
Hungary	9.69	9.47	1.43	7.20	4.93	12.06	53.68	4.00	4.12
	(4.16)	(4.42)	(0.86)	(4.22)	(3.09)	(8.17)	(1.27)	(0.00)	(1.39)
Latvia	5.75	4.89	2.05	2.33	3.78	11.36	63.59	3.45	2.56
	(3.19)	(2.33)	(1.08)	(1.69)	(2.36)	(7.91)	(2.10)	(0.33)	(2.09)
Lithuania	7.12	5.17	1.77	2.73	4.98	13.23	84.40	3.20	6.01
	(2.92)	(1.86)	(0.93)	(1.27)	(2.22)	(7.76)	(4.28)	(0.25)	(4.22)
Poland	9.15	8.94	1.40	6.18	4.24	13.02	49.99	3.38	18.50
	(3.70)	(4.30)	(1.03)	(3.39)	(2.00)	(10.94)	(3.29)	(0.12)	(4.64)
Romania	13.92	12.89	2.68	8.06	6.79	19.35	62.77	2.76	10.73
	(8.24)	(8.46)	(1.88)	(6.20)	(3.42)	(10.70)	(3.03)	(0.19)	(14.15)
Slovakia	7.54	7.14	1.05	4.99	3.28	9.80	65.06	3.26	18.10
	(3.11)	(2.93)	(0.65)	(3.21)	(1.62)	(7.22)	(2.93)	(0.34)	(12.28)
Slovenia	6.80	6.82	1.48	4.63	3.07	9.80	64.91	3.29	8.89
	(1.77)	(1.99)	(0.54)	(1.59)	(0.79)	(3.86)	(2.11)	(0.10)	(1.21)
CEE	8.33	7.73	1.68	5.01	4.45	13.49	61.19	3.39	10.70
	(4.89)	(4.77)	(1.25)	(4.12)	(2.62)	(10.09)	(10.27)	(0.41)	(9.62)

The table presents mean values with standard deviations in parentheses. C/A, total cost to assets; y_1/A, interest income to assets; y_2/A, non-interest income to assets; p_1, interest expenses/deposits and short-term funding; p_2, overheads/total assets; n_1/A, equity to assets; CR_5, five-firm concentration ratio, defined as the sum of market share of the five largest banks in terms of total assets; EBRD, the index of banking sector reform published in the EBRD Transition Reports; NPL, country-level ratio of non-performing loans to total loans. All outputs, quasi-fixed netputs and total cost are expressed as percentages of total assets. All control variables are in percentages (except for the EBRD Index for banking reform, which ranges from 1 to 4; a score of 1 represents little change other than the separation of the Central Bank and commercial banks, while a score of 4 represents a level of reform that approximates the institutional standards and norms of an open-market economy, as defined by the Basle Committee's Core Principles on Effective Banking Supervision and Regulation).

this indicator, Hungary appears to be a high flier, achieving an impressive value of 4, while Romania has not done quite as well with an average EBRD index of 2.76.

5. Empirical results

5.1. Cost efficiency under a quantile regression analysis

Next we estimate for each quantile (0.05, 0.25, 0.5, 0.75 and 0.95) a translog cost function in order to derive the technical efficiency scores (see table 2). The estimation method of technical efficiency scores is based on simultaneous quantile regression analysis. This regression analysis estimates the entire variance–covariance matrix. This approach allows us to test the hypothesis of whether the coefficients differ across different quantiles. [y]

Table 3 presents the test results on whether the cost coefficients between different quantiles are equal. All empirical tests show that coefficients are not equal from one quantile to another. This, in turn, gives value to opting for quantile regression analysis.

In addition, we estimate cost efficiency scores for each bank using the DFA across quantiles. Figure 1 presents the average efficiency scores by country across quantiles (0.05 to 0.95).

These results provide an interesting picture, as a marked variability in bank efficiency scores across quantiles is observed, indicating that previous research on efficiency, using regression analysis of the mean function of the conditional distribution, may not provide an accurate detailed account of the efficiency dispersion across banks. More specifically, the average efficiency score ranges from 0.39 in high-order quantiles to 0.85 in quantile 0.05. In addition, cost efficiency estimates across quantiles, and especially in the tail of the distribution, are substantially different from the conditional mean (OLS) point estimates. These results show the advantage of quantile regression analysis compared with classical mean regression, as the former presents a broader picture of the whole range of variability in bank cost efficiency.

However, it appears that there is a common pattern across quantiles. The average efficiency appears to follow a negative trend across quantiles from low to high order, indicating the existence of monotonically decreasing quantile efficiency. Average cost efficiency across banks takes values of around 0.85 in quantiles 0.05 and 0.25, then it sharply declines to 0.63 and 0.5 in quantiles 0.50

[y] Coefficient standard errors were derived by bootstrapping with 100 sample replications.

Table 2. Cost function estimates under different quantiles.

	Q5		Q25		Q50		Q75		Q95	
ln *C*	Coeff.	*t*	Coeff.	*t*	Coeff.	*t*	Coeff.	*t*	Coeff.	*t*
ln(p_1)	−0.058	−0.49	0.089	1.59	0.153	2.42	0.103	1.29	0.414	1.88
ln(p_2)	0.671	32.86	0.624	35.84	0.591	42.8	0.587	34.56	0.517	16.69
ln(y_1)	0.546	4.87	0.552	7.5	0.581	9.05	0.561	7.11	0.293	1.13
ln(y_2)	0.629	5.62	0.459	6.77	0.479	9.45	0.474	6.19	0.447	3.46
ln(p_1^2)	0.023	0.61	0.111	6.44	0.125	6.72	0.170	10.13	0.183	5.22
ln(y_1^2)	0.125	8.66	0.143	17.61	0.160	20.9	0.167	14.48	0.197	6.7
ln(y_2^2)	0.117	6.93	0.143	14.87	0.168	19.95	0.173	13.44	0.177	11.9
ln(y_1)ln(y_2)	−0.127	−8.65	−0.145	16.03	−0.169	19.52	−0.175	15.76	−0.180	11.85
ln(p_1)ln(y_1)	0.006	0.23	−0.001	−0.05	0.029	1.69	0.028	2.18	−0.011	−0.36
ln(p_1)ln(y_2)	0.002	0.08	0.057	4.21	0.037	3.26	0.044	3.74	0.053	2.55
ln(n_1)	−0.183	−1.55	−0.031	−0.3	−0.052	−0.57	−0.028	−0.29	−0.083	−0.44
ln(n_1^2)	0.010	0.84	0.006	0.5	0.010	0.96	0.009	1.01	0.012	0.8
ln(n_1)ln(p_1)	0.027	0.97	−0.047	−2.42	−0.063	−2.63	−0.070	−3.88	−0.063	−1.52
BG	0.009	0.37	0.046	3.09	0.080	5.45	0.080	3.94	0.214	4.47
CZ	0.061	1.67	0.042	2.75	0.060	3.29	0.110	4.58	0.176	3.36
EE	0.003	0.05	0.097	2.38	0.127	5.17	0.146	3.73	0.143	3.9
HU	0.020	0.6	0.049	3.06	0.063	3.92	0.073	3.2	0.118	2.42
LV	0.065	2.47	0.079	4.97	0.079	5.77	0.059	3.14	0.060	1.12
LT	0.102	2.49	0.126	4.06	0.184	9.24	0.190	5.31	0.229	4.44
PL	0.043	1.47	0.030	2.34	0.029	2.28	0.032	1.82	0.047	1.41
RO	0.062	2.01	0.107	4.14	0.160	6.84	0.176	7.54	0.194	4.47
SK	0.057	2.17	0.068	4.15	0.052	3.13	0.100	2.93	0.144	4.02
SI	−0.021	−0.67	0.019	1.46	0.014	1.03	−0.004	−0.26	0.007	0.22
CONS	−3.216	−7.89	−2.972	10.73	−3.098	14.83	−2.949	10.35	−0.613	−0.72
R^2	0.9153		0.9211		0.9192		0.9152		0.903	

Quantiles were 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 ln p_2 are excluded. BG, Bulgaria; CZ, Czech Republic; EE, Estonia; HU, Hungary; LV, Latvia; LT, Lithuania; PL, Poland; RO, Romania; SK, Slovakia; SI, Slovenia. The county dummy for Croatia is excluded to avoid perfect collinearity.

Table 3. Post-estimation linear hypotheses testing.

H_0: Q_5 ¼ Q_{25}	H_0: Q_{25} ¼ Q_{50}	H_0: Q_{50} ¼ Q_{75}	H_0: Q_{75} ¼ Q_{95}
Test whether: Translog cost function coefficients are equal between quantiles Q_5 and Q_{25}	Test whether: Translog cost function coefficients are equal between quantiles Q_{25} and Q_{50}	Test whether: Translog cost function coefficients are equal between quantiles Q_{50} and Q_{75}	Test whether: Translog cost function coefficients are equal between quantiles Q_{75} and Q_{95}
F(19, 1363) ¼ 231.72	*F*(19, 1363) ¼ 20.14	*F*(19, 1363) ¼ 287.3	*F*(19, 1363) ¼ 374.18
Probability 4 *F* ¼ 0.000	Probability 4 *F* ¼ 0.000	Probability 4 *F* ¼ 0.000	Probability 4 *F* ¼ 0.000

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

and 0.75, respectively, while it rises somewhat to 0.52 when the cost function is calculated at the 0.95 quantile. In addition, cost efficiency demonstrates some variability across countries. More specifically, the average cost efficiency for Polish banks records a large drop from 0.85 in quantile 0.05 to around 0.47 in quantiles 0.75 and 0.95.[y] Similarly, in the case of Slovenia, average cost efficiency drops from 0.85 in quantile 0.05 to 0.48 in quantile 0.95, whereas the average cost efficiency of Bulgarian banks falls from 0.84 in quantile 0.05 to 0.5 in quantile 0.75, but it recovers some losses in quantile 0.95 as it reaches the value of 0.6. A similar recovery in cost efficiency in quantile 0.95 from quantile 0.75 was also observe for banks in the Czech Republic, Latvia, Lithuania and Romania. Overall, a distinct pattern emerges: efficiency scores exhibit a negative trend at higher quantiles for all countries. This implies that bank efficiency declines in the upper tail of the conditional distribution.

As a further step in our analysis, table 4 reports bank efficiency scores for each bank across different quantiles. The reported evidence is in line with previous results,

[y]Note that Poland has the highest ratio of non-performing loans to loans across our sample.

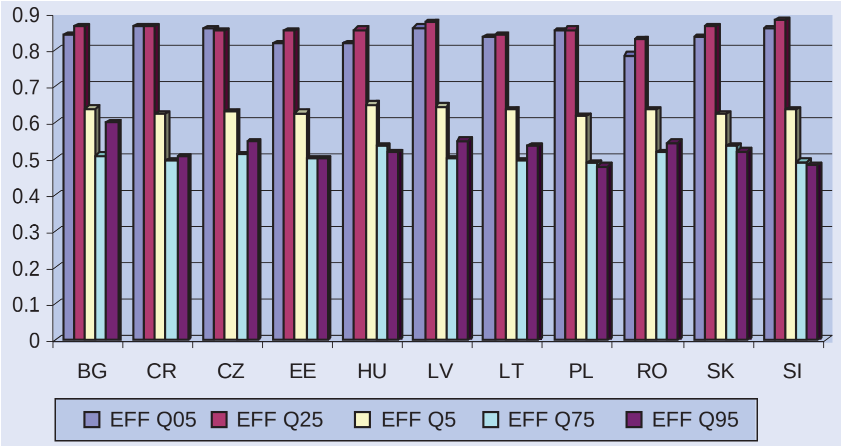

Figure 1. Quantile cost efficiency across countries. The horizontal axis describes the range of different quantiles (0.05, 0.25, 0.5, 0.75 and 0.95) and the vertical axis the corresponding average cost efficiency by country, as measured on a scale from 0 to 1. BG, Bulgaria; CZ, Czech Republic; EE, Estonia; HU, Hungary; LV, Latvia; LT, Lithuania; PL, Poland; RO, Romania; SK, Slovakia; SI, Slovenia.

showing a negative trend in cost efficiency scores across quantiles. Thus, for most banks, cost efficiency scores decline in higher quantiles.

For some countries, however, notably for Bulgaria, Czech Republic, Lithuania, Romania and to a lesser extent Latvia, there is some reversal of the negative trend in cost efficiency from quantile 0.75 to 0.95. For example, in the case of Emporiki Bank Romania and Emporiki Bank Bulgaria the cost efficiency rises from 0.56 and 0.59 in quantile 0.75 to 0.7 and 0.79 in quantile 0.95, respectively. A similar situation is found for the evolution of cost efficiency in higher quantiles for the Czech Moravian Guarantee and Development Bank in the Czech Republic, UAB Medicinos Bankas in Lithuania, and also Sampo Banka in Latvia. This would imply that there is some variability in the cost efficiency across banks and quantiles given that, for some banks, cost efficiency recovers somewhat in the upper tail of the distribution.

These results are also of importance in light of the recent financial crisis, given that the typical regression analysis can overestimate the true underlying bank efficiency scores. The value added of the current quantile regression analysis rests on the fact that it discovers the variability in the efficiency scores across conditional distributions. In turn, this information is of crucial importance for correctly measuring bank performance, which could make a difference especially for those banks on the tails of the distribution, which may have to fight to maintain their stability.

5.2. *The impact of risk on cost efficiency across quantiles*

The previous section clearly demonstrates that there is substantial variability in the cost efficiency of CEE banks across conditional distributions. This result has not been recorded, although it could have implications for assessing bank performance in CEE countries. In this section, we go a step further and examine the relationship between cost efficiency and risk. We measure risk using NPL and loans loss provisions (LLP) as they provide information regarding the quality of loans and credit risk, respectively.

The relationship between efficiency and risk has been studied previously (Mester 1996, Berger and DeYoung 1997, Hughes 1999, Altunbas *et al*. 2000, 2007, Hughes *et al*. 2001). Reports in the literature have proposed several hypotheses for the relationship between risk and efficiency. This relationship can be negative according to the '*bad management*' and the '*bad luck*' hypotheses, or could be positive according to the '*skimping*' hypothesis (Berger and DeYoung 1997).

At a preliminary stage we scatter plot the average cost efficiency scores for all banks in our sample with risk as measured by NPL (see figure 2). Figure 2 demonstrates that the link between NPL and efficiency is stable for low values of NPL, whereas for higher values a negative trend is observed. This result suggests that the average quantile efficiency is negatively related to NPL. Nevertheless, one needs to recall that efficiency scores in figure 2 depict average scores across banks, and a bias cannot be excluded. Note also that there exist some extreme cases.

Furthermore, figure 3 shows efficiency scores under different quantiles plotted against NPL. Note that, for large values of NPL and high-order quantiles, cost efficiency exhibits a slight negative trend. Furthermore, the average cost efficiency in quantile 0.05 is the highest across quantiles for most values of NPL, apart from NPL values from 1.08 to 1.2, where the cost efficiency in quantile 0.25 is higher than the cost efficiency in quantile 0.05. Note that, in the case of high-order conditional distributions, the cost efficiency score in quantile 0.95 is higher than the average efficiency score in quantile 0.75 for most values of NPL. This observation is worth noting since, in the upper tails of the distribution, bank cost efficiency is small.

Most importantly, figure 3 suggests that the relationship between bank cost efficiency and NPL is different across various quantiles, but also across different levels of risk. Moreover, for high-order quantiles and large values

Table 4. Quantile cost efficiency scores across banks.

Bank	Country	EFF Q05	EFF Q25	EFF Q5	EFF Q75	EFF Q95
DSK Bank Plc	BG	0.854202	0.843657	0.607461	0.471037	0.506959
Bulbank AD	BG	0.782083	0.843871	0.622676	0.494869	0.548493
United Bulgarian Bank (UBB)	BG	0.73703	0.784217	0.582284	0.466919	0.501005
Raiffeisenbank (Bulgaria) EAD	BG	0.914108	0.928012	0.670536	0.52298	0.602008
First Investment Bank	BG	0.800912	0.827803	0.617841	0.489103	0.568486
Bulgarian Post Bank JSC	BG	0.801255	0.800206	0.581679	0.454566	0.500503
Societe Generale Expressbank	BG	0.873785	0.881172	0.64431	0.503423	0.563402
DZI Bank AD	BG	0.893453	0.893055	0.664884	0.518973	0.608832
Central Cooperative Bank AD	BG	0.86612	0.843411	0.614107	0.48219	0.533033
Commercial Bank Allianz Bulgaria AD	BG	0.856484	0.852332	0.634114	0.490992	0.59142
ProCredit Bank (Bulgaria) AD	BG	0.915396	0.948359	0.702966	0.552435	0.659039
Piraeus Bank Bulgaria AD	BG	0.817236	0.810779	0.588279	0.457079	0.54581
Corporate Commercial Bank AD	BG	0.852368	0.860653	0.627678	0.49505	0.587873
UnionBank Commercial Bank AD	BG	0.934459	0.948426	0.700169	0.560162	0.653263
Municipal Bank Plc	BG	0.826311	0.803118	0.602671	0.474036	0.512568
Bulgarian–American Credit Bank	BG	0.918824	0.999471	0.765107	0.629671	0.757697
Investbank Bulgaria	BG	0.876857	0.892509	0.652772	0.539607	0.641705
International Asset Bank AD	BG	0.655357	0.686785	0.504611	0.412792	0.503419
Alpha Bank	BG	0.798652	0.932669	0.669885	0.552346	0.740798
Emporiki Bank – Bulgaria EAD	BG	0.779534	0.875287	0.672574	0.597411	0.795922
D Commerce Bank AD	BG	0.847907	0.883849	0.658566	0.537751	0.701119
Tokuda Bank	BG	0.889749	0.890989	0.643589	0.508367	0.600575
Zagrebacka Banka dd	CR	0.934553	0.907246	0.638809	0.484413	0.457142
Privredna Banka Zagreb Group	CR	0.923592	0.894191	0.62909	0.480552	0.452733
Erste & Steierma¨ rkische Bank dd	CR	0.889633	0.882057	0.636944	0.494865	0.476037
Raiffeisenbank Austria d.d., Zagreb	CR	0.949845	0.925891	0.663232	0.511953	0.491843
Hypo Alpe-Adria-Bank dd	CR	0.76842	0.783615	0.569144	0.448351	0.458464
OTP banka Hrvatska dd	CR	0.952953	0.922189	0.661181	0.513274	0.482196
Hrvatska Postanska Bank DD	CR	0.930747	0.900917	0.643821	0.506389	0.47853
Volksbank dd	CR	0.920698	0.914394	0.658115	0.513179	0.510144
Medimurska banka dd	CR	0.869138	0.869362	0.627667	0.491108	0.498137
Podravska Banka	CR	0.928127	0.895938	0.640619	0.496621	0.495573
Istarska Kreditna Bank Umag d.d.	CR	0.950532	0.918078	0.656945	0.509629	0.512973
Jadranska Banka dd	CR	0.924559	0.933562	0.677872	0.535808	0.543709
Croatia Banka dd	CR	0.916667	0.908639	0.650283	0.512112	0.506304
Partner Banka dd	CR	0.768454	0.75708	0.542556	0.44608	0.462865
Credo banka d.d. Split	CR	0.734649	0.773439	0.569679	0.46166	0.513762
Kreditna Banka Zagreb	CR	0.797378	0.805036	0.584496	0.473844	0.497956
StedBanka d.d.	CR	0.815702	0.877135	0.655555	0.556652	0.619011
Slatinska Banka dd	CR	0.901211	0.903753	0.651187	0.518156	0.54461
Centar Banka dd	CR	0.76853	0.797584	0.594935	0.497177	0.542755
Gospodarsko Kreditna Banka	CR	0.782054	0.771773	0.562015	0.495493	0.547732
Nava Banka dd	CR	0.767048	0.809189	0.593524	0.482154	0.556329
Kvarner Banka dd	CR	0.854429	0.852034	0.606959	0.485807	0.521796
Ceska Sporitelna a.s.	CZ	0.855957	0.841974	0.608087	0.469311	0.491512
Komercni Banka	CZ	0.923195	0.919171	0.665208	0.519299	0.533376
HVB Bank Czech Republic AS	CZ	0.84401	0.829511	0.618486	0.49258	0.527421
Ceskomoravska Stavebni Sporitelna	CZ	0.739157	0.729712	0.555889	0.447544	0.477366
Stavebnı´ Sporitelna Ceske´ Sporitelny	CZ	0.669556	0.672951	0.521486	0.42243	0.458296
Raiffeisenbank akciova spolecnost	CZ	0.943987	0.919316	0.666031	0.530371	0.549418
Citibank a.s.	CZ	0.91142	0.900374	0.658462	0.527597	0.543983
Modra pyramida stavebni sporitelna	CZ	0.82555	0.795824	0.587774	0.476604	0.502902
Zivnostenska banka, a.s.	CZ	0.897161	0.882698	0.645219	0.519039	0.538026
Ceskomoravska Zarucni a Rozvojova	CZ	0.873014	0.935983	0.70736	0.590314	0.651017
Raiffeisen stavebnı´ sporitelna AS	CZ	0.825806	0.801896	0.59957	0.483117	0.510924
BAWAG Bank CZ a.s	CZ	0.918299	0.903436	0.666611	0.543941	0.587405
PPF banka a.s.	CZ	0.79482	0.788655	0.603551	0.502518	0.562679
Volksbank CZ as	CZ	0.901964	0.902877	0.640619	0.518508	0.565962
J&T Banka as	CZ	0.916264	0.910752	0.656794	0.559458	0.612372
IC Banka AS	CZ	0.893569	0.933945	0.686375	0.576065	0.630933
HansaPank-HansaBank	EE	0.827084	0.858267	0.623435	0.490853	0.492145
SEB Eesti Ü hispank	EE	0.715689	0.778241	0.585468	0.483009	0.490763
AS Sampo Pank	EE	0.89456	0.950969	0.702488	0.555434	0.549804
Eesti Krediidipank-Estonian Credit	EE	0.775488	0.794042	0.582165	0.457571	0.478543
SBM Bank	EE	0.886751	0.89269	0.63852	0.505217	0.499238
National Savings and Commercial	HU	0.932152	0.923216	0.65711	0.506877	0.478109

(*continued*)

Table 4. Continued.

Bank	Country	EFF Q05	EFF Q25	EFF Q5	EFF Q75	EFF Q95
K&H Bank-Kereskedelmi es Hitelbank	HU	0.95343	0.936903	0.679052	0.533533	0.508971
MKB Bank Nyrt	HU	0.82034	0.827895	0.609137	0.480991	0.486
CIB Ko¨ ze´ p-Europai Nemzetko¨ zi Bank	HU	0.827794	0.828057	0.606196	0.480107	0.490126
Erste Bank Hungary Rt	HU	0.885368	0.867714	0.636181	0.505561	0.50697
Raiffeisen Bank Zrt	HU	0.891071	0.875328	0.64375	0.512785	0.512066
HVB Bank Hungary Rt.	HU	0.94253	0.956792	0.703413	0.556632	0.559871
Budapest Hitel-e´ s Fejlesze´ si Bank	HU	0.896698	0.88856	0.639783	0.512949	0.477506
Citibank Zrt	HU	0.902354	0.945052	0.698164	0.567571	0.530438
Magyar Takarekszo¨ vetkezeti Bank Rt	HU	0.693804	0.78355	0.599127	0.499411	0.513048
Altalanos Ertekforgalmi Bank	HU	0.846961	0.894188	0.661463	0.539569	0.539093
Inter-Europa Bank Ltd	HU	0.899983	0.929092	0.69428	0.558805	0.557188
Commerzbank (Budapest) Rt	HU	0.707588	0.768408	0.583803	0.469867	0.493154
BNP Paribas Hungaria Bank Rt.	HU	0.826303	0.854784	0.640052	0.510673	0.52743
WestLB Hungaria Bank Rt	HU	0.647826	0.744053	0.564178	0.466056	0.510695
KDB Bank (Hungary) Ltd	HU	0.816308	0.816255	0.603716	0.49722	0.508517
Porsche Bank Hungaria	HU	0.683157	0.774962	0.642806	0.568902	0.662626
IC Bank Co Ltd-IC Bank Rt	HU	0.684294	0.706162	0.518359	0.436701	0.485165
Sopron Bank und Hypo Bank	HU	0.797303	0.821427	0.614972	0.531238	0.575771
Hansabanka	LV	0.866338	0.897072	0.625025	0.476926	0.507256
SEB Latvijas Unibanka	LV	0.852087	0.869841	0.612319	0.469668	0.48873
Parekss Banka-JSC Parex Bank	LV	0.924788	0.930028	0.661021	0.498952	0.501122
AS DnB NORD Banka	LV	0.856005	0.861981	0.627234	0.483211	0.480583
Rietumu Banka-Rietumu Bank Group	LV	0.875584	0.853542	0.620763	0.475092	0.460916
Aizkraukles Banka A/S	LV	0.88326	0.886737	0.6439	0.498442	0.497085
Latvijas Hipoteku un zemes banka	LV	0.869978	0.8511	0.626251	0.484812	0.482334
Latvian Economic Commercial Bank	LV	0.842801	0.79674	0.587318	0.449099	0.456167
HVB Bank Latvia AS	LV	0.903081	0.952503	0.681536	0.530278	0.574622
Latvian Savings Bank	LV	0.888713	0.824528	0.567776	0.438319	0.422493
Baltijas Tranzitu Bank	LV	0.814457	0.801801	0.614938	0.470397	0.512705
Trust Commercial Bank	LV	0.721132	0.713377	0.525743	0.410675	0.45669
Latvijas Biznesa banka	LV	0.906349	0.897793	0.643232	0.488907	0.546237
Baltijas Starptautiska Banka	LV	0.881236	0.893682	0.638521	0.487894	0.578807
Banka Paritate-Paritate Bank	LV	0.797934	0.858718	0.641505	0.514575	0.606735
Sampo Banka	LV	0.82038	0.896858	0.667993	0.5415	0.660464
Akciju Komercbanka Baltikums	LV	0.971985	0.954711	0.691311	0.537382	0.563575
Multibanka	LV	0.953364	0.954115	0.701339	0.548805	0.596344
Regional Investment Bank	LV	0.924395	0.94498	0.696018	0.5407	0.602865
SEB Vilniaus Bankas AB	LT	0.865264	0.870755	0.654079	0.505076	0.532126
AB Bankas Hansabankas	LT	0.885593	0.907707	0.673558	0.518114	0.555453
AB DnB NORD Bankas	LT	0.863407	0.859562	0.643571	0.49451	0.51355
Bankas Snoras	LT	0.808958	0.81586	0.617402	0.486904	0.507027
AB Sampo Bankas	LT	0.84482	0.876324	0.669662	0.521534	0.562506
AB Ukio Bankas	LT	0.685026	0.673597	0.518578	0.407178	0.433773
Siauliu Bankas	LT	0.842984	0.855897	0.653044	0.511954	0.564175
AB Parex Bankas	LT	0.893922	0.873029	0.651542	0.510653	0.563123
UAB Medicinos Bankas	LT	0.851605	0.854809	0.64665	0.508097	0.595373
Powszechna Kasa Oszczednosci	PL	0.920645	0.902381	0.622412	0.464648	0.46492
Bank Pekao SA	PL	0.907679	0.900972	0.62484	0.4714	0.458324
Bank BPH SA	PL	0.910593	0.901074	0.630412	0.476328	0.462083
ING Bank Slaski S.A. – Capital Group	PL	0.918742	0.89953	0.630136	0.477424	0.45077
Bank Handlowy w Warszawie S.A.	PL	0.94345	0.902105	0.62611	0.477382	0.450238
BRE Bank SA	PL	0.950798	0.894854	0.623983	0.478606	0.451471
Bank Zachodni WBK S.A.	PL	0.926094	0.879349	0.617223	0.47952	0.445793
Bank Millennium	PL	0.972448	0.917289	0.639576	0.490817	0.459584
Raiffeisen Bank Polska SA	PL	0.962097	0.914547	0.643047	0.502955	0.469667
Bank Polskiej Spoldzielczosci SA	PL	0.85927	0.864421	0.630663	0.497838	0.494451
Bank Ochrony Srodowiska	PL	0.900757	0.900527	0.649095	0.510954	0.494519
Getin Bank SA	PL	0.873658	0.902227	0.659142	0.524703	0.511257
Fortis Bank Polska SA	PL	0.869894	0.855065	0.611685	0.485726	0.470148
Deutsche Bank Polska S.A.	PL	0.760655	0.809778	0.593498	0.487567	0.472268
Nordea Bank Polska SA	PL	0.807994	0.796685	0.577483	0.462412	0.446668
Lukas Bank SA	PL	0.689813	0.694214	0.512972	0.414692	0.409356
Rabobank Polska SA	PL	0.587747	0.631274	0.480006	0.39045	0.414343
Gospodarczy Bank Wielkopolski S.A.	PL	0.800684	0.838735	0.618672	0.491451	0.50127
ABN Amro Bank (Polska) SA	PL	0.768395	0.830674	0.616092	0.497451	0.492465
WestLB Bank Polska SA	PL	0.702045	0.754035	0.561132	0.448424	0.461077

(*continued*)

Table 4. Continued.

Bank	Country	EFF Q05	EFF Q25	EFF Q5	EFF Q75	EFF Q95
DZ Bank Polska SA	PL	0.865348	0.87838	0.644187	0.515232	0.521891
Danske Bank Polska	PL	0.828009	0.860882	0.642409	0.52462	0.543074
Bank Dnb NORD Polska SA	PL	0.807096	0.843664	0.632046	0.515398	0.530376
Calyon Bank Polska SA.	PL	0.813101	0.840464	0.612756	0.494899	0.501769
East European Bank	PL	0.837787	0.852286	0.616923	0.494235	0.511812
Romanian Commercial Bank SA	RO	0.81641	0.839222	0.615822	0.495459	0.43896
BRD-Groupe Societe Generale SA	RO	0.834689	0.8481	0.633143	0.514608	0.459326
Raiffeisen Bank SA	RO	0.918549	0.926291	0.705898	0.545305	0.52625
HVB Bank Romania SA	RO	0.964553	0.973158	0.745329	0.572674	0.575281
Bancpost SA	RO	0.781925	0.836827	0.623429	0.513162	0.461838
Banca Transilvania SA	RO	0.819247	0.836673	0.639382	0.507317	0.497587
Alpha Bank Romania	RO	0.822454	0.856444	0.663414	0.5264	0.523422
Banca Tiriac	RO	0.825493	0.850945	0.645955	0.516618	0.482752
Citibank Romania SA	RO	0.805321	0.830169	0.639175	0.49674	0.489233
Banca Romaneasca S.A.	RO	0.767881	0.791485	0.608536	0.491865	0.494049
UniCredit Romania SA	RO	0.635494	0.71087	0.55019	0.46209	0.494827
Volksbank Romania	RO	0.745949	0.800182	0.621556	0.496341	0.53273
Finansbank (Romania) SA	RO	0.774283	0.810907	0.626677	0.508299	0.519854
Banca de Credit si Dezvoltare	RO	0.815777	0.851909	0.650404	0.523901	0.53887
Piraeus Bank Romania	RO	0.877166	0.918999	0.703028	0.567651	0.598624
Banca Comerciala Carpatica SA	RO	0.853358	0.893997	0.688938	0.566475	0.591726
OTP Bank Romania SA	RO	0.792824	0.833183	0.644594	0.527851	0.547165
Sanpaolo IMI Bank Romania SA	RO	0.70405	0.750747	0.597464	0.499893	0.547427
ProCredit Bank S.A	RO	0.686033	0.736561	0.591696	0.50591	0.560935
Bank Leumi Romania	RO	0.775965	0.816102	0.633422	0.52181	0.586159
Emporiki Bank - Romania SA	RO	0.822426	0.888143	0.687429	0.564701	0.702817
Egnatia Bank (Romania) SA	RO	0.775601	0.8311	0.637403	0.532388	0.605506
Banca pentru Mica Industrie si Libera	RO	0.671461	0.725218	0.552741	0.489857	0.592824
Romanian International Bank SA	RO	0.696565	0.786397	0.613373	0.517074	0.625109
Banca CR Firenze Romania SA	RO	0.674765	0.762779	0.594427	0.505372	0.626657
Slovak Savings Bank	SK	0.785123	0.834173	0.612416	0.503349	0.475948
Vseobecna Uverova Banka a.s.	SK	0.843891	0.867058	0.62087	0.502746	0.485665
Tatra Banka a.s.	SK	0.867106	0.885623	0.631409	0.512784	0.517787
HVB Bank Slovakia a.s.	SK	0.789347	0.81044	0.58548	0.481243	0.493372
UniBanka, a.s.	SK	0.891922	0.924805	0.659939	0.68991	0.626227
Dexia banka Slovensko a.s.	SK	0.841697	0.867456	0.628133	0.520575	0.529594
OTP Banka Slovensko, as	SK	0.695851	0.726066	0.526823	0.441446	0.450526
Istrobanka	SK	0.740688	0.790893	0.576937	0.484048	0.494257
Citibank (Slovakia) a.s.	SK	0.722856	0.776029	0.570072	0.483147	0.504899
Postova Banka, A.S.-Post Bank JSC	SK	0.871847	0.870105	0.621082	0.510102	0.492754
Komercni Banka Bratislava a.s.	SK	0.788408	0.849207	0.622687	0.518434	0.583279
CSOB Stavebna Sporitelna	SK	0.864755	0.881382	0.640265	0.533948	0.586413
Nova Ljubljanska Banka d.d.-NLB dd	SI	0.91911	0.927445	0.652125	0.488937	0.465609
Nova Kreditna Banka Maribor d.d.	SI	0.88398	0.894989	0.636189	0.485167	0.449936
Abanka Vipa dd	SI	0.849997	0.871657	0.626728	0.479867	0.46461
SKB Banka DD	SI	0.850943	0.857769	0.61092	0.469824	0.441732
Bank Austria Creditanstalt d.d	SI	0.857949	0.888116	0.640116	0.49089	0.490597
Banka Koper d.d.	SI	0.88849	0.900785	0.640402	0.491895	0.468358
Banka Celje dd	SI	0.876354	0.900528	0.649213	0.501937	0.482482
Gorenjska Banka d.d. Kranj	SI	0.875086	0.916601	0.660992	0.520545	0.504447
Hypo Alpe-Adria-Bank dd	SI	0.789791	0.828472	0.600382	0.466203	0.475543
Probanka d.d. Maribor	SI	0.870685	0.889099	0.644727	0.504049	0.496957
Postna Banka Slovenije dd	SI	0.861318	0.858592	0.616529	0.481018	0.468946
Dezelna Banka Slovenije dd.	SI	0.845497	0.882158	0.638406	0.49391	0.500011
Volksbank-Ljudska Banka - d.d	SI	0.879474	0.914579	0.648778	0.503828	0.517722
Factor Banka d.d.	SI	0.760386	0.843699	0.626393	0.489877	0.535044

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. BG, Bulgaria; CR, Croatia; CZ, Czech Republic; EE, Estonia; HU, Hungary; LV, Latvia; LT, Lithuania; PL, Poland; RO, Romania; SK, Slovakia; SI, Slovenia.

of NPL, we observe a slight but clear negative relationship between cost efficiency and NPL. This implies that cost efficiency declines at higher values of NPL, or in other words at higher levels of risk. On the other hand, the relationship between cost efficiency and risk for banks with NPL values around the median of the distribution is rather stable, although it varies across quantiles. In detail, for banks with NPL values around 0.8 we observe a rather stable relationship between cost efficiency and bank risk for quantile 0.5. This is, however, less evident in

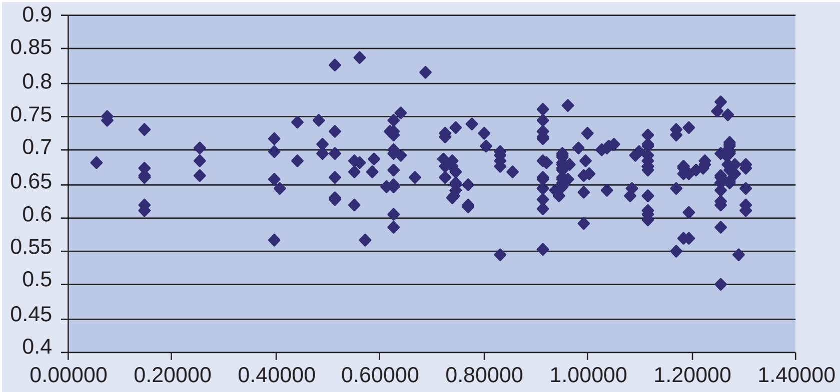

Figure 2. Average quantile cost efficiency and NPL/L. The horizontal axis describes the range of NPL/L and the vertical axis the corresponding total cost efficiency, as measured on a scale from 0 to 1.

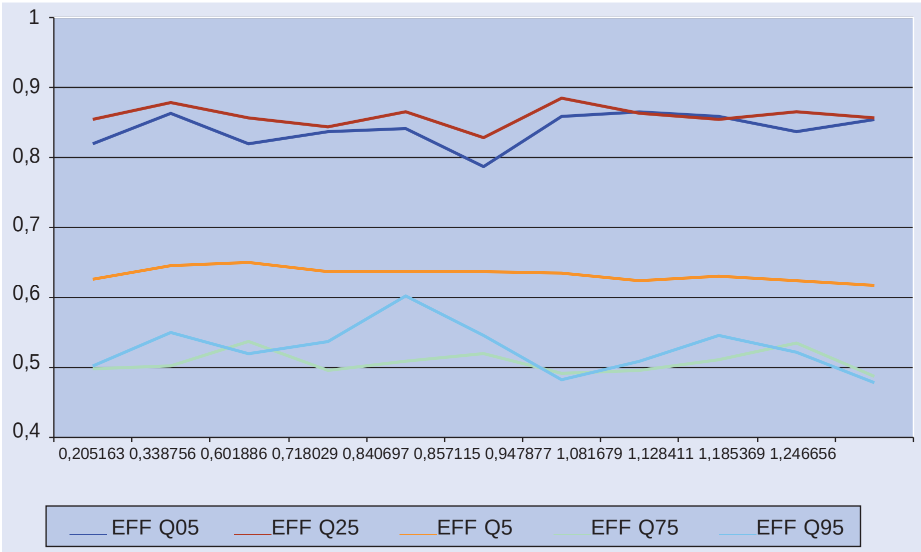

Figure 3. Quantile cost efficiency scores and NPL. The horizontal axis shows the scale of NPL, and the vertical axis describes the range of the cost efficiency, as measured on a scale from 0 to 1.

the case of quantiles 0.25 and 0.05. Overall, this descriptive analysis suggests that there are certain indications of a negative relationship between cost efficiency and risk, especially in high-order quantiles. Thus, further analysis is warranted.

To this end, we estimate regressions with risk, as measured by NPL and LLP, as independent variables and cost efficiency the dependent variable derived at different quantiles. The results are presented in table 5.[†] Note that most of the variation in cost efficiency is not explained by NPL and LLP. Moreover, we can observe a clear negative relationship between risk and efficiency across quantiles. The magnitude of the negative impact of risk on cost efficiency is larger for the case of LLP and also for high-order quantiles that contain banks with low scores for bank cost efficiency. This would suggest that the negative relationship between risk and efficiency becomes stronger for banks with low values of cost efficiency observed in high-order conditional distributions of quantiles 0.75 and 0.95. For these quantiles the coefficient of LLP becomes statistically significant and also increases in magnitude, whereas for low-order quantiles, that is quantiles 0.05 and 0.25, the coefficient of NPL and LLP loses magnitude and significance.

The above findings further suggest that an OLS analysis, related to the median quantile (0.5), fails to present the plethora of underlying relationships since it would misreport the variability of the impact of risk across quantiles and especially the importance of risk for banks with a low level of cost efficiency. Also, in light of the recent financial crisis, policy advice would be that, for those banks with low levels of cost efficiency in high-order quantiles, extra effort is warranted to safeguard their stability.

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

Table 5. Bank cost efficiency and risk.

	Q5		Q25		Q50		Q75		Q95	
	Coeff.	*t*	Coeff.	*t*	Coeff.	*t*	Coeff.	*t*	Coeff.	*t*
NPL	−0.0074	1.48	−0.00206	−2.46	−0.0002	−2.07	−0.04	−2.32	0.12	0.6
LLP	0.0033	1.25	−0.15	−2.05	−0.310	−1.35	−0.5856	−2.94	−0.5592	−2.33
CONS	0.8209	5.90	0.856734	9.02	0.6270	3.39	0.4980	31.79	0.5031	4.79
R^2	0.1226		0.0715		0.0496		0.0762		0.2493	
F	2.25		2.75		2.22		2.63		7.08	

The table presents cross-section regressions of quantile cost efficiency on Non-Performing Loans (NPL) and Loan Loss Provisions (LLP). *t*-Statistics have been estimated using robust standard errors. Country dummies are also included but not reported.

Table 6. Bank-specific '*z*' variables and cost efficiency across quantiles.

	Q5		Q25		Q50		Q75		Q95	
	Coeff.	*t*	Coeff.	*t*	Coeff.	*t*	Coeff.	*t*	Coeff.	*t*
NPL	−0.070621	−2.03	−0.067794	−2.44	−0.01295	−0.68	−0.0487	−2.22	−0.07574	−3.53
LLP	4.14E−07	0.73	3.55E−07	0.72	3.14E−07	0.89	−0.0027	−1.71	−0.0029	−2.19
CR_5	1.496742	2.01	1.505035	2.52	0.28138	0.68	−1.00259	−2.24	−1.57181	−3.42
EBRD	−0.76614	−1.71	−0.80255	−2.24	−0.30052	−1.26	0.589019	1.84	0.858207	2.87
TA	−0.0172	−1.4	−0.01001	−0.61	0.002353	0.11	−0.00721	−0.32	0.008821	0.23
CASH	−3.95E−08	−2.13	−3.1E−08	−1.85	−2.39E−08	−1.84	−5.93E−09	−0.56	−7.76E−09	−0.46
ROE	2.95E−07	2.34	2.36E−07	2.44	6.84E−08	1.06	−2.64E−08	−0.47	−6.76E−08	−0.58
E/A	0.030722	2.83	0.015044	0.98	−0.00222	−0.11	−8.7E−05	−0.67	−0.03223	−2.86
CONS	−5.05471	−1.82	−4.88972	−2.2	−0.2597	−0.17	4.348427	2.69	6.748295	3.98
R^2	0.2516		0.1188		0.0565		0.1144		0.4548	
F	6.11		3.69		2.22		2.42		11.02	

The table presents cross-section regressions of cost efficiency derived under different quantiles on Non-Performing Loans (NPL), Loan Loss Provisions (LLP), CR_5, EBRD, total assets (TA), CASH to account for liquidity, return on equity (ROE), and capitalization ratio (E/A). *t*-Statistics have been estimated using robust standard errors. Country dummies are also included but not reported.

5.3. The impact of 'z' variables on cost efficiency across quantiles

In this section we go a step further and run second-stage cross-section regressions, where we examine the impact of a set of 'z' bank variables on cost efficiency scores. In addition to NPL and LLP, we opt for: the capitalization ratio (E/A) to account for bank soundness, the return on equity ratio (ROE) that captures bank profitability, the logarithm of total assets (TA) to control for bank size, the five-firm concentration ratio (CR_5) that captures market structure, and the EBRD index to capture the impact of structural reforms. OLS is employed in the second-stage regression.yTable 6 reports the results of the estimation. The overall significance of the regressions is substantial and the results do not differ from previous findings as risk asserts a negative impact on cost efficiency.

Moreover, the sign of the NPL coefficient is negative across all quantiles, which implies that the higher the NPL the lower the level of efficiency. Similarly for the coefficient of LLP, it takes negative values in quantiles 0.75 and 0.95, while for other quantiles it is not significant. The negative impact of LLP and NPL on cost efficiency indicates that the '*bad management*' hypothesis of Berger and DeYoung (1997) can explain correctly the behaviour of the CEE banks. Berger and DeYoung (1997) argue that loan quality is endogenous to the quality of bank management, thus suggesting that underperforming managers would poorly manage the bank loan portfolio and thereby a negative relationship between efficiency and risk would be observed. We observe, in line with findings of the previous section, that the least efficient banks, banks in quantiles 0.75 and 0.95, are more responsive to risk.

In addition, several interesting results emerge. Concentration negatively affects cost efficiency in high-order quantiles. This result is of interest. According to Demsetz (1973) if market concentration reflects the fact that some banks benefit from market power, concentration may increase bank costs for the sector and thus impair efficiency. The evidence in high-order quantiles appears to justify Demsetz's views. On the other hand, in low-order quantiles, that is quantiles 0.05 and 0.25, concentration asserts a positive impact on efficiency. This result may reflect a consolidation process for banks with high levels of cost efficiency by the survival of more efficient banks, while the market remains contestable. In detail, for banks in quantiles 0.05 and 0.25, a higher level of bank concentration affects cost efficiency positively,

yCoefficient standard errors were obtained by bootstrapping with 100 sample replications.

suggesting that competitive outcomes are plausible even in concentrated markets (Baumol 1982). Overall, our evidence justifies quantile regression analysis as the relationship between concentration and efficiency pertains to complexities in line with Casu and Girardone (2006).

Finally, in high-order quantile 0.95, table 6 reports that efficiency and the capitalization ratio are negatively related, as captured by the coefficient of E/A. Thus, lowering the capitalisation ratio through its negative impact on bank stability would also impair cost efficiency. Bank efficiency has a negative relationship with structural change (EBRD index) in low-order quantiles, 0.05 and 0.25, that is for high levels of cost efficiency, whereas this impact turns positive for low levels of cost efficiency in high-order quantiles. According to Fries and Taci (2005), the EBRD index should have a positive impact on bank efficiency, as reforms would require sufficient capital adequacy and other prudential actions against risk taking. This is verified only in high-order quantiles and thus low levels of cost efficiency. Finally, profitability as measured by ROE has a positive impact on efficiency whenever significant. Also, CASH, which accounts for liquidity, asserts a negative impact (low in magnitude) on cost efficiency.

6. Conclusion

This paper examines the cost efficiency of CEE banks over the period 1998–2005 using quantile regression analysis, which has the advantage of allowing the estimation of bank-specific cost efficiency for various quantiles of the conditional distribution, permitting study of the tail behaviour of that distribution. This analysis reveals that there is substantial heterogeneity in bank efficiency in CEE countries. In addition, the results show significant differences in the average efficiency across quantiles. Moreover, bank cost efficiency is high for low-order quantiles of the conditional distribution. As far as the relationship between cost efficiency and risk is concerned, a negative relationship is reported, especially for high-order quantiles. Overall, the results suggest that risk asserts a large magnitude impact on banks with low cost efficiency in high-order quantiles. Thus, banks in quantiles 0.75 and 0.95 react more to risk than banks in quantiles 0.05 and 0.25. Moreover, the negative impact of LLP and NPL on cost efficiency indicates that the '*bad management*' hypothesis of Berger and DeYoung (1997) prevails. In addition, the second-stage regression analysis show that concentration and capitalisation negatively affect cost efficiency, whereas structural changes positively affect cost efficiency in high-order quantiles.

In terms of policy advice, some useful lessons can be drawn. Clearly, due to the reported variability in bank efficiency in CEE countries, it is warranted to estimate the entire family of conditional quantile functions. This is the only way to have a comprehensive analysis of efficiency scores. Otherwise, bank efficiency scores could be substantially overestimated, especially for banks that are placed at the tails of the distribution in high-order quantiles. Thus, the intensity of bank response to risk and other bank-specific variables would depend on their location in the conditional distribution of cost efficiency.

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