Deteriorating cost efficiency in commercial banks signals increasing risk of failure

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Abstract

In this paper we show, using estimated cost efficiency scores for the Czech banking sector, that the cost inefficient management was the leading indicator of bank failure during years of banking sector's consolidation. Since the monetary policy rate influences the efficiency of all banks through cost of funds and demand for loans, we speculate that the surge in rates in 1998 lowered sector's mean efficiency and likely speeded up failures of least efficient banks. On the other side, the subsequent monetary easing have gradually enhanced sector's mean efficiency.

JEL Classification: J21, J28, E58

Key words: bank failure, cost efficiency, stochastic cost frontier

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1 Introduction

The weak performance and failures of the commercial banks operating in the Czech Republic has repeatedly emerged as a conundrum during the course of economic transition started in early 1990s. Out of 47 commercial banks in 1994 and two later registered banks, 19 have failed until 2002 and except for 2001, no other year passed without at least one bank failure. These frequent failures required significant financial participation of government authorities.

The majority of measures undertaken by the Czech authorities to prevent multiple failures aimed at the improvement of banks' financial ratios. Although banks' CAMELS rating (C-capital, A-asset quality, M-management, E-earnings, L-liquidity, S-market risk) constructed and used by the supervisory authority contains on the top of standard financial indicators also the management quality assessment, Derviz and Podpiera (2004) show that this rating can be almost entirely explained by only few financial ratios. This implies that the banking supervision used dominantly these ratios. However, the targeted standard financial ratios, such as ROA, ROE, capital adequacy, etc. mirror the mismanagement only shortly prior to bank failure. Moreover, they seem to contain little additional information compared to publicly available information. Hanousek and Roland (2001) tested variety of predictors of failed banks in the Czech Republic in 1994-96 and concluded that the financial ratios did not outperform the simple deposit interest rates.

Given the weak performance of financial ratios for timely diagnostics of adverse development in commercial banks in the Czech Republic during the episode of sector's transformation, the potential relevance of advanced measures of managerial performance, such as the cost efficiency scores, ought to be tested. A bank that is weak in cost management is much more vulnerable to both internal and external shocks than a more efficient bank. Therefore, we presume that a link between relative cost efficiency and the risk of bank failure might exist. The cost efficiency is the most conventional concept of efficiency pursued in studies of bank performance. This concept has recently gained on popularity because of its property to remove the effect of differences in prices or other exogenous market factors which could, if not accounted for, shade the correct assessment of managerial performance (Bauer *et al.*, 1998).

The cost efficiency analysis implies that banks are being ranked according to their performance to the best practice bank in terms of managing the operating costs of producing the same output under the same conditions, such as output quality, production function and market conditions, (see Berger and Humphrey, 1997, for a literature survey).

The existing cost efficiency studies on the Czech banking sector are conducted predominantly in cross-country framework, accounting for only a fraction of operating banks and focus on the cost efficiency and its determining factors (Stavárek 2003; Grigorian and Manole 2002; Weill 2003a and Weill 2003b). However, a study relating cost efficiency to banking failure is still missing, which is probably due to limited data accessibility on failing banks.

In this study, we address the correlation between cost inefficient management and bank failure by carrying out a cost efficiency analysis and proportional hazard model estimation. We use a quarterly panel of all operating banks in the Czech banking sector over its consolidation period 1994-2002. This enhances the statistical efficiency of the estimates especially in the relatively small Czech banking sector and permits for the year-by-year evaluation of relative efficiency scores and thus for tracking banks' relative efficiencies in time. In order to expose the results to a robustness check we employ three different parametric methods: stochastic frontier analysis, yearly (four quarters) fixed effects model and random effects model. Subsequently, we use our estimated efficiency scores and test their relation to bank failures in a proportional hazard model.

The rank-orders of banks based on relative efficiency scores derived by alternative methods exhibit high congruence. We found significant correspondence among best-practice banks (top ten efficient banks) identified by all three methods. The same holds for the worst-practice banks (bottom ten efficient banks).

Our results unambiguously show that the banks' rank-order based on relative efficiency scores possesses the ability to predict the risk of bank failure. A monitoring of the rank-order of the failing banks in the years preceding occurrence of their failure shows that two years prior to the failure, these banks are in either the fourth or the third quartile of banks' ranking. One year prior to failure, 86% of the failed banks are among the worst performers (in the fourth quartile of the efficiency scores) and in 7% of the cases they are located in the third quartile.

The results for the proportional hazard model confirmed a negative and significant relation between efficiency and the risk of bank failure regardless the technique used for derivation of the efficiency scores. The results of our analysis thus validate the high relevance of regular cost efficiency screening for early warning signals of managerial problems in commercial banks.

The rest of the paper is organized as follows. A brief description of the consolidation process in the Czech banking sector is outlined in Section 2. Section 3 presents the methodological approach to cost efficiency analysis and data description. Section 4 contains the results of estimating cost efficiency and proportional hazard model. Section 5 concludes.

2 Consolidating the Czech banking sector

The consolidation of the Czech banking sector started in 1994 by reducing the distribution of banking licences. This was a precautionary response by the Czech National Bank (CNB) to a surge in the number of licensed banks in previous period, low level of capital in small and medium banks and high and growing share of non-performing loans in the portfolio of banks.

During 1995-1996 occurred first four bank failures. To prevent a domino bankruptcy effect, the CNB carried out a quality control of bank portfolios and by setting the necessary volumes of provisions and reserves it prepared for more radical action towards banks with insufficiency of reserves. In 1996, a more realistic assessment of the risk positions was imposed, i.e., an obligatory transfer of potential loss from asset operations into real loss (CNB 1996). This step placed capital adequacy of many banks under the required threshold of 8 %. As a consequence, shareholders of 15 banks were obliged to increase the capital with the aim to reach the threshold until the end of 1996.

Nevertheless, the low quality assets remaining in the portfolios of small banks still represented a potential for adverse development in these banks. A stabilization program for small banks was designed to provide with the opportunity of gradual creation of reserves. In particular, the poor-quality assets were temporarily purchased by Česká finanční a.s.[1] i.e., replaced by liquidity, and only later (after sufficient reserves were created) purchased back by banks. Despite these measures, the cases of bank failures continued to occur. Within two subsequent years 1997-1998, eight banks failed.

In 1998, the privatization plan of the remaining state-owned banks was on the way. Operations of Konsolidační banka contributed in cleaning the portfolios of these banks in the process of preparation for the strategic privatization. As a result of privatization, mergers and failures, from 29 Czech-owned commercial banks (out of which 5 were state-owned) in 1994, at the end of 2002 remained only 7 competing with 14 foreign commercial banks and 9 branches of foreign banks.

During following years, the cases of bank failure diminished, however they did not disappear: in 1999-2002, four banks declared bankruptcy. Notwithstanding substantial measures taken by the Czech authorities, with the sole exception of 2001 there was no single year without a bank failure since 1994. As a result, the decrease in number of commercial banks from 47 in 1994 to 30 in 2002 left the Czech authorities with a financial consolidation bill for 2.3 bn Euro, see Pospíšil (2003).

3 The model

3.1 The choice of method

The range of applied methods for evaluating efficiency is wide. Applicability of particular method is usually given by data specifics and the purpose of analysis. Basically, there are two groups of methods: parametric and nonparametric. The former is represented by *Data envelopment analysis* (DEA) and *the Free disposable hull* (FDH). The latter comprises *the Stochastic frontier approach* in

[1] An institution hundred percent-owned by Konsolidační banka (Consolidation Bank), a bank with the unique scope of managing non-performing loans. This banks was created in 1993 and starting 2001 transformed into Konsolidační Agentura (Consolidation Agency).

cross-section (SFA-CS) or panel data framework (SFA), cross-section or panel data *Thick Frontier Approach* (TFA), and panel data techniques of *the Distribution free approach* (DFA) and *the Fixed and Random effects models* (FEM and REM). For a comprehensive survey and detail description of these methods, see Berger and Humphrey (1997).

In this analysis, we favored parametric over nonparametric methods for two reasons. First, parametric methods study economic efficiency, i.e., technological as well as allocative efficiency, whereas the nonparametric techniques focus on analyzing technological efficiency only. Second, the identification of the frontier by nonparametric methods consumes large number of observations, since the construction of the cost frontier is done through enveloping the data observations. Thus, in small samples (the case of the small size of the Czech banking industry) we encounter problems with impossibility of more subtle performance distinction between banks as too many banks, in extreme case all, are identified as fully efficient.

Aiming to apply multiple parametric techniques to check for results consistency among methods, we employed three panel data parametric methods: SFA, FEM and REM. Small number of banks in the Czech banking sector did not permit for application of the cross-section analysis in SFA and TFA. At the same time, application of methods that necessitate long periods of constant relative efficiency performance, such as DFA, deem inappropriate due to expected significant changes in the relative performance during the banking sector transformation.

The core principle of parametric techniques is that they allow for an error term and disentangle the inefficiency component from it. Following Kumbhakar and Lovell (2000), a stochastic cost frontier can be expressed as:

$$E_i \geqq c(y_i, w_i, \beta)e^{v_i}$$

where $E_i = \sum_n w_{ni}x_{ni}$ is the total expenditure incurred by the firm i facing the prices $w_{ni} > 0$ for the inputs x_{ni} and producing a vector of outputs y_{mi}; β is a vector of parameters to be estimated. The right hand side of the inequality ($c(y_i, w_i, \beta)e^{v_i}$) is the stochastic cost frontier. It consists of two parts: a deterministic part $c(y_i, w_i, \beta)$, common to all firms, and a firm-specific random part, e^{v_i}, representing the random shocks faced by an individual firm (error term). Usually, the random shock is considered as a composite error term, $v_i = u_i + \varepsilon_i$, consisting of u_i representing the inefficiency factor which brings the costs above those of the best-performing bank and ε_i standing for the random error to account for measurement error or other exogenous factors which can temporarily either increase or decrease the costs. The differences among particular parametric methods come from the way they disentangle inefficiency from the random part of the stochastic cost frontier.

The SFA assumes that the inefficiency term u_i has an asymmetric distribution (either half-normal or truncated normal or exponential) whereas the random error ε_i has a symmetric distribution, usually the normal distribution. The inefficiency is then inferred indirectly from the estimated mean of the conditional distribution of u given $u+\varepsilon$; i.e., $\widehat{u} = \widehat{E}(u|u+\varepsilon)$. Following Greene (1993), we assume that the inefficiency term has a truncated normal distribution, which implies that the point estimator of u_i is:

$$E(u_i|u_i+\varepsilon_i) = \frac{\sigma\lambda}{(1+\lambda^2)}\left[\frac{\phi\left(\frac{(u_i+\varepsilon_i)\lambda}{\sigma}+\frac{\mu}{\sigma\lambda}\right)}{\Phi\left(\frac{(u_i+\varepsilon_i)\lambda}{\sigma}+\frac{\mu}{\sigma\lambda}\right)} - \left(\frac{(u_i+\varepsilon_i)\,\lambda}{\sigma}+\frac{\mu}{\sigma\lambda}\right)\right]$$

where $\lambda = \frac{\sigma_u}{\sigma_v}$, $\sigma^2 = \sigma_u^2 + \sigma_v^2$. The cost efficiency for bank i is computed as $CE_i = e^{(-u_i)}$.

The FEM assumes that bank cost (in)efficiency is time invariant implying that differences in efficiency among banks are constant within a year (four quarters). $\varepsilon_{i,t}$ is a random error, i.i.d. $(0, \sigma_\varepsilon)$, and is uncorrelated with the regressors.

In the REM the u_i are randomly distributed with constant mean and variance and uncorrelated with ε_i and with the regressors (Kumbhakar and Lovell, 2000). The use of REM implies that the measured inefficiency stems from the variability across banks while the variation within banks is exclusively due to the ordinary operating cost fluctuations for each bank.

The calculation of the efficiency scores for the FEM and REM follows $\widehat{u}_i = \widehat{\alpha}_i - \min_i(\widehat{\alpha}_i)$, where $\widehat{\alpha}_i$ is the set of bank-specific constants.

Making use of multiple estimation techniques, differing in embedding distributional assumptions, is a compelling means to validate results and strengthen their policy impact. In order to compare the results of each estimation technique, we follow the consistency criteria formulated by Bauer *et al.* (1998). In particular, we compare the distributional characteristics of the inefficiency scores, such as their means and standard deviations. More crucially, we assess whether the three techniques generate similar ranking of banks and compute the number of banks that are jointly identified by each pair of techniques in the top and bottom ten banks.

3.2 The cost efficiency frontier

The specification of the cost frontier function takes the translog form as it is the most commonly estimated one in the literature:[2]

$$\begin{aligned} LnTC &= \alpha_0 + \sum_j^2 \beta_j \ln Y_j + \frac{1}{2}\sum_j^2\sum_k^2 \beta_{j,k} \ln Y_j Y_k + \sum_m^3 \gamma_m \ln w_m + \\ &\quad + \frac{1}{2}\sum_m^3\sum_n^3 \gamma_{m,n} \ln w_m w_n + \sum_j^2\sum_m^3 \rho_{j,m} \ln Y_j \ln w_m \end{aligned}$$

[2]Some studies include the factor share equations derived from Shepard's lemma (Mester, 1996; Weill, 2003a). However, following Berger (1993), we are aware of that including share equations would impose unnecessarily ex ante restriction of allocative efficiency of given input proportions. Nevertheless, Berger (1993) concludes that there are not significant differences among the results of estimates with no share equations and with share equations (fully-restricted specification).

TC denotes total costs, which represents the sum of expenditures incurred for labor, physical capital and borrowed funds. The vector of input prices for labor, physical capital and borrowed funds is denoted by w. Y is a vector of outputs including demand deposits and total loans excluding bad loans.[3] Demand deposits are included as an output because significant costs are associated with their production and maintenance (see, Bauer *et al.* 1998).

The total loans in this study, besides the usual industrial and commercial loans, real estate loans and loans to individuals, comprises also the interbank market loans. This is motivated by fact that the Czech banking sector interbank loans represent a significant share of total bank loans. Loans to other banks and to central bank account on average over 1994-2002 for 30% of total loans. Moreover, as Dinger and von Hagen (2003) claim, the Czech banking sector operates as a two-tier system in which the interbank market is an important source of financing for small banks. In these conditions, excluding the interbank market would imply that the cost efficiency would be systematically biased upwards for the small banks and would likely contaminate the relation between cost efficiency and risk of failure.

From the total loans were excluded bad loans since their inclusion would potentially overstate the performance of careless banks. Although the administration of bad loans might be costly and hence the exclusion of bad loans biases downwards the cost efficiency of banks with large portfolio of bad loans, it only helps to unveil banks' suspicious practices and as such helps to detect problematic management since in our view, the bad loans were to significant extent not simply due to "bad luck" (see Berger and DeYoung, 1997). Moreover, a peculiarity of the Czech banking sector development was the accumulation of huge amounts of bad loans in the accounts of Czech banks and the creation of the Konsolidační banka, to which Czech banks have from time to time transferred their bad loans. Therefore, the inclusion of the bad loans would artificially make considerable differences among banks' outputs: those banks still having the bad loans in the accounts at some point in time would appear with higher output then those without bad loans or with already transferred bad loans. In addition, the inclusion of bad loans could hide the problems with bank's administration, as a lose bank that is not risk averse, having large share of bad loans and practically negligible cost of customer screening, would turn out to be super cost efficient, but in fact possess very high risk of failure.

[3]Some authors, e.g. Weill (2003a), include "other earnings assets than loans" as an additional output. However, we do not include these since we believe that the production of "other earning assets" is not a key financial intermediation function. In addition, they constitute an equal investment opportunity for all banks, in the sense that any bank can opt to invest in these assets and finally, they do not involve substantial costs unlike attracting deposits and granting loans.

3.3 Data description and construction of variables

Quarterly real data[4], used in the analysis, covers all commercial banks operating in the Czech Republic during the period 1994-2002. The data is based on balance sheets and income statements of banks collected by the Banking Supervision of the Czech National Bank.

The **outputs** are defines as follows: *Total loans minus bad loans* comprises the quarterly average of the Czech Koruna value of loans denominated in all currencies granted to both resident and non-resident clients, loans given to government, loans to and deposits at the Central Bank and loans to and deposits at the other financial institutions. From the total we subtract the amount of bad loans (loans past due 361 days). *Demand deposits* represent quarterly average of the Czech Koruna value of client demand deposits denominated in all currencies.

Table 1 presents the descriptive statistics for outputs of banking sector in a yearly frequency (averages over quarters within banks). In both outputs we observe a faster growth in smaller banks than in the case of large banks. This is apparent from max/min values and from the faster growth of average relatively to the growth in variability.

Table 1: Descriptive statistics of outputs

	1994	1995	1996	1997	1998	1999	2000	2001	2002
Total loans minus bad loans									
Mean	22234	20982	23241	27392	27354	32493	30299	34070	35332
Standard Dev.	56282	50516	51758	56220	53386	54323	51944	56979	60839
Maximum	262911	233656	255038	271600	250050	224880	217324	216930	108169
Minimum	394	48	307	340	222	492	369	262	212
Demand deposits									
Mean	4978	4583	4525	6925	6242	7720	8087	10109	12378
Standard Dev.	16446	14165	13152	19033	16385	17595	18491	22770	27680
Maximum	104402	88869	78543	86539	72511	72102	75492	84435	104038
Minimum	3.5	9.13	1.02	1.26	11.1	19	15.4	20.2	20.9

Note: Data represents an average over bank-quarterly averaged real LCU (Czech Koruna) values of 1994 (in 10^6).

On the side of **inputs**, *Price of labor* represents the unit price of labor and is constructed as the quarterly average of total expenses for employees divided by the end-of-quarter number of employees. *Price of physical capital* represents the unit price of physical capital and is constructed as the quarterly average of expenses for rents, leasing, amortization and materials divided by the book value of fixed assets. *Price of borrowed funds* is the quarterly average of expenses incurred for interest paid for borrowed funds from government, central bank, other banks, clients and for issued securities, divided by the amount of these funds. Table 2 describes the input prices.

[4]Nominal data were deflated by the CPI with the base of average of 1994.

Table 2: Descriptive statistics of input prices

	1994	1995	1996	1997	1998	1999	2000	2001	2002
Price of Labor									
Mean	53776	58130	69078	71285	80362	87791	89261	91101	122038
Standard Dev.	40280	40373	42690	43035	54949	55043	57104	51621	60360
Maximum	198643	197032	178993	188133	286526	237587	231971	244516	259479
Minimum	22513	25023	16223	26602	29128	33076	30154	31530	44521
Price of Physical capital									
Mean	0.093	0.1	0.15	0.12	0.15	0.14	0.16	0.17	0.17
Standard Dev.	0.06	0.1	0.21	0.11	0.13	0.09	0.09	0.11	0.12
Maximum	0.26	0.57	1.05	0.61	0.63	0.34	0.38	0.42	0.58
Minimum	0.016	0.016	0.016	0.03	0.03	0.02	0.02	0.016	0.025
Price of Borrowed funds									
Mean	0.022	0.021	0.021	0.022	0.025	0.017	0.011	0.011	0.009
Standard Dev.	0.007	0.005	0.006	0.008	0.011	0.01	0.004	0.011	0.004
Maximum	0.033	0.032	0.035	0.044	0.059	0.05	0.023	0.066	0.022
Minimum	0.011	0.01	0.004	0.007	0.005	0.006	0.003	0.004	0.005

Note: Price of b. funds is quarterly interest rate; price of labor is in real (1994) CZK expenditures per employee.

The raising variability of price of labor, up by 50% in 2002 as compared to 1994, speaks for increasing differences among remuneration of labor within the banking sector, which is probably connected to higher remuneration of the imported management during the privatization. The real average price of physical capital exhibited a moderate rising trend over the analyzed period. The development in the simple average of the real price of borrowed funds across banking sector tends to follow the trend in the Czech interbank short-term real interest rate.

In all variables, the ratios max/min, mean/min and the coefficient of variation are closely comparable with those characterizing the data used in similar studies of banking efficiency (see Mester, 1992; Bauer *et. al*, 1998; Weill, 2003b; Kasman, 2002; Kamberoglu *et al.*, 2004; Shaffer, 2004; Williams and Gardener, 2000; Casu and Girardone 2004).

4 Results

4.1 Efficiency scores

The cost efficiency frontier was estimated on nine yearly panels of four quarters for nine consecutive years 1994-2002. The descriptive statistics of the main results of estimating the cost frontier by the three parametric methods are presented in Table 3. The mean efficiency suggests the percentage of resources for the average bank that would suffice for producing the same output if the average bank were on the efficiency frontier. Thus, for instance a score of 0.46 (SFA in 1994) says that the average bank is wasting 54% of its resources relative to the best-practice bank.

Table 3: Descriptive statistics of estimated efficiency scores

	1994	1995	1996	1997	1998	1999	2000	2001	2002
SFA									
Mean	0.46	0.82	0.41	0.57	0.28	0.53	0.52	0.62	0.82
Standard Dev.	0.15	0.17	0.13	0.18	0.17	0.18	0.20	0.17	0.18
Minimum	0.18	0.17	0.19	0.23	0.12	0.25	0.23	0.26	0.33
REM									
Mean	0.55	0.72	0.43	0.53	0.33	0.55	0.54	0.60	0.62
Standard Dev.	0.13	0.24	0.12	0.16	0.17	0.17	0.17	0.16	0.13
Minimum	0.29	0.29	0.21	0.24	0.15	0.27	0.28	0.28	0.31
FEM									
Mean	0.41	0.36	0.36	0.45	0.18	0.29	0.36	0.49	0.52
Standard Dev.	0.18	0.18	0.22	0.20	0.19	0.26	0.25	0.24	0.22
Minimum	0.12	0.06	0.05	0.07	0.03	0.05	0.13	0.16	0.17
Observations	168	180	172	147	144	135	128	120	120

Note: SFA scores were rescaled to its max value to be consist with the rest of methods. Max is one in all.

The heteroscedasticity of mean efficiency scores (especially those of the SFA and REM) is induced by high sensitivity of results to the changing sample (entry and exist of banks). This is apparent from the comparison between two subperiods, 1994-1999 and 2000-2002. Whereas in the first subperiod, the bank failures and entry of new banks were more frequent (3-4 per year), in the second subperiod there was only one exit a year or none.

Our results seems plausible in the context of the available studies conducted on the Czech banking sector. Weill (2003a), employing SFA for the year 1997 on a mixed sample of large Czech and Polish banks finds a median efficiency of 0.73. The median of our efficiency scores for the same year but for the whole Czech banking sector is 0.61. Employing DEA for 17 transition countries over 1995-1998, Grigorian and Manole (2002) find average efficiency scores for the sample of large Czech banks between 0.55 and 0.8 with the lowest value during 1996-1997. Using the same technique for the period 1999-2002, Stavárek (2003) finds average efficiency scores between 0.7 and 0.85. Even though the results of non-parametric methods are not directly comparable to the ones derived by parametric methods and in addition, the sample of banks in the listed studies differs from ours, the trend found in these studies (decline in average efficiency during 1995-1998 and an increase during 1999-2002) in general confirms our findings of an efficiency decrease during 1994-1998 and subsequently rising trend to levels of 0.52-0.82 in 2002. The trends in mean efficiency are displayed in Figure 1.

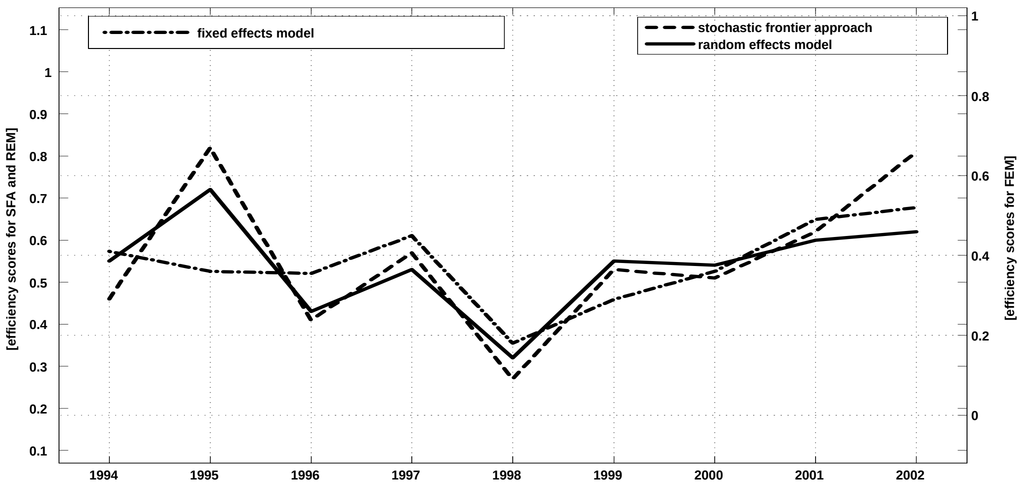

Figure 1: Average efficiency scores

The evolution of the mean efficiency presented in Figure 1 correlates with the macroeconomic development in the analyzed period. In the 1998 the Czech National Bank began to target inflation. Surge in interest rates caused weaker demand for loans and increased the cost of funds for all banks. As a consequence, the mean efficiency of banks significantly declined. Since 1999 the economy enjoyed sequence of lowering interest rates as the forecasted inflation suggested that targets will be met. This move supported economic activity and lead to higher demand for loans, which together with cheaper borrowed funds have gradually lead to an increase in mean cost efficiency. In addition, in this period many least efficient banks have already exited the market which also contributed to an increase in mean efficiency. And finally, based on the results of Weill (2003a) stipulating the role of foreign ownership on performance in the Czech Republic and Poland, the 1998-2002 restructuring and the new managerial wave in the case of privatized banks likely contributed to enhancing the mean efficiency.

The levels of mean efficiency in 2002 (0.52-0.82) suggest a convergence of the Czech banking sector in average efficiency level to those found for both the U.S. and the European banking sectors. According to the survey of Berger and Humphrey (1997), the efficiency scores from 50 U.S. bank efficiency studies displayed a mean of 0.72 for non-parametric techniques and a mean of 0.84 for parametric techniques. Bukh *et al.* (1995), in a DEA study of bank efficiency for Norway, Sweden, Finland and Denmark, find mean efficiency scores between 0.54 and 0.85. Fecher and Pestieau (1995) obtained mean efficiency scores in the range 0.71 and 0.98 when applying DFA for 11 OECD countries.

4.2 Consistency among methods

In the spirit of the consistency conditions formulated by Bauer *et al.* (1998), we compare the outcomes of the SFA, REM and FEM in terms of rank-order correlation and correspondence between the ten best (worst) performing banks as independently identified by each method. A high rank-order correlation and percentage of jointly identified banks among the top (bottom) ten banks would validate the results as pinpointing for further policy decisions. Therefore, a correlation check between the rank-orders as derived from each of the three estimation techniques is necessary for endorsing the reliability of our results. We report two correlation statistics: Spearman and Kendall correlation coefficients. The differences between the two measures come from their different theoretical background.[5] Table 4 presents the sample period average of rank correlations. Both measures show high correlation in bank rankings identified by the three techniques. The yearly average Spearman's correlation coefficient (upper triangle in Table 4) between SFA and FEM over the analyzed period is 0.72, between SFA and REM is 0.95 and between REM and FEM it is 0.68.[6] The Kendall's tau-a coefficients of correlation (lower triangle) show lower values, but the qualitative result remains unchanged. All correlation coefficients are significantly different from zero at 1% significance level.

Table 4. Spearman and Kendall correlation

SFA	SFA	REM	FEM
SFA	1	0.95***	0.72***
REM	0.84***	1	0.68***
FEM	0.55***	0.50***	1

Note: Spearman (upper triangle), Kendall's tau-a (lower triangle),***1% sign. level

Table 5. Top ten and bottom ten correspondence

SFA	SFA	REM	FEM
SFA	1	0.82***	0.70***
REM	0.93***	1	0.67***
FEM	0.70***	0.60***	1

Note: bottom ten corresp. (lower triangle), top ten corresp. (upper triangle),***1% sign. level

Table 5 presents the results of the proportion of banks that were identified by one estimation technique in the top (bottom) ten best-practice (worst-practice) banks that were also identified in the top ten (bottom ten) banks by another estimation technique. The correspondence among the best-practice banks according to SFA and FEM averages 70% over the whole period. The same degree of consistency was found for the worst-practice banks. The correspondence between

[5]The Spearman correlation is based on ranking the two variables, making no assumption about the distribution of the values. The Spearman correlation measure depends on the sample size, which is not the case for the Kendall's correlation. With the Spearman formula, X is ranked, Y is ranked separately from X, and the Pearson correlation coefficient of the ranks of X and Y is calculated. The Kendall formula is based on the probability of observing $Y_2 > Y_1$ when $X_2 > X_1$. For both the Spearman and Kendall correlation coefficients, a value of -1 indicates a perfect trend for Y to decrease as X increases, while a value of 1 indicates a perfect trend for Y to increase as X increases.

[6]In Bauer *et al.* (1998), Spearman rank-order correlation among the efficiency scores produced by various techniques vary between –0.195 and 0.895 (0.49 between SFA and FEM). Eisenbeis, Ferrier and Kwan (1996) find Spearman ranking between 0.44 and 0.59 when applying DEA and SFA. Ferrier and Lovell (1990) obtain a ranking correlation of 0.02. Bauer and Hancock (1993) obtain a coefficient of 0.7 across parametric and non-parametric techniques.

SFA and REM in the case of best-practice banks is 82%, and 93% for the worst-practice banks. Between REM and FEM the proportion of jointly identified banks is 67% for best-practice banks and 60% for the worst-practice banks. These results imply high consistency among the used techniques, especially between SFA and RE. In comparison to Bauer *et al.* (1998), who found banks correspondence in the U.S. between the SFA and FEM rankings 50% for the best-practice and 52% for the worst-practice banks, our correspondence seems significantly higher. This might be connected with our approach of short subsamples, which allows for more flexible re-ranking and thus minimizes the long sample bias stemming from averaging the efficiency scores.

4.3 Rank-order and proportional hazard

The analysis of the relationship between relative efficiency scores and the likelihood of bank failure uses two approaches: a simple assessment of the rank-order placement of failing banks prior to their failure and estimation of a proportional-hazard model.

The former approach is based on year-by-year systematic recording the position of failed banks in the quartile of banks' rank-order. We ordered the failed banks according to their survival length and labeled them accordingly (i.e. Bank 1 has the shortest survival length, Bank 19 has the longest survival length). For each year prior to the year of their failure we recorded their placement in the quartiles of rank-ordered banks. The results are presented in Table 6 for SFA and in Table 7 for FEM and REM.

Table 6. Placement in quartile prior-to-failure; SFA

Bank	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
1	F									
2	n.a.	F								
3	4(2)	4(1)	F							
4	4(3)	4(9)	F							
5	1	3	F							
6	2	3	4(8)	F						
7	3	3	4(2)	F						
8	4(1)	4(2)	4(1)	F						
9	n.a	4(8)	n.a.	F						
10	4(5)	4(11)	4(4)	4(7)	F					
11	3	3	4(7)	4(1)	F					
12	n.a.	n.a.	2	4(2)	F					
13	4	3	3	3	4(6)	F				
14	1	1	2	1	4(1)	F				
15	1	2	3	4(3)	4(2)	F				
16	4	3	4(10)	4(8)	4(3)	n.a.	F			
17	2	2	3	4	3	2	F			
18	3	3	3	4(10)	4(5)	4(2)	4(1)	4(1)	4(1) F	
19	1	2	1	1	1	1	1	4	1	F
Sample	42	45	43	37	36	35	32	30	30	–

Note: The number in the cell xy represent the quartile in which the bank x was in period y prior to its failure (1 denotes first quartile, 2 stands for second quartile, etc.). F denotes fail; In parenthesis is given the actual ranking within the last quartile: 1 denotes the least efficient bank, etc.

At the bottom of the Table 6 is given number of banks in the sample. As appears in the table, the failing banks five years prior to failure were found around the second quartile. Within three to four years prior to failure, the banks tended to move towards the third quartile. Two years prior to failure, 59% of banks were in the bottom cost efficiency quartile and 23% of them were in the third quartile. One year prior to failure, 86% of banks were in the fourth quartile and 7% in the third quartile. Besides the tendency of failing banks to locate in the bottom quartile prior to their failure, banks tend to descent even to the lowest places within the bottom quartile. This can be seen from the numbers in parenthesis in Table 6, which show the placement of banks within the fourth quartile (1 denotes the least efficient bank, 2 stands for the second least efficient bank, etc.). Table 7 presents the quartile placements identified by FEM and REM, respectively.

Table 7. Placement in quartile prior-to-failure; FEM / REM

Bank	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
1	F									
2	n.a.	F								
3	4/4	4/4	F							
4	4/4	4/4	F							
5	1/2	2/2	F							
6	3/2	3/3	2/4	F						
7	4/3	4/4	4/4	F						
8	4/4	4/4	4/4	F						
9	n.a	2/4	n.a.	F						
10	4/4	4/3	4/4	3/4	F					
11	3/2	3/3	2/4	4/4	F					
12	n.a.	n.a.	2/2	4/4	F					
13	4/3	3/3	3/3	3/3	4/4	F				
14	2/1	2/1	1/1	4/4	4/4	F				
15	1/1	2/2	3/3	4/4	4/4	F				
16	4/4	4/3	3/3	3/4	4/4	n.a.	F			
17	2/2	4/3	4/3	4/4	4/2	4/2	F			
18	3/3	3/3	3/2	4/4	4/4	4/4	4/4	4/4	4/4 F	
19	1/1	2/1	1/1	1/1	1/1	1/1	1/2	1/4	1/3	F
Sample	42	45	43	37	36	35	32	30	30	–

Note: The number in the cell xy represent the quartile in which the bank x was in period y prior to its failure (1 denotes first quartile, 2 stands for second quartile, etc.). F denotes fail;

The placement of banks according to their efficiency scores into quartiles of FEM and REM closely resemble to the SFA placement. With the exception of one or two banks, the results are practically identical across all three methods.

In order to formally analyze whether cost efficiency is a valid predictor of bank failure, we estimate Cox's (1972) proportional hazard model, which captures the effect of covariates on the hazard rate, represented in the following specification:

$$\lambda(t|z) = \lambda_0(t)\, e^{z\beta},$$

where $\lambda(t|z)$ is the hazard rate, which, in our context, represents the probability of "failure" in a given (short) time interval, conditional on the surviving to period t. $\lambda_0(t)$ is a baseline hazard, z is a vector of measured explanatory variables and β is a vector of parameters. The literature focused on predicting banks' failure emphasizes the advantage of estimating a hazard model over estimating single period models. Shumway (2001) provides three main reasons to prefer hazard models for forecasting bankruptcy: 1. single-period models fail to control for each firm's period at risk; 2. hazard models incorporate explanatory variables that change with time; and 3. hazard models seem to produce more efficient out-of-sample forecasts.

We include as explanatory variables the efficiency scores (SFA, FEM or REM) and the ratio of bad loans to total assets. Since we excluded the bad loans from the total loans when estimating the efficiency scores we lowered output for banks with bad loans and thus possibly also lowered their cost efficiency. In order to account for possible link between bad loans - low efficiency - risk of failure, we include into the hazard model the ratio of bad loans to total assets. The results of estimating the proportional hazard model are displayed in Table 8.

Table 8: Proportional hazard model estimates

	BL/TA	EFF	Log Likelihood	pseudo-R^2
SFA	0.044(0.008)***	-3.34(1.5)**	-69.023	0.20
REM	0.041(0.009)***	-5.43(2.04)***	-67.75	0.22
FEM	0.05(0.008)***	-3.46(1.78)**	-69.35	0.20

Note: BL/TA represents the ratio of bad loans over total assets; s.e. in parenthesis; EFF represents efficiency scores; number of observations: 326; number of failures: 17; reported are coefficients.

Our results confirm that the efficiency score significantly explains the risk of failure regardless the method used for efficiency evaluation, i.e., SFA, FEM or REM. The coefficients on the variable EFF (efficiency scores) are negative and significant, implying that a decrease in efficiency increases the risk of bank failure. The ratio of bad loans to total assets also contributes to explaining the risk of failure, however does not dominate. The coefficient on the ratio is positive and significant in all regressions, that is, the higher the ratio, the higher the risk of bank failure.

All in all, the efficiency scores derived by all three estimation techniques proved to be valid predictors of risk of bank failure and identified the majority of failing banks among least efficient quartile one year prior their failure. However, each method failed to identify one or two banks as worst performers. Nevertheless, by combining all three methods we could identify complete set of failing banks. Our results thus underline the findings concerning the relationship between cost efficiency and bank failure of Berger and Humphrey (1992), Barr and Siems (1994) and Wheelock and Wilson (1995), who conclude that failing banks tend to locate far from the efficiency frontier. In our case, the vast majority of failed banks were in the fourth quartile one year prior to failure. The fact that combination of three methods resulted in identification of all failed banks stipulates the importance of employing more methods for policy purposes.

5 Concluding remarks

This paper studies the signalling effect of cost ineffective management for the risk of bank failure. Finding reliable early warning indicators of problematic management in banks becomes increasingly important issue as the commonly applied financial ratios do not provide sufficiently early warnings.

We show, using data for the complete set of commercial banks (including exits and entry) in the Czech banking sector during the period of its substantial transformation that the risks of bank failure are closely correlated with cost inefficient management. Estimates of relative cost efficiency scores, using three alternative parametric methods proved to be significant predictors of the risk of bank failure. Besides, we observed that the banks that failed tends to gradually descent in the relative ranking of efficiency to the bottom quartiles and one year prior to fail, all failed banks were placed at least by one method in the least efficient quartile. Our findings thus validates the signalling effect of deteriorating efficiency for risk of bank failure and underline the use of multiple methods for detecting the set of problematic banks in policy applications.

Based on the correlation between weak cost efficiency and risk of failure and additionally on the link between monetary policy rate and sector's mean cost efficiency, we conclude that the Czech disinflationary policy through monetary tightening in 1998 was one of the factors lowering efficiency in all banks and in the case of least efficient banks it speeded up their failures. On contrary, since 1999 the policy had an opposite effect through monetary easing partially contributing to an increase in sector's mean efficiency.

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