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# Deteriorating Cost Efficiency in Commercial Banks Signals an Increasing Risk of Failure

Anca Podpiera and Jiří Podpiera*

## Abstract

While it is generally consented that management quality is often the key determinant of banks' success in a risky world, somewhat paradoxically early warning systems are mainly built on financial ratios driving management quality assessment to the periphery. In this paper we show, using estimated cost efficiency scores for the Czech banking sector, that cost inefficient management was a predictor of bank failures during the years of banking sector consolidation, and thus suggest the inclusion of cost efficiency in early warning systems.

**JEL Codes:** J21, J28, E58.
**Keywords:** Bank failure, cost efficiency, stochastic frontier, hazard model.

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## Nontechnical Summary

While it is generally consented that management quality is often the key determinant of banks' success in a risky world, somewhat paradoxically early warning systems are mainly build on financial ratios driving management quality assessment to the periphery. However, financial ratios seem to contain little additional information compared to that available to the public making the early warning systems ineffective. Therefore, we aim to suggest to measure management quality through banks' relative cost efficiency and to study its signaling effect for the risk of bank failure.

We employ three stochastic frontier efficiency estimation methods to evaluate the relative cost efficiency on data for the complete set of commercial banks (including exits and entries) in the Czech banking sector during the period of its substantial transformation and study their relation to the risk of bank failure. We find that the risk of bank failure is closely correlated with cost inefficient management. Besides, we observed that the banks that failed tend to gradually descend in the relative ranking of efficiency to the bottom quartiles and one year prior to failure the vast majority of them located in the last quartile.

Our findings thus validate the signaling effect of deteriorating efficiency for risk of bank failure and support the inclusion of cost efficiency assessment in regular systems of early warning. The constructed power functions for each estimation technique showed that the stochastic frontier approach and random effects model are preferred for early warning systems to fixed effects model.

# 1. Introduction

The weak performance and failures of commercial banks operating in the Czech Republic has repeatedly emerged as a conundrum during the economic transition that started in the early 1990s. Out of the 48 commercial banks operating in 1994 and another six licensed later on, 21 banks had failed by 2003, and except for 2001 and 2002 no year passed without at least one bank failure. This tendency in the Czech banking sector has not been an isolated case. Rather, it has been a general feature of banking sector transformation in the Central and Eastern European countries,[1] and has required significant financial participation by government authorities (billions of euros).

The majority of the measures undertaken by the Czech authorities to prevent multiple failures were aimed at improving banks' financial ratios. Indeed, financial ratios play a dominant role in the early warning systems developed for classifying banks into failures and non-failures (Barr and Siems, 1994). In addition to standard financial indicators, early warning systems such as CAMELS, ORAP and PATROL[2] contain an assessment of management quality. However, this component appears underrepresented and, in addition, it is based on ad hoc information available to the supervisory authority. The Czech supervisory authority bases its assessment on a CAMELS rating. Derviz and Podpiera (2004) tested the marginal importance of the management component on a peer group of Czech banks and found that the rating can be almost entirely explained by just a few financial ratios. This confirms that the supervisory authority was relying on these ratios and that assessment of management quality played a minor role. However, the standard financial ratios targeted, such as ROA, ROE and capital adequacy, mirror mismanagement only shortly prior to the occurrence of bank failure. Moreover, they seem to contain little additional information compared to the publicly available information. Hanousek and Roland (2001) tested a variety of predictors of failed banks in the Czech Republic in 1994–1996 and concluded that the financial ratios did not outperform simple deposit interest rates.[3]

Numerous studies, for instance Seballos and Thomson (1990), Looney *et al.* (1989) and Cates (1985), emphasize management quality as the key determinant of banks' success in a risky world. Given the weak performance of the described early warning systems for timely diagnosis of adverse developments in commercial banks in the Czech Republic during the sector's transformation, we aim to test the potential relevance of advanced measures of managerial performance, such as cost efficiency scores. Barr and Siems (1994) used cost efficiency to proxy management quality and found that it had significant explanatory power for explaining bankruptcy in the USA.

[1] Poland and Slovakia, for instance, recorded similar developments. In Poland, at least one bank every year declared failure during 1993–2001, and from the 87 commercial banks operating in 1993, 23 banks were either in liquidation or bankruptcy or had been taken over by the end of 2001. In Slovakia, the total number of banks in the system decreased from 29 in 1997 to 20 in early 2002.

[2] CAMELS stands for C-capital, A-asset quality, M-management, E-earnings, L-liquidity, and S-market risk. This rating system was implemented in the USA in the 1980s. ORAP stands for Organization and Reinforcement of Preventive Action and has been in use in France since 1997. The five components of PATROL are: capital adequacy, profitability, credit duality, organization and liquidity. It was implemented in Italy in 1993 (for an extensive survey, see Sahajwala and Bergh, 2000).

[3] When a bank is in financial distress, it raises interest rates on deposits in order to collect liquidity and thereby signals its status.

Cost efficiency is the most conventional concept of efficiency pursued in studies of bank performance. In particular, stochastic frontier techniques have recently gained in popularity because of their property of removing the effect of differences in prices or other exogenous market factors, which could, if not accounted for, distort the correct assessment of managerial performance (Bauer *et al.*, 1998).

Cost efficiency analysis implies that banks are ranked according to their performance relative 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). Thus, a deterioration in the bank's relative cost efficiency might signal its increasing vulnerability.

The existing cost efficiency studies on the Czech banking sector are conducted predominantly in a cross-country framework, account for only a fraction of the banks operating, and focus on identifying cost efficiency and its determining factors (Stavárek, 2003; Grigorian and Manole, 2002; Weill, 2003a; and Weill, 2003b). However, there is no study relating cost efficiency to bank failure.

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

The results of our analysis validate the high relevance of regular cost efficiency screening for early warning signals of managerial problems in commercial 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. Monitoring of the rank-order of failed banks in the years preceding their failure shows that two years prior to failure these banks are placed in either the fourth or third quartile of the ranking. One year prior to failure, the vast majority of the failed banks were among the worst performers. The results of the Cox proportional hazards model (i.e., assessing the probability of failure conditional on the relative cost efficiency score) confirmed a negative and significant relationship between cost efficiency and the risk of bank failure regardless of the technique used to derive the efficiency scores.

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 the Cox proportional hazards model. Section 5 concludes.

## 2. Consolidating the Czech Banking Sector

The consolidation of the Czech banking sector started in 1994 with a reduction in the number of banking licenses granted. This was a precautionary response by the Czech National Bank (CNB) to a surge in the number of licensed banks in the previous period, the low level of capital in small and medium-sized banks, and a high and growing share of non-performing loans in banks' portfolios.

The first six bank failures occurred during 1994–1996. 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 against banks with insufficient reserves. In 1996, more realistic assessment of risk positions was imposed, i.e., obligatory transfer of the potential loss from asset operations into a real loss (CNB, 1996). This step took the capital adequacy of many banks under the required threshold of 8%. As a consequence, shareholders of 15 banks were obliged to increase capital so as to reach the threshold by the end of 1996.

Nevertheless, the low quality assets remaining in the portfolios of small banks meant that there was still potential for adverse developments in these banks. A stabilization program was designed for small banks to give them an opportunity to gradually accumulate reserves. In particular, poor-quality assets were temporarily purchased by Česká finanční a.s.,[4] i.e., replaced by liquidity, and only later (after sufficient reserves were created) purchased back by the banks. Despite these measures, bank failures continued to occur. Over the next two years (1997–1998), eight banks failed.

In 1998, a privatization plan was prepared for the remaining state-owned banks. The operations of Konsolidační banka helped to clean up the portfolios of these banks in the process of preparation for strategic privatization. As a result of privatizations, mergers and failures, of the 29 Czech-owned commercial banks (five of which were state-owned) operating in 1994, only four remained at the end of 2003. They were competing with 15 foreign commercial banks and nine branches of foreign banks.

Between 1999 and 2003, the cases of bank failure diminished, but they did not disappear: seven banks declared bankruptcy. Notwithstanding the substantial measures taken by the Czech authorities, with the sole exception of 2001 and 2002 there was no single year without a bank failure between 1994 and 2003. The developments in the Czech banking sector left the Czech authorities with a financial consolidation bill for EUR 3.3 billion (IMF, 2005).

[4] An institution wholly owned by Konsolidační banka (Consolidation Bank). Konsolidační banka had the unique remit of managing non-performing loans. This bank was created in 1993 and was converted into Konsolidační Agentura (Consolidation Agency) at the start of 2001.

## 3. The Model

### 3.1 The Choice of Method

The methods for evaluating frontier efficiency basically break down into nonparametric and parametric methods. The former category is represented by *Data Envelopment Analysis* (DEA) and the *Free Disposable Hull* technique. The latter comprises the *Stochastic Frontier Approach* (SFA) in a cross-section or panel data framework, the cross-section or panel data *Thick Frontier Approach*, and the panel data techniques of the Random Effects Model (REM) and the *Distribution Free Approach* (DFA). For a comprehensive survey and detailed description of these methods, see Berger and Humphrey (1997).

In the analysis, we favored parametric over nonparametric methods for the reason that parametric methods study economic efficiency, i.e., allocative as well as technological efficiency, whereas the nonparametric techniques focus on analyzing technological efficiency only.[5]

The core principle of the parametric methods is based on introducing a composite error term and disentangling the inefficiency component from it. Following Kumbhakar and Lovell (2000), a stochastic cost frontier can be expressed as:

$$E_i \geq c(y_i, w_i, \beta) * \exp\{\upsilon_i\} \tag{1}$$

where $E_i = \sum_n w_{ni} x_{ni}$ is the total expenditure incurred by the bank $i$ facing the prices $w_{ni} > 0$ for the inputs $x_{ni}$ and producing a vector of outputs $y_i$ ; $\beta$ is a vector of the parameters to be estimated. The right-hand side of the inequality, i.e., $c(y_i, w_i, \beta) * \exp\{\upsilon_i\}$, represents the stochastic cost frontier. It consists of two parts: a deterministic part $c(y_i, w_i, \beta)$ that is common to all banks, and a bank-specific random part (error term), $\exp\{\upsilon_i\}$, representing the random shocks faced by each bank.

The random shock is considered as a composite error term, $\upsilon_i = u_i + \varepsilon_i$, consisting of the inefficiency factor $u_i$, which brings the costs above those of the best-performing bank, and $\varepsilon_i$, standing for the random error, to account for measurement error or other exogenous factors which can temporarily either increase or decrease the costs.

Making use of alternative estimation methods, differing in their embedded distributional assumptions, is a compelling means to validate the results and strengthen their policy impact. Therefore, we employed three panel data parametric methods, namely the SFA, REM and DFA (in the form of the *Fixed Effects Model* – FEM). The small number of banks in the Czech banking sector prevented the application of cross-section analysis in the SFA and TFA. At the same time, application of methods that necessitate long periods of constant relative efficiency performance was deemed inappropriate due to expected significant changes in relative performance during the banking sector's transformation.

[5] By ignoring prices, technological efficiency (as in the nonparametric methods) limits the consideration to too little output or too much input.

The differences between the particular parametric methods stem from the way inefficiency is disentangled 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, truncated normal or exponential) whereas the random error $\varepsilon_i$ has a symmetric distribution, usually normal. The inefficiency is then inferred indirectly from the estimated mean of the conditional distribution of $u$ given $u+\varepsilon$, $\hat{u} \equiv \hat{E}(u / u + \varepsilon)$. Following Greene (1993), we assume that the inefficiency term has a truncated normal distribution – being a more general alternative. This implies that the point estimator of $u_i$ is:

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

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

The FEM framework assumes that bank cost (in)efficiency is time invariant, implying that differences in efficiency among banks are constant within a year (four quarters). $\varepsilon_{it}$ is a random error, i.i.d. (0, $\sigma_\varepsilon$), and is uncorrelated with the regressors. No additional distributional assumptions are needed (see Fried *et al.*, 1993).

The assumption of the FEM regarding time invariant cost (in)efficiency could be a strong one, since over a year the relative efficiency might shift as a result of technical changes, interest rate changes, etc. Therefore, we employ the REM to relax this assumption. The use of the 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 $u_i$ are randomly distributed with constant mean and variance and uncorrelated with $\varepsilon_i$ and with the regressors (see Kumbhakar and Lovell, 2000).

The calculation of the inefficiency in the case of the FEM and REM follows $\hat{u}_i = \hat{\alpha}_i - \min_j \{\hat{\alpha}_j \mid j = 1,...,n\}$, where $\hat{\alpha}_j$ is the j-th bank-specific constant derived by the respective method. Whereas in the case of the FEM, the bank-specific constants are directly estimated through a bank dummy, in the case of the REM, we compute for bank $i$

$$\hat{\alpha}_i = \tfrac{1}{T_i}\sum_t (y_{it} - a^* - b' x_{it}).$$

Given the estimate of $u_i$, the cost efficiency for bank $i$ is computed: $CE_i=exp\{-u_i\}$.

In order to compare the results of the estimation methods, 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 a similar ranking of banks and compute the number of banks that are jointly identified by each pair of methods in the top ten and bottom ten banks.

### 3.2 The Cost Efficiency Frontier

The specification of the cost frontier function takes the translog form. The translog function is the most commonly estimated one in the literature due to its sufficiently flexible functional form (Taylor expansion around the mean), which has proven an effective tool for empirical assessment of efficiency:[6, 7]

$$\ln TC_i = \alpha_0 +$$

$$\sum_j^l \beta_j \ln Y_j + \frac{1}{2}\sum_j^2\sum_k^2 \beta_{jk} \ln Y_j Y_k + \sum_m^3 \gamma_m \ln w_m + \frac{1}{2}\sum_m^3\sum_n^3 \gamma_{mn} \ln w_m w_n + \sum_j^2\sum_m^3 \rho_{jm} \ln Y_j \ln w_m + \upsilon_i$$

where $\upsilon_i$ is the composite error term and *TC* denotes the total costs, namely, 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 the vector of outputs including demand deposits and total loans net of bad loans.[8] Demand deposits are included as an output because significant costs are associated with their production and maintenance (see Bauer *et al.*, 1998).[9]

Besides the usual industrial and commercial loans, real estate loans and loans to individuals, the total loans in this study also comprise interbank market loans. This is motivated by the fact that in the Czech banking sector interbank loans represent a significant share of total bank loans. Loans to other banks and to the central bank accounted on average for 30% of total loans over 1994–2002. 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 relationship between cost efficiency and risk of failure.

Bad loans were excluded from total 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 a large portfolio of bad loans, it only helps to unveil banks' suspicious practices and as such helps to

[6] While the Cobb-Douglas function would be too simple, the Fourier transformation would be unnecessarily complicated (see Bikker, 2004).

[7] Some studies include the factor share equations derived from Shepard's lemma (Mester, 1996; Weill, 2003a). However, following Berger (1993), we are aware that including share equations would impose unnecessarily ex ante restriction of the allocative efficiency of the given input proportions. Nevertheless, Berger (1993) concludes that there are no significant differences between the results of estimates without share equations and with share equations (the fully restricted specification).

[8] Some authors, e.g. Weill (2003a), include *earning assets other than loans* as an additional output. However, we carried out the estimation of efficiency scores both including and excluding *other earning assets* and found very negligible differences in the rank-order of banks. Therefore, we opt for the more parsimonious specification because the production of *other earning assets* is not a key financial intermediation function. 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.

[9] Besides, the recent advances in the classification of outputs and inputs using the opportunity cost approach, as employed by Guarda and Rouabah (2005), show that *deposits* are the only type of activity that is for some banks an output and for others an input. Therefore, to allow for a more flexible specification, we introduced deposits as both outputs and inputs.

detect problematic management, since in our view the bad loans were to significant extent not simply due to "bad luck" but to excessive risk taking (see Berger and DeYoung, 1997). Moreover, a peculiarity of the Czech banking sector's development was the accumulation of huge amounts of bad loans in the accounts of Czech banks and the creation of Konsolidační banka, to which Czech banks have from time to time transferred their bad loans. Therefore, the inclusion of bad loans would artificially make considerable differences between banks' outputs: those banks still having bad loans in their accounts at some point in time would appear with a higher output than those without bad loans or with their bad loans already transferred. In addition, the inclusion of bad loans could hide problems with a bank's administration, as a bank that is not risk averse, having a large share of bad loans and a practically negligible cost of customer screening, would turn out to be very cost efficient, but would in fact possess a very high risk of failure.

### 3.3 Data Description and Construction of Variables

The quarterly real data[10] used in the analysis cover all commercial banks operating in the Czech Republic during the period 1994–2002 (see the list of banks in Table A-1 in the Appendix). The data are based on balance sheets and income statements of banks reported to CNB Banking Supervision.

Since the analyzed period had been characterized by bank mergers, failures and entries, standardized treatment of these occurrences was required. Bank mergers were treated as follows: from the year of occurrence of the merger onwards, the bank resulting from the merger was considered as a single joint-bank (i.e., the data for the banks in the merger was consolidated in the year of the merger). Banks that failed within a particular year were considered as not operating in the whole year. For periods where some quarters of data for a bank were missing, the bank was excluded from the sample. Table 1 provides an overview of the entries, exits and mergers of banks and gives the number of banks in the system and the sample of banks used in the analysis. For more details on particular banks, see Table A-1 in the Appendix.

***Table 1: Developments in the Banking Sector***

| | **1994** | **1995** | **1996** | **1997** | **1998** | **1999** | **2000** | **2001** | **2002** | **2003** |
|---|---|---|---|---|---|---|---|---|---|---|
| Entries* | - | 1 | 3 | - | 2 | - | - | - | - | - |
| Exits – official year of failure** | 1 | 2 | 3 | 5 | 3 | 3 | 2 | - | - | 2 |
| Mergers | - | - | - | - | 2 | - | 1 | 1 | 1 | - |
| Banks in the system at the beginning of the year | 48 | 47 | 46 | 46 | 41 | 38 | 35 | 32 | 31 | 30 |
| Excluded banks (incomplete year – missing data) | 5 | 1 | 3 | 4 | 2 | 1 | - | 1 | - | 2 |
| of which: due to exit or entry within the year | - | - | 1 | 4 | 2 | - | - | - | - | 2 |
| Sample of banks for analysis | 42 | 45 | 43 | 37 | 36 | 34 | 32 | 30 | 30 | 28 |

***Note:*** *the entry of GE Capital Bank in 1998 took place via a purchase of part of Agrobanka.
**revocation of license, conservatorship or liquidation; IP Banka and Agrobanka were treated as failures.

[10] Nominal data were deflated by the CPI with the 1994 average as the base.

As for the construction of the variables, demand deposits and total loans net of bad loans are considered as the outputs. *Demand deposits* represent the quarterly average of the Czech koruna real value of client demand deposits denominated in all currencies. *Total loans net of bad loans* comprise the quarterly average of the Czech koruna real value of loans denominated in all currencies granted to both resident and non-resident clients, loans to government, loans to and deposits with the central bank and loans to and deposits with other financial institutions. The amount of bad loans (loans 361 days past due) has been subtracted from the total.

The price of labor, the price of physical capital and the price of borrowed funds were considered as the input prices. The *price of labor* represents the unit price of labor and is constructed as the quarterly average of the total expenses for employees divided by the end-of-quarter number of employees. The *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. And finally, the *price of borrowed funds* is the quarterly average of interest expenses on funds borrowed from the government, central bank, other banks and clients and on securities issued, divided by the amount of these funds.

Table 2 provides the descriptive statistics for the variables used in this study. Table A-2 in the Appendix compares our data to similar data sets in selected studies in terms of the max/min and mean/min ratios and the coefficient of variation. As we can see, our data are closely comparable with those used in similar studies of banking efficiency (see, for instance, Mester, 1992; Bauer *et al.*, 1998; Weill, 2003b; Kasman, 2002; Kamberoglou *et al.*, 2004; Shaffer, 2004; Williams and Gardener, 2000; Casu and Girardone, 2004). The highest similarity to the Czech data can be found in Western European countries such as France or the UK.

***Table 2: Descriptive Statistics of Output Quantities and Input Prices***

| | | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 |
|---|---|---|---|---|---|---|---|---|---|---|
| Total loans adjusted for bad loans (a,b) | Mean | 22234 | 20982 | 23241 | 27392 | 27354 | 32493 | 30299 | 34070 | 35332 |
| | S.D. | 56282 | 50516 | 51758 | 56220 | 53386 | 54323 | 51944 | 56979 | 60839 |
| | Max | 262911 | 233656 | 255038 | 271600 | 250050 | 224880 | 217324 | 216930 | 108169 |
| | Min | 394 | 48 | 307 | 340 | 222 | 492 | 369 | 262 | 212 |
| Demand Deposits (a,b,c) | Mean | 4978 | 4583 | 4525 | 6925 | 6242 | 7720 | 8087 | 10109 | 12378 |
| | S.D. | 16446 | 14165 | 13152 | 19033 | 16385 | 17595 | 18491 | 22770 | 27680 |
| | Max | 104402 | 88869 | 78543 | 86539 | 72511 | 72102 | 75492 | 84435 | 104038 |
| | Min | 4 | 9 | 1 | 1 | 11 | 19 | 15 | 20 | 21 |
| Price of Labor (a,b,d) | Mean | 53776 | 58130 | 69078 | 71285 | 80362 | 87791 | 89261 | 91101 | 122038 |
| | S.D. | 40280 | 40373 | 42690 | 43035 | 54949 | 55043 | 57104 | 51621 | 60360 |
| | Max | 198643 | 197032 | 178993 | 188133 | 286526 | 237587 | 231971 | 244516 | 259479 |
| | Min | 22513 | 25023 | 16223 | 26602 | 29128 | 33076 | 30154 | 31530 | 44521 |
| Price of Physical Capital (a,b) | Mean | 0.093 | 0.1 | 0.15 | 0.12 | 0.15 | 0.14 | 0.16 | 0.17 | 0.17 |
| | S.D. | 0.06 | 0.1 | 0.21 | 0.11 | 0.13 | 0.09 | 0.09 | 0.11 | 0.12 |
| | Max | 0.26 | 0.57 | 1.05 | 0.61 | 0.63 | 0.34 | 0.38 | 0.42 | 0.58 |
| | Min | 0.016 | 0.016 | 0.016 | 0.03 | 0.03 | 0.02 | 0.02 | 0.016 | 0.025 |
| Price of Borrowed Funds (a,b,e) | Mean | 0.022 | 0.021 | 0.021 | 0.022 | 0.025 | 0.017 | 0.011 | 0.011 | 0.009 |
| | S.D. | 0.007 | 0.005 | 0.006 | 0.008 | 0.011 | 0.01 | 0.004 | 0.011 | 0.004 |
| | Max | 0.033 | 0.032 | 0.035 | 0.044 | 0.059 | 0.05 | 0.023 | 0.066 | 0.022 |
| | Min | 0.011 | 0.01 | 0.004 | 0.007 | 0.005 | 0.006 | 0.003 | 0.004 | 0.005 |

***Notes:*** (a) Bad loans are those 361 days past due.
(b) The statistics were computed on bank-yearly averaged data.
(c) Real values in $10^6$ of 1994 Czech koruna.
(d) Price of labor is in real (1994) Czech koruna expenditure per employee.
(e) Price of borrowed funds is the quarterly interest rate.

# 4. Results

## 4.1 Statistics on Efficiency Scores

The cost efficiency frontier was estimated on nine yearly panels of four quarters for the nine consecutive years 1994–2002. The descriptive statistics of the main results of the three parametric methods for each year are presented in Table 3a.

The mean cost efficiency, which is the percentage of the resources of the average bank sufficient to produce the same output if it were on the efficiency frontier, exhibits a decline in 1995–1998 and an increase in 1999–2002. Taking the SFA results, for instance, the score of 0.46 in 1994 indicates that the average bank was in that year wasting 54% of its resources relative to the best-practice bank. By 2002, however, the figure was only 18%.

Our findings of a stronger mean efficiency performance in the period following 1999 seem intuitive, as many of the least efficient banks had already exited the market by that time and the restructuring and privatization had an efficiency enhancing effect (see Weill, 2003a, for evidence on the impact of foreign ownership on efficiency in Czech and Polish banks during 1998–2002).

Table 3b summarizes the results of estimating the cost efficiency on pooled data[11] for different samples of banks – the full sample and the sample excluding entries and exits. The mean efficiency for the full sample appears to be 20 percentage points lower than that for the alternative sample. This finding shows that the mean efficiency is crucially dependent on the choice of the sample of banks, which complicates the comparison of efficiency development across studies that use different samples of banks.

Even more crucially, estimating the efficiency scores on three sub-periods for the full sample and the sample excluding entries and exits, the derived mean efficiencies for the different samples differ even in their trend (see Table 3c). Whereas the results for the full sample show a decline in 1997–1999 and an upswing in 2000–2002, the results for the alternative sample (two out of three techniques[12]) suggest an increase in 1997–1999 and a decline in 2000–2002. Given our findings, we stress the need to analyze the entire banking sector in order to derive more conclusive results regarding the mean efficiency development of the whole banking sector. In the light of our findings, an exact comparison between the mean efficiency results of different studies working with different samples of banks is not advisable.

Despite the limited comparability of the mean efficiency between studies, we found broad support in the existing literature for our results. Weill (2003a) analyzed a mixed sample of large Czech and Polish banks in 1997 using the SFA and found a median efficiency of 0.73; this compares with our median in that year for the entire Czech banking sector of 0.61. Employing DEA for 17 transition countries over 1995–1998, Grigorian and Manole (2002) find mean efficiency scores for the sample

[11] Assuming a constant ranking of banks during the investigated period to analyze the difference in mean efficiency between the different samples of banks.

[12] The third technique, i.e., the REM, is less reliable in small homogenous samples, as the inefficiency is derived from the variation across banks, which is limited in small homogenous samples.

of large Czech banks between 0.55 and 0.8, with the lowest value during 1996–1997. Stavárek (2003) analyzed a large set of Czech banks during 1999–2002 using DEA and derived a mean efficiency of between 0.7 and 0.85.

In the light of the cost efficiency findings for banking sectors internationally, the levels of mean efficiency in 2002 (0.52–0.82) suggest a convergence of the Czech banking sector in average efficiency to that found for both the U.S. and 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 of between 0.54 and 0.85. Fecher and Pestieau (1995) obtained mean efficiency scores in the range 0.71–0.98 when applying the DFA for 11 OECD countries.

***Table 3a: Descriptive Statistics of Estimated Efficiency Scores: Full Sample of Banks***

| | | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 |
|---|---|---|---|---|---|---|---|---|---|---|
| Stochastic frontier approach | Mean | 0.46 | 0.82 | 0.41 | 0.57 | 0.28 | 0.53 | 0.52 | 0.62 | 0.82 |
| | S.D. | 0.15 | 0.17 | 0.13 | 0.18 | 0.17 | 0.18 | 0.20 | 0.17 | 0.18 |
| | Min | 0.18 | 0.17 | 0.19 | 0.23 | 0.12 | 0.25 | 0.23 | 0.26 | 0.33 |
| Random effects model | Mean | 0.55 | 0.72 | 0.43 | 0.53 | 0.33 | 0.55 | 0.54 | 0.60 | 0.62 |
| | S.D. | 0.13 | 0.24 | 0.12 | 0.16 | 0.17 | 0.17 | 0.17 | 0.16 | 0.13 |
| | Min | 0.29 | 0.29 | 0.21 | 0.24 | 0.15 | 0.27 | 0.28 | 0.28 | 0.31 |
| Fixed effects model | Mean | 0.41 | 0.36 | 0.36 | 0.45 | 0.18 | 0.29 | 0.36 | 0.49 | 0.52 |
| | S.D. | 0.18 | 0.18 | 0.22 | 0.20 | 0.19 | 0.26 | 0.25 | 0.24 | 0.22 |
| | Min | 0.12 | 0.06 | 0.05 | 0.07 | 0.03 | 0.05 | 0.13 | 0.16 | 0.17 |
| Sample of banks | number | 42 | 45 | 43 | 37 | 36 | 34 | 32 | 30 | 30 |

***Table 3b: Efficiency Scores; Pooled Data 1994–2002***

| | | full sample | w/o ee* |
|---|---|---|---|
| Stochastic frontier approach | Mean | 0.42 | 0.61 |
| | S.D. | 0.20 | 0.15 |
| | Min | 0.15 | 0.36 |
| Random effects Model | Mean | 0.45 | 0.66 |
| | S.D. | 0.18 | 0.12 |
| | Min | 0.19 | 0.46 |
| Fixed effects model | Mean | 0.41 | 0.58 |
| | S.D. | 0.20 | 0.17 |
| | Min | 0.14 | 0.26 |
| Sample of banks | number | 45 | 22 |

***Table 3c: Descriptive Statistics of Estimated Efficiency Scores; Three-year Periods***

| | | full sample | | | w/o entries and exits* | | |
|---|---|---|---|---|---|---|---|
| | | 1994–96 | 1997–99 | 2000–02 | 1994–96 | 1997–99 | 2000–02 |
| Stochastic frontier approach | Mean | 0.47 | 0.43 | 0.56 | 0.70 | 0.75 | 0.73 |
| | S.D. | 0.14 | 0.18 | 0.14 | 0.11 | 0.18 | 0.13 |
| | Min | 0.18 | 0.21 | 0.32 | 0.47 | 0.28 | 0.5 |
| Random effects model | Mean | 0.61 | 0.47 | 0.57 | 0.86 | 0.73 | 0.94 |
| | S.D. | 0.13 | 0.17 | 0.14 | 0.06 | 0.16 | 0.02 |
| | Min | 0.29 | 0.24 | 0.34 | 0.68 | 0.33 | 0.89 |
| Fixed effects model | Mean | 0.39 | 0.37 | 0.44 | 0.61 | 0.64 | 0.48 |
| | S.D. | 0.15 | 0.19 | 0.18 | 0.14 | 0.24 | 0.17 |
| | Min | 0.15 | 0.09 | 0.19 | 0.38 | 0.13 | 0.29 |
| Sample of banks | number | 45 | 37 | 32 | 22 | 22 | 22 |

***Notes:*** The efficiency scores, derived using the stochastic frontier approach, were rescaled to the maximum outcome to achieve consistency among the results of the different methods.

* Excluding exits and entries, i.e., banks continuously operating throughout 1994–2002: Komerční banka, Československá obchodní banka, Živnostenská banka, GE Capital Bank, Česká spořitelna, Českomoravská hypoteční banka, eBanka, Interbanka, Citibank, HVB Bank Czech Republic, ING Bank, Dresdner Bank CZ, Českomoravská záruční a rozvojová banka, Credit Lyonnais Bank Praha, J & T Banka, ABN AMRO Bank, Raiffeisenbank, IC banka, Commerzbank, Všeobecná úvěrová banka, Volksbank and Deutsche Bank.

### 4.2 Ranking Consistency between 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 for further policy decisions. Therefore, a correlation check between the rank-orders as derived from each of the three estimation techniques is necessary to endorse the reliability of our results. We report two correlation statistics: the Spearman and Kendall correlation coefficients. The differences between the two measures come from their different theoretical backgrounds.[13] Table 4 presents the sample period average of the rank correlations. Both measures show a high correlation in the bank rankings identified by the three techniques. The average of the yearly Spearman correlation coefficients (the upper triangle in Table 4) between the SFA and the FEM is 0.72, between the SFA and the REM it is 0.95 and between the REM and the FEM it is 0.68.[14] The Kendall's tau-a coefficients of correlation (the lower triangle) show lower values, but the qualitative result remains unchanged. All the correlation coefficients are significantly different from zero at the 1% significance level.

***Table 4: Spearman and Kendall Correlations***

| Average | SFA | REM | FEM |
|---|---|---|---|
| SFA | 1.00 | 0.95*** | 0.72*** |
| REM | 0.84*** | 1.00 | 0.68*** |
| FEM | 0.55*** | 0.50*** | 1.00 |

***Note***: Kendall's tau-a (lower triangular),
Spearman (upper triangular)
*** denotes 1% significance level

***Table 5: Top and Bottom Ten Correspondence***

| Average | SFA | REM | FEM |
|---|---|---|---|
| SFA | 1.00 | 0.82 | 0.70 |
| REM | 0.93 | 1.00 | 0.67 |
| FEM | 0.70 | 0.60 | 1.00 |

***Note:*** bottom ten correspondence (lower triangular)
top ten correspondence (upper triangular)

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 the SFA and the FEM averages 70% over the whole period. The same degree of consistency was found for the worst-practice banks. The correspondence between the SFA and the REM is 82% in the case of the best-practice banks and 93% for the worst-practice banks. Between the REM and the FEM the proportion of jointly identified banks is 67% for the

[13] 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 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.

[14] In Bauer *et al.* (1998), the Spearman rank-order correlations among the efficiency scores produced by the various techniques vary between -0.195 and 0.895 (0.49 between the SFA and the FEM). Eisenbeis, Ferrier and Kwan (1996) find a Spearman ranking of 0.44 and 0.59 between the DEA and the 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.

best-practice banks and 60% for the worst-practice banks. These results imply high consistency between the techniques used, and especially between the SFA and the REM, i.e., much higher than that found by Bauer *et al.* (1998).[15]

### 4.3 Rank-Order and Cox Proportional Hazards Model

The analysis of the relationship between the 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 the Cox proportional hazards model.

The former approach is based on year-by-year systematic recording of the position of failed banks in the quartiles of the 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 21 has the longest survival length). For each year prior to the year of their failure we recorded their placement in the quartiles of the rank-ordered banks. The results are presented in Table 6 for the SFA and in Table 7 for the FEM and the REM. At the bottom of the tables we give the number of banks in the sample.

As Table 6 shows, five years prior to failure the failing banks were found around the second quartile. Within three to four years prior to failure, the banks tended to descend towards the third quartile. Two years prior to failure, 56% of the banks were in the bottom cost efficiency quartile and 23% of them were in the third quartile. One year prior to failure, 83% of the banks were in the fourth quartile and 6% in the third quartile. Besides the tendency of failing banks to be located in the bottom quartile prior to their failure, banks tend to descend even to the lowest places within the bottom quartile. This can be seen from the numbers in parentheses 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.).

The placements of banks according to their efficiency scores in the quartiles of the FEM and the REM (see Table 7) closely resemble the SFA placement. With the exception of one or two banks, the results are practically identical across all three methods.

[15] In the U.S. banking sector, Bauer *et al.* (1998) found a correspondence between the SFA and FEM bank rankings of 50% for the best-practice and 52% for the worst-practice banks.

***Table 6: Placement in Quartile of Cost Efficiency Scores Prior to Failure; SFA***

| Bank | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | F | | | | | | | | | |
| 2 | n.a. | F | | | | | | | | |
| 3 | 3 | 4(3) F | | | | | | | | |
| 4 | 4(2) | 4(1) | F | | | | | | | |
| 5 | 4(3) | 4(9) | F | | | | | | | |
| 6 | 1 | 3 | F | | | | | | | |
| 7 | 2 | 1 | 4(5) | F | | | | | | |
| 8 | 2 | 3 | 4(8) | F | | | | | | |
| 9 | 3 | 3 | 4(2) | F | | | | | | |
| 10 | 4(1) | 4(2) | 4(1) | F | | | | | | |
| 11 | n.a. | 4(8) | n.a. | F | | | | | | |
| 12 | 4(5) | 4(11) | 4(4) | 4(7) | F | | | | | |
| 13 | 3 | 3 | 4(7) | 4(1) | F | | | | | |
| 14 | n.a. | n.a. | 2 | 4(2) | F | | | | | |
| 15 | 4 | 3 | 3 | 3 | 4(6) | F | | | | |
| 16 | 1 | 1 | 2 | 1 | 4(1) | F | | | | |
| 17 | 1 | 2 | 3 | 4(3) | 4(2) | F | | | | |
| 18 | 4 | 3 | 4(10) | 4(8) | 4(3) | n.a. | F | | | |
| 19 | 2 | 2 | 3 | 4 | 3 | 2 | F | | | |
| 20 | 3 | 3 | 3 | 4(10) | 4(5) | 4(2) | 4(1) | 4(1) | 4(1) | F |
| 21 | 1 | 2 | 1 | 1 | 1 | 1 | 1 | 4(7) | 1 | F |
| Sample | 42 | 45 | 43 | 37 | 36 | 34 | 32 | 30 | 30 | 28 |

***Notes:*** The number in the cell *xy* represents 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.). In parenthesis is the actual ranking from the bottom: 1 denotes the least efficient bank; F denotes failure.

***Table 7: Placement in Quartile of Cost Efficiency Scores Prior to Failure; FEM/REM***

| | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | F | | | | | | | | | |
| 2 | n.a. | F | | | | | | | | |
| 3 | 3/3 | 4/4 F | | | | | | | | |
| 4 | 4/4 | 4/4 | F | | | | | | | |
| 5 | 4/4 | 4/4 | F | | | | | | | |
| 6 | ½ | 2/2 | F | | | | | | | |
| 7 | ½ | 2/4 | 4/4 | F | | | | | | |
| 8 | 3/2 | 3/3 | 2/4 | F | | | | | | |
| 9 | 4/3 | 4/4 | 4/4 | F | | | | | | |
| 10 | 4/4 | 4/4 | 4/4 | F | | | | | | |
| 11 | n.a. | 2/4 | n.a. | F | | | | | | |
| 12 | 4/4 | 4/3 | 4/4 | 3/4 | F | | | | | |
| 13 | 3/2 | 3/3 | 2/4 | 4/4 | F | | | | | |
| 14 | n.a. | n.a. | 2/2 | 4/4 | F | | | | | |
| 15 | 4/3 | 3/3 | 3/3 | 3/3 | 4/4 | F | | | | |
| 16 | 2/1 | 2/1 | 1/1 | 4/4 | 4/4 | F | | | | |
| 17 | 1/1 | 2/2 | 3/3 | 4/4 | 4/4 | F | | | | |
| 18 | 4/4 | 4/3 | 3/3 | 3/4 | 4/4 | n.a. | F | | | |
| 19 | 2/2 | 4/3 | 4/3 | 4/4 | 4/2 | 4/2 | F | | | |
| 20 | 3/3 | 3/3 | 3/2 | 4/4 | 4/4 | 4/4 | 4/4 | 4/4 | 4/4 | F |
| 21 | 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 | 34 | 32 | 30 | 30 | 28 |

***Notes:*** The number x/y denotes the quartile of the scores derived by the FEM/REM.

The evidence on failing banks' descending tendency in rank-order towards the bottom efficiency quartiles prior to failure suggests that cost efficiency scores should be included among the early warning indicators. In order to formally test whether a cost efficiency score is a valid predictor of bank failure, i.e., the probability of bank failure given cost efficiency scores – the standard early warning model, we estimate Cox's (1972) proportional hazards model similarly to the mainstream literature on bank failures – see, for instance, Lane *et al.* (1986) or Whalen (1991).[16]

The literature dealing with predicting bank failure emphasizes the advantages of estimating a hazard model over single period models. Shumway (2001) summarizes three main reasons for preferring hazard models for forecasting bankruptcy. First, single-period models fail to control for each firm's period at risk. Second, hazard models incorporate explanatory variables that change with time, and finally, hazard models appear to produce more efficient out-of-sample forecasts.

Given the survival-time data, the Cox proportional hazards model capturing the effect of covariates on the hazard rate is represented by the following specification:

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

where $\lambda(t|z)$ is the hazard rate, which represents the probability of 'failure' in a given (short) time interval, conditional on surviving to period $t$. The estimated hazard rate is based on empirical observations of banks' continuous operation until time $t$ (the dependent variable takes the value zero – the empirical probability of failure equals zero) and the occurrence of failure at time $t+1$ (the dependent variable takes the value 1 – the empirical probability of failure is certainty). Further, $\lambda_0(t)$ is a baseline hazard, $z$ is a vector of the measured explanatory variables and $\beta$ is a vector of parameters.

We perform the hazard rate estimations against the efficiency scores derived by the SFA, FEM and REM. In an additional estimation, we include the ratio of bad loans to total assets to control for the possible effect of bad loans on the efficiency scores. By excluding bad loans for the sake of comparability of the outputs between banks in terms of quality when estimating the efficiency scores, we lowered output for banks with bad loans and thus possibly also lowered their cost efficiency. However, as Table 8 shows, the correlation between the cost efficiency scores and the share of bad loans in total assets appears rather low, thus not confirming that bad loans determine the efficiency scores.

***Table 8: Correlations***

| | SFA | REM | FEM |
|---|---|---|---|
| BL/TA | -0.28*** | -0.31*** | -0.23*** |

*** denotes 1% significance level.

[16]Although the Cox proportional hazards model is advantageous for avoiding the strong distributional assumptions associated with the parametric survival-time models and is thus preferred in this study, Cole and Gunther (1995) suggested possible benefits of separating the likelihood of failure from the time to failure, as they might generally have different determinants.

Nevertheless, we present the Cox proportional hazards model for both the single factor model (cost efficiency) and the two-factor model (which also includes bad loans/total assets in order to account for the effect of bad loans). The results are displayed in Table 9.

***Table 9: Cox Proportional Hazards Model (reported are coefficients)***

| | BL/TA | EFF | Log-likelihood | ps-$R^2$ |
|---|---|---|---|---|
| HR=f(SFA,BL/TA) | 0.044(0.008)$^{***}$ | -3.34(1.51)$^{**}$ | -69.02 | 0.20 |
| HR=f(REM, BL/TA) | 0.041(0.009)$^{***}$ | -5.43(2.04)$^{***}$ | -67.75 | 0.22 |
| HR=f(FEM, BL/TA) | 0.05(0.008)$^{***}$ | -3.46(1.78)$^{**}$ | -69.35 | 0.20 |
| HR=f(SFA) | - | -4.96(1.42)$^{***}$ | -78.79 | 0.10 |
| HR=f(REM) | - | -7.71(1.88)$^{***}$ | -75.91 | 0.14 |
| HR=f(FEM) | - | -3.97(1.58)$^{**}$ | -82.27 | 0.06 |

***Note***: HR stands for hazard rate; BL/TA represents the ratio of bad loans to total assets; EFF stands for efficiency scores; standard errors are in parentheses; number of observations: 326; failures: 19; asterisks denote significance level: *10%, **5%, and ***1%.

Our results confirm that after controlling for the effect of bad loans (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), the efficiency score significantly explains the risk of failure regardless of the method used for the efficiency evaluation, i.e., the SFA, FEM or REM. The coefficients on the variable EFF (efficiency scores) are negative and significant (see the upper half of Table 9), implying that a decrease in efficiency increases the risk of bank failure. This conclusion is confirmed by the hazard model estimation with the single factor (see the lower half of Table 9) – a negative and significant relation between efficiency and the risk of bank failure.

All in all, the relative efficiency scores derived by all three estimation methods proved to be valid predictors of the risk of bank failure and placed the majority of failing banks in the least efficient quartile one year prior to their failure. 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 the failed banks were in the fourth quartile one year prior to failure.

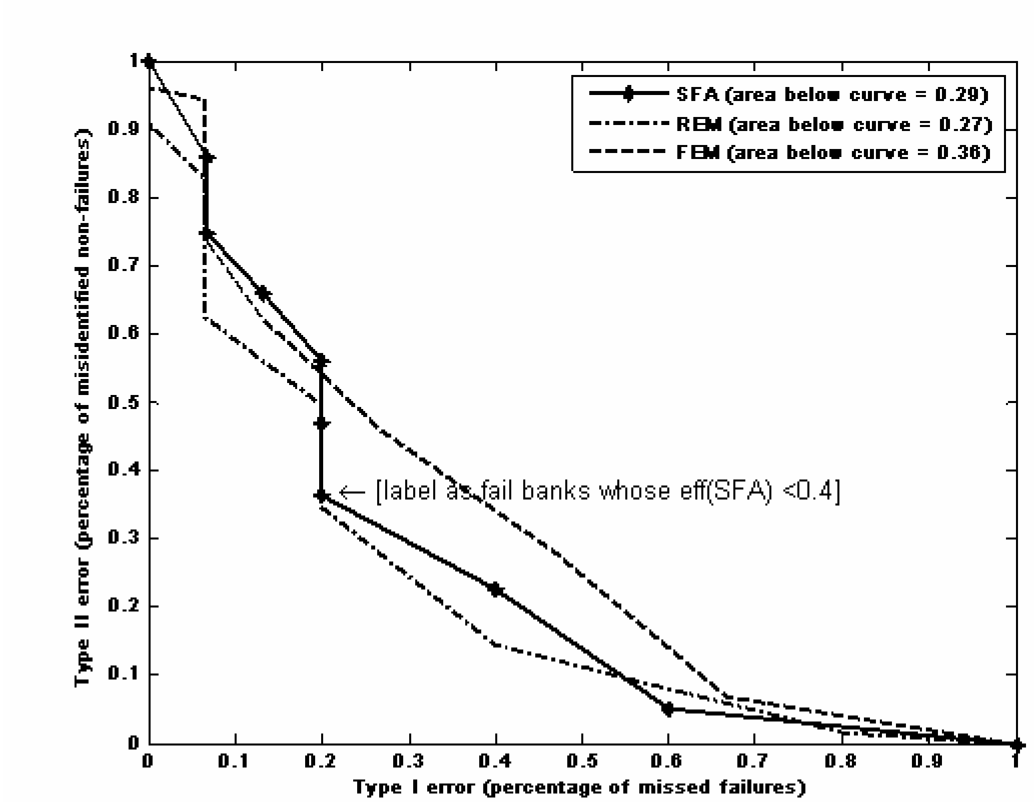
### 4.4 Power Functions and Early Warning Model Selection

Although it has been shown that the rank-orders based on the SFA, the REM and the FEM exhibit strong correlation and very close correspondence in terms of the top ten and bottom ten banks, it might be beneficial to discriminate among the methods in terms of their performance for an early warning model.

A convenient criterion for selecting the best performing early warning model is based on evaluation of power functions (see Gilbert et al., 2000). Usually, the construction of the power function is done through the successive computation of type I (false negative) and type II (false positive) errors[17] for different cut-off predicted probabilities of failure. Since we focus on the predictive performance of the cost efficiency scores, we employ this framework on the domain of efficiency scores instead of through the hazard model mapped probabilities of failure.[18] In order to compute the power function, we set ten cut-off efficiency scores, i.e., 0, 0.1, …, 1, and for each of them evaluate both the type I and type II errors. Thus, for instance, if the cut-off point is an efficiency score of 1 (all banks that have efficiency below 1 are labeled as failures, i.e., in this case all banks), the type I error is zero percent (of missed next-year bank failures), and the type II error is one hundred percent (of misidentified next-year non-failures).

The plot of the two types of errors represents a trade-off between excessive screening of banks that do not fail on the one hand and failing to identify failed banks on the other. The errors constructed from the data over nine years (i.e., the number of next-year failures weighted average of the in each year evaluated type I and type II errors) can be seen in Figure 1.

***Figure 1: Plot of Power Functions***




[17] The type I error stands for the probability of omitting to select a failed bank among potentially failing ones, whereas the type II error represents the probability of labeling a bank as likely to fail which does not actually fail.

[18] This is due to the fact that the predicted probabilities from the estimated hazard model (the one factor model) only map the efficiency domain into the domain of probability of failure. Thus, using the efficiency scores directly simplifies the application of the efficiency evaluation for the power function computation. If the early warning model consisted of more indicators than efficiency scores, it would be necessary to perform the hazard model estimation and apply the power function to the results of the hazard model.

The smallest area under the curves pertains to the most effective early warning model, since such a model minimizes the type II error for all values of the type I error. In other words, for any given share of missed next-year bank failures, it minimizes cost of screening healthy banks. The smallest area corresponds to the REM (0.27), closely followed by the SFA (0.29). The FEM (0.36) seems to be outperformed by the previous two estimation methods.

Furthermore, as indicated on the plot, a cut-off efficiency score of 0.4 for the SFA is probably optimal, since a higher cut-off score would add to the type II error without lowering the type I error, and similarly a lower cut-off score would lower the type II error by 10% but double the type I error to 40%. Taking a 0.4 cut-off means that two out of every ten next-year failed banks will remain unidentified and roughly three out of every ten non-failed banks will be screened.

## 5. Concluding Remarks

This paper studies the signaling effect of cost inefficient management for the risk of bank failure. Finding reliable early warning indicators of problematic management in banks is becoming an increasingly important issue, given the low signaling performance of the commonly applied financial ratios.

Using data for the complete set of commercial banks (including exits and entries) in the Czech banking sector during the period of substantial transformation of the sector, we show that the risk of bank failure is 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. Moreover, we observed that the banks that failed tended to gradually descend down the relative efficiency ranking to the bottom quartiles, and one year prior to failure all failed banks were placed in the least efficient quartile by at least one method. Our findings thus validate the signaling effect of deteriorating efficiency for the risk of bank failure. The power functions constructed for each estimation technique showed that for early warning systems, the stochastic frontier approach and random effects model are preferred to the fixed effects model.

In addition, by comparing the mean efficiency derived from the full sample of banks and that from a sample of banks excluding entries and exits, we noted a substantial dependence of the mean efficiency on sample selection. It follows that mean efficiency results derived on different samples in different periods are rather difficult to compare.

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# Appendix

| Table A-1 | 1994 | | 2002 | |
|---|---|---|---|---|
| **Bank (order of CNB's register)** | **Assets** (CZK mln) | **Ownership** | **Assets** (CZK mln) | **Ownership / Status** |
| Komerční Banka, a.s. | 316 815 | Czech | 473 703 | Foreign |
| Československá Obchodní Banka, a.s. | 145 534 | Czech | 540 077 | Foreign |
| Živnostenská Banka, a.s. | 25 627 | Czech | 51 801 | Foreign |
| Agrobanka, a.s. | 61 399 | Czech | | **Failure (1997)** |
| GE Capital Bank, a.s. | - | - | 53 084 | Foreign (**entry 1998**) |
| Česká Spořitelna, a.s. | 344 837 | Czech | 467 299 | Foreign |
| Banka Bohemia, a.s. | 13 408 | Czech | | **Failure (1994)** |
| Banka Baska, a.s. | 5 442 | Czech | | **Failure (1997)** |
| Pragobanka, a.s. | 14 545 | Czech | | **Failure (1998)** |
| Kreditní a průmyslová banka, a.s. | 2 436 | Czech | | **Failure (1995)** |
| Ekoagrobanka, a.s. | 15 482 | Czech | | **Failure (1997)** |
| SOCIETE GENERALE | 7 393 | Foreign | | **Merger (2002)** |
| Kreditní Banka Plzeň, a.s. | 14 654 | Czech | | **Failure (1996)** |
| Českomoravská hypoteční banka, a.s. | 5 153 | Czech | 16 861 | Czech |
| Banka Haná, a.s. | 13 312 | Czech | | **Failure (2000)** |
| AB BANKA, a.s. | 13 903 | Czech | | **Failure (1995)** |
| eBanka, a.s. | 5 558 | Czech | 14 793 | Foreign |
| Interbanka, a.s. | 2 708 | Foreign | 9 598 | Foreign |
| Citibank, a.s. | 12 444 | Foreign | 76 771 | Foreign |
| Creditanstalt, a.s. | 8 921 | Foreign | | **Merger (1998)** |
| Bank Austria, a.s. | 4 477 | Foreign | | **Merger (1998)** |
| Evrobanka, a.s. | 6 115 | Czech | | **Failure (1997)** |
| HVB Bank Czech Republic, a.s. | - | - | 124 806 | Foreign (**merger 2001**) |
| UNION Banka, a.s. | 5 735 | Czech | 24 449 | Czech (**failure in 2003**) |
| ING Bank N.V. | 6 507 | Foreign bank branch | 44 614 | Foreign bank branch |
| Realitbanka, a.s. | 1 140 | Czech | | **Failure (1997)** |
| COOP Banka, a.s. | 5 830 | Czech | | **Failure (1998)** |
| Vereinsbank CZ, a.s. | 9 298 | Foreign | | **Merger (1998)** |
| HYPO-BANK CZ, a.s. | 3 617 | Foreign | | **Merger (1998)** |
| Dresdner Bank CZ, a.s. | 5 716 | Foreign | 18 812 | Foreign |
| Česká Banka Praha, a.s. | 8 413 | Czech | | **Failure (1995)** |
| Českomoravská záruční a rozvojová banka, a.s. | 5 562 | Czech | 70 645 | Czech |
| Erste Bank Sparkassen (ČR), a.s. | 4 367 | Foreign | | **Merger (2000)** |
| Moravia Banka, a.s. | 8 126 | Czech | | **Failure (1999)** |
| Plzeňská Banka, a.s. | 1 007 | Czech | 1 263 | Czech (**failure in 2003**) |
| Credit Lyonnais Bank Praha, a.s. | 7 127 | Foreign | 15 884 | Foreign |
| IP Banka, a.s. | 147 940 | Czech | | **Failure (2000)** |
| První Slezská Banka, a.s. | 1 135 | Czech | | **Failure (1996)** |
| ABN AMRO Bank N.V | 1 427 | Foreign bank branch | 37 840 | Foreign bank branch |
| Raiffeisenbank, a.s. | 2 720 | Foreign | 53 960 | Foreign |
| Velkomoravská Banka, a.s. | 3 002 | Czech | | **Failure (1998)** |
| J & T Banka, a.s. | 2 735 | Foreign | 4 537 | Foreign |
| První Městská Banka, a.s. | 719 | Czech | 7 972 | Czech |
| IC banka, a.s. | 545 | Foreign | 1 282 | Foreign |
| Commerzbank AG, a.s. | 12 742 | Foreign bank branch | 85 326 | Foreign bank branch |
| Universal Banka, a.s. | 2 780 | Czech | | **Failure (1999)** |
| Všeobecná Úvěrová Banka, a.s. | 1 324 | Foreign bank branch | 2 428 | Foreign bank branch |
| Volksbank, a.s. | 492 | Foreign | 14 462 | Foreign |

| **Table A-1 (cont.)** | | | | |
|---|---|---|---|---|
| Deutsche Bank A.G. | 2 622 | Foreign bank branch | 40 053 | Foreign bank branch |
| Foresbank, a.s. | 1 043 | Czech | | **Failure (1999)** |
| Waldviertler Sparkasse von 1842 | - | - | 4 121 | Foreign bank branch (**entry in 1996**) |
| Raiffeisenbank im Stiftland, Cheb | - | - | 1 246 | Foreign bank branch (**entry in 1995**) |
| Sparkasse Muehlviertel-West | - | - | 4 356 | Foreign bank branch (**entry in 1996**) |
| Česká exportní banka, a.s. | - | - | 24 597 | Czech (**entry in 1996**) |
| HSBC Bank plc - Pobočka Praha | - | - | 22 392 | Foreign bank branch (**entry in 1998**) |

***Note:*** GE Capital bank entered the market by purchasing a part of Agrobanka in 1998.
Bank Austria merged with Creditanstalt and formed Bank Austria Creditanstalt in 1998.
Vereinsbank merged with HYPO-Bank and formed Hypovereinsbank in 1998.
Česká Spořitelna merged with Erste Bank Sparkassen in 2000 and continued as Česká Spořitelna.
Hypovereinsbank merged with Bank Austria Creditanstalt and formed HVB Bank in 2001.
Komerční banka merged with the foreign bank branch of Société Générale in 2002 and continued as Komerční banka.

| Table A-2 | Country | Year | Banks (number of institutions) | Definition | mean/min | max/min | coef of var |
|---|---|---|---|---|---|---|---|
| **Price of Labor** | | | | | | | |
| Podpiera and Podpiera (2005) | Czech Republic | 2000 | all | employee expenses / number of employees | 2.96 | 7.69 | 0.64 |
| Mester (1992) | USA | 1991 | Mutual S&Ls (807 institutions) | labor expenses/number of full-time equiv. emplo. | 2.05 | 4.6 | - |
| | | | Stock S&Ls (208 institutions) | labor expenses/number of full-time equiv. emplo. | 2.2 | 6.06 | - |
| Kamberoglou *et al.* (2004) | Greece | 1999 | all | employee expenses / number of employees | 1.59 | 1.93 | - |
| Shaffer (2004) | USA | 2000 | U.S. overall (deposit rate) | employee expenses / number of employees | - | - | 0.46 |
| | | | Texas (deposit rate) | employee expenses / number of employees | - | - | 0.24 |
| Williams and Gardener (2000) | Western Europe | 1998 | Western European countries | employee expenses / number of employees | 4.44 | 9.96 | 0.36 |
| Bauer *et al.* (1998) | USA | 1997-88 | U.S. | employee expenses / number of employees | 2.84 | 14.37 | 0.22 |
| **Price of Borrowed Funds** | | | | | | | |
| Podpiera and Podpiera (2005) | Czech Republic | 2000 | all | interest expenses / (accepted deposits, issued sec.) | 3.67 | 7.67 | 0.36 |
| Mester (1992) | USA | 1991 | Mutual S&Ls (807 institutions) | interest expenses borrowed money / its stock | 2 | 2 | - |
| | | | Stock S&Ls (208 institutions) | interest expenses borrowed money / its stock | 2 | 2 | - |
| Weill (2003) | Poland, Czech Rep. | 1997 | domestically owned (selected banks) | interest paid / all funding | - | - | 0.73 |
| | | | foreign owned (selected banks) | interest paid / all funding | - | - | 0.26 |
| Kasman (2002) | Turkey | 1998 | all | expenses on borrowed funds / funds | 5.85 | 15.15 | 1.04 |
| Kamberoglou *et al.* (2004) | Greece | 1999 | all | total interest paid / (deposits and repos) | 1.77 | 2.46 | - |
| Shaffer (2004) | USA | 2000 | U.S. overall (deposit rate) | interest on deposits / total deposits | - | - | 0.29 |
| | | | Texas (deposit rate) | interest on deposits / total deposits | - | - | 0.22 |
| Williams and Gardener (2000) | Western Europe | 1998 | Western European countries | interest rate on deposits | 2.01 | 3.78 | 0.23 |
| Bauer *et al.* (1998) | USA | 1977–1988 | U.S. | interest costs / total deposits | 80 | 1730 | 0.5 |
| Casu and Girardone (2004) | Selected Europe | 1994–2000 | France | interest expenses / total customer deposits | 3.53 | 20.12 | 0.62 |
| | | | Germany | interest expenses / total customer deposits | 1.91 | 4.39 | 0.25 |
| | | | Italy | interest expenses / total customer deposits | 5.08 | 16 | 0.44 |
| | | | Spain | interest expenses / total customer deposits | 0.67 | 21.06 | 0.27 |
| | | | UK (50 banks) | interest expenses / total customer deposits | 2 | 3.43 | 0.16 |
| **Price of Physical Capital** | | | | | | | |
| Podpiera and Podpiera (2005) | Czech Republic | 2000 | all | expenses on premises and equipment/total fixed assets | 7.5 | 19 | 0.6 |
| Weill (2003) | Poland, Czech Rep. | 1997 | domestically owned (selected banks) | non-interest expenses / total fixed assets | - | - | 0.67 |
| | | | foreign owned (selected banks) | non-interest expenses / total fixed assets | - | - | 0.91 |
| Kasman (2002) | Turkey | 1998 | all | expenses on premises and equipment/total fixed assets | 56.57 | 235.71 | 0.95 |
| Williams and Gardener (2000) | Western Europe | 1998 | Western European countries | expenses on physical capital / fixed assets | 4.35 | 9.24 | 0.38 |
| *Bauer et al.* (1998) | USA | 1977–1988 | U.S. | expenses on premises and equipment/total fixed assets | 1.77 | 2.81 | 0.13 |
| Casu and Girardone (2004) | Selected Europe | 1994–2000 | France | non-interest expenses / total fixed assets | 8.44 | 34.67 | 0.74 |
| | | | Germany | non-interest expenses / total fixed assets | 5.69 | 116.33 | 1.71 |
| | | | Italy | non-interest expenses / total fixed assets | 5.8 | 62.46 | 0.71 |
| | | | Spain | non-interest expenses / total fixed assets | 4.22 | 28.86 | 0.72 |
| | | | UK (50 banks) | non-interest expenses / total fixed assets | 4.12 | 15.04 | 0.47 |

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