POLISH BANKING INDUSTRY EFFICIENCY: DEA WINDOW ANALYSIS APPROACH

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Abstract

The Polish banking industry has been transformed since the country's transition to a market economy which began at the end of the 1980s. The industry has now developed and expanded to encompass more than 60 participants and it can thus be described today as a relatively competitive market. Against this background, this paper evaluates the financial performance of the industry over time, based on the ten largest Polish banks that represent around 80 percent of the total sector in terms of assets. In particular, cost efficiency of the banks is analyzed on the basis of six production models. Efficiency scores are obtained using *Data Envelopment Analysis* between 1995-2003 period, using *intertemporal* and *locally intertemporal* data. Productivity changes within the sector are investigated using the *Malmquist Index* approach.

JEL Classification: G11
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1. Introduction

In this paper, we analyze the performance of Poland's largest ten commercial banks over 1995-2003. The banks included are: Bank Gospodarki _ywno_ciowej (BG_), Bank Przemys_owo-Handlowy (BPH), Bank Rozwoju Eksportu (BRE), Bank Zachodni WBK (BZ WBK), Bank Handlowy w Warszawie (HANDLOWY), ING Bank _l_ski (ING B_), Kredyt Bank (KREDYT BANK), Bank Millennium (MILLENNIUM), Bank Polska Kasa Opieki (PEKAO) and, finally, Bank Powszechna Kasa Oszcz_dno_ci (PKO BP). In total, these ten banks represent around 80 percent of the sector's assets.

The Polish banking sector has gone through developmental changes since the beginning of the country's transformation process in 1989. Many financial institutions were restructured while some were newly established, e.g. the Warsaw

Stock Exchange. The process has also led to the re-capitalisation of banks attracting more and more strategic investors since 1998. Today, over 75 percent of the capital in the Polish banking sector is owned by foreigners.

Bank's performance has been traditionally examined using various methods and techniques ranging from traditional ratio analysis to more complex tools based on efficiency frontier approach. Ratio analysis, which encompasses key performance indicators is commonly used by all market participants. However, the approach brings only one-dimensional measure through a set of indicators that may add confusion and inconsistencies, which is increasingly pushing the industry to choose more robust approaches. This limitation gave rise to development of more sophisticated methods known as frontier efficiency techniques. Unlike ratio analysis, these techniques allow for the identification of strengths and weaknesses as well as report on the overall value of efficiency. In this context, *Data Envelopment Analysis* (DEA), representing non-parametric approach in production frontier analyses, could be used as a complement to ratio analysis and could potentially yield a more comprehensive appraisal of business performance. For a detailed comparison of DEA and other efficiency frontier methods in the context of banking, see Weill (2004).

We develop six production models in which banks are mainly considered as producers of deposit accounts and loans services to examine the performance of the banks. A DEA window analysis approach is applied in order to accommodate a relatively small sample size with a large number of performance variables. We, then, analyse the cost efficiency of the banks based on these models, employing intertemporal and locally intertemporal data.

To assess productivity changes over time, we use the *Malmquist Index* approach. Calculating Malmquist indices from DEA window analysis scores raises the problem of definition of the same period frontier. In that regard, we apply an approach proposed by Asmild *et al.* (2004) in order to calculate productivity changes.

The remainder of the paper is organized as follows. Section 2 introduces the methodologies used, namely DEA analysis and the Malmquist Index. In Section 3, the six production models for measuring the performance of the banks are presented. Section 4 describes the data. Section 5 identifies the results, while Section 6 discusses the significance of the findings. Finally, Section 7 draws together the conclusions of this study.

2. Theory, models and test methodology

The DEA approach to efficiency measurement is a deterministic method where there is no need for defining a functional relationship between inputs and outputs. The methodology is based on the concept of productivity as originally developed by Debreu (1951) and Farrell (1957) and extended by Charnes *et al.*

(1978).[1] Productivity is defined as the ratio between a single output and a single input. Extending this notion to a multi-dimensional case with more than one input and more than one output gives rise to the concept of an efficiency frontier for a particular decision-making unit (DMU) generated using linear programming methods. A unit such as a bank may be considered to be technologically efficient if it is lying on the efficiency frontier; in contrast, those lying below the frontier may be described as being technologically *in*efficient. The efficiency of a given decision-making unit is measured in relation to other comparable units being analyzed. DMU's lying on the efficiency frontier – described as efficient[2] – are assigned an efficiency coefficient equal to 1 (i.e. 100 percent), while any units lying below the frontier described as *in*efficient will have coefficients of less than 1. Efficient ones thus have values equal to greater than 1.

DEA models can be classified along two criteria: type of scale effects; and model orientation. The first criterion determines the assumptions concerning the scale effects consistent with the model (increasing, decreasing, or constant returns to scale). The model orientation approach, on the other hand, indicates whether the objective is the minimization of input(s), such as the cost of production, or the maximization of a particular output, such as profits. Having briefly described the principles of DEA, we now explain the particular methodologies used in this paper to assess efficiency and productivity changes using Data Envelopment Analysis and Malmquist Productivity Index.

A: Data envelopment window analysis

DEA, in its basic approach as described above, treats each DMU as it is observed at a point in time (cross-sectional data). However, observations for DMUs are frequently available over multiple time periods (time series data), and it is often important to perform an analysis when the research interest focuses on *changes* in efficiency over time. In such cases, it is possible to perform DEA over time using a moving average principle, where a DMU in each different period is treated as if it were a different DMU in the next period. In this way, the performance of a unit in a particular time period is compared not only against performance of other units in all periods specified for simultaneous analysis but also against its own performance in these periods. Window width may then vary between one and all periods in question, resulting in so called contemporaneous, intertemporal and locally intertemporal analyses (see Asmild, *et al.*, 2004).

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[1] For a comprehensive description and discussion of DEA and frontier techniques see Cooper *et. al.* (2000), Färe *et. al.* (1994) and Fried *et. al.* (1993).

[2] There are situations in which an object, lying on the efficiency frontier, may nevertheless be described as being inefficient. This situation gives rise to the concept of a so-called *boundary object*. See Charnes *et. al.* (1990) and Seiford and Thrall (1990).

Contemporaneous analysis comes down to comparing units only within the same time period (window width equals one) and represents basic DEA approach, while *intertemporal* analysis assumes that units can be fairly compared against each other within all time periods under consideration. Finally, in *locally intertemporal* analysis, window width is larger than one and less than one in all periods. Both, *intertemporal* and *locally intertemporal* analyses result in an increase in the sample size and thus enable us to conduct DEA within industries with few participants.[3] In these cases, however, it is important to ensure that the analysis work under the assumption of fair and realistic comparisons of units viewed simultaneously within a well defined time periods.

B: Malmquist productivity index

The Malmquist Productivity Index was introduced as a theoretical index by Caves *et al.* (1982) who extended the Malmquist deflation idea (see Malmquist, 1953) into the area of productivity.[4] As in other indices, Malmquist index may be referred to as a base-period Malmquist Index and adjacent Malmquist Index (see Althin, 2001; Berg *et al.*, 1992). In this paper, we use the adjacent period version.

When DEA scores are calculated from window analysis, the performance of a unit in a particular time period (window) is calculated more than once and as such included in several windows.[5] Thus, it is not obvious how to define the frontier in the same period (see Asmild *et al.*, 2004). According to Asmild *et al.* (2004) there is a need for a choice: i.e. should the frontier be defined by the first (F), the middle (M) or the last (L) period in the window? is unknown. Asmild *et al.* (2004) define Malmquist indices under each of these formulations. In that context, we follow this approach in our study of the Polish banking industry.[6]

3. Data and methodology

A critical element of DEA concerns the appropriate selection of the input and output variables. With respect to the evaluation of efficiency in the financial sector, using DEA, various models are available.[7] In our study, we employ six different models on the basis of a production approach, which considers banks as producers of fee-based services. Products and services such as loans, deposits and investments are outputs in these models and the resources consumed such as

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[3] In short, the number of DMUs should be at least two to three times the total number of inputs plus outputs used in the models. See Paradi *et. al.* (2004).

[4] This approach has been further developed in the non-parametric framework by other authors. See Färe and Grosskopf (1992) and Thrall (2000).

[5] It is not the case of the first and the last periods under consideration as they appear only once, i.e. in the first and the last window respectively.

[6] Asmild *et. al.* (2004) conclude that it is not appropriate to decompose Malmquist indices based on window DEA into standard *frontier shift* and *catching up* effects, contrary to several other studies. (See Thore *et al.*, 1994; Goto and Tsutsui, 1998; and Sueyoshi and Aoki, 2001).

lab, capital and operating expenses are inputs. This approach is used for studying *cost efficiency* and results in *input oriented* DEA models.

Table 1 is a summary that describes the main categories of resources used (inputs) and the products and services provided (outputs) for the six production models. The selection of a particular set of models is at the discretion of the analyst since input and output variables can be coupled together in a variety of ways to examine performance. The models we have adopted – labelled 1, 1A, 2, 2A, 3 and 4 represent only one possible set amongst many; however, they are the most commonly used in the context of the banking industry.

It should be noted that models 1 and 1A and 2 and 2A differ only with respect to one input: model 1 includes fixed assets as an input while model 1A replaces this with depreciation. The input and output variables are defined on the standard basis for the banking industry.

Table 1: Production models applied to cost efficiency of banks, Poland

Model	Inputs	Outputs
Model 1	• general costs • fixed assets	• loans • deposits
Model 1A	• general costs • depreciation	• loans • deposits
Model 2	• general costs • fixed assets	• loans • deposits • gross profit on banking activities
Model 2A	• depreciation • general costs	• loans • deposits • gross profit on banking activities
Model 3	• general costs • fixed assets • interest expenses • commission expenses	• interest income • commission income • foreign exchange result
Model 4	• general costs • fixed assets • interest expenses	• loans • deposits • securities • deposits with other banks • commission income

[7] A number of studies attempt to make comparisons between results obtained using non-parametric (such as DEA) and parametric approaches to efficiency. For a comprehensive study comprising both methods and models in assessing efficiency of financial institutions see Berger and Humphrey (1997) and Weill (2004).

We have specifically compiled a dataset for the models defined above based on information from published bank statistics reported to Monitor Polski B.[8] The dataset has been manipulated to take into account any significant mergers and acquisitions (M&A) activity involving banks during the analyzed period. All modeling variables of banks participating in the M&A process were summed up for the periods before. A total of 19 mergers or acquisitions took place involving the banks included in our sample.[9]

Descriptive statistics for the performance variables used in the analyses are given in Table 2 below. Note that the second column identifies the particular performance (see Table 1 for the variables).

Table 2: Descriptive statistics of performance variables (000 PLN)

Variable type (model)	Mean	Minimum	Maximum	Standard deviation
General costs	Input (1, 1A, 2, 2A, 3, 4)	85 251	3 109 319	673 421
Fixed assets	Input (1, 2, 3, 4)	92 509	2 165 073	485 573
Depreciation	Input (1A, 2A)	10 359	469 829	96 836
Interest expenses	Input (3, 4)	157 353	6 484 000	1 354 033
Commission expenses	Input (3)	843	231 250	51 951
Loans	Output (1, 1A, 2, 2A, 4)	676 895	38 278 464	7 897 862
Deposits	Output(1, 1A, 2, 2A, 4)	788 935	71 552 963	16 546 700
Gross profit on Banking Activities	Output (2, 2A)	99 755	5 576 258	1 230 480
Interest income	Output (3)	215 769	10 274 164	2 071 880
Commission income	Output (3, 4)	26 281	1 606 340	327 616
Foreign exchange result	Output (3)	17 051	981 731	199 284
Securities	Output (4)	211 539	29 587 425	7 451 697
Deposits with other banks	Output (4)	64 458		

This sample of ten large banks shows a relatively high degree of diversity in terms of scale. It is worth nothing that out of the 10 banks, two banks (PEKAO and PKO BP) were of similar asset size in 2003 (valued at 62.9 billion PLN and 84.4 billion PLN respectively) and the total asset value of the other eight banks ranged from 16.5 billion PLN to 45.5 billion PLN. In the context of such diversity, it is appropriate to employ constant returns to scale models (see Asmild *et al.*, 2004), which is the approach adopted below. Constant returns to scale models have also higher discriminatory power than those based on variable returns to scale.

4. Findings and analysis

As explained earlier, by combining information on inputs and outputs for the sample of ten banks over nine-year period, we were able to examine efficiency

[8] Information was supplied by Infocredit, an inquiry agency providing financial databases of companies - www.infocredit.pl.

[9] In the interest of brevity, details of the M&A activity are not given here but a full description may be obtained from the authors.

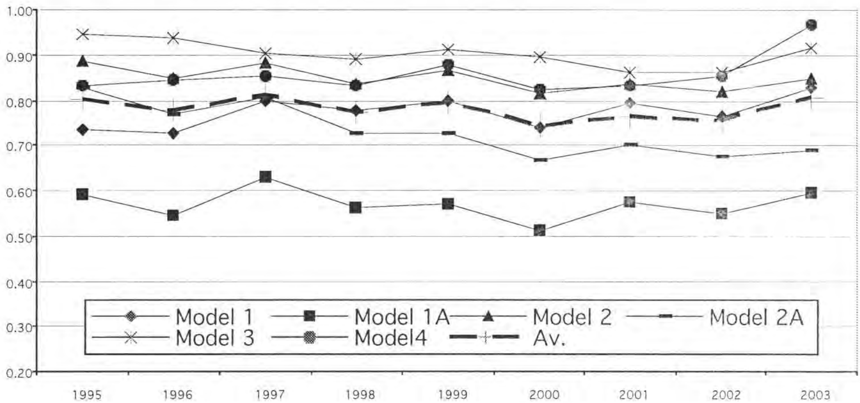
on an *intertemporal* basis (i.e. using panel data with a total of 90 observations). This is a simplistic approach since we are assuming that the state of technology within the sector is the same each year (from the first to the last time period). Clearly, efficiency is a function of changes in technology over time, hence the there is a need to adopt a locally intertemporal approach (see below). Nevertheless, intertemporal data using window DEA is a useful starting point in our understanding of relative efficiency within the sector.[10]

A: Window DEA – intertemporal data

As noted above, the six performance models used are based on the assumption of constant returns to scale. The results from the models allow us to illustrate how the efficiency factor changes over time as well as to capture the performance of different banks relative to each other. These results are summarized in Figure 1, illustrating average cost efficiency scores for all six models employed in this study. The appendix sets out the detailed results obtained for each model.

Figure 1 shows that average cost efficiency estimates within each particular model were relatively stable during the years in question. Depending on the model applied, average efficiency across our sample banks rose and fell between 1995 and 2003. The minimum average estimates are obtained with model 1A (57 percent) and maximum with model 3 (90 percent). These two models have the lowest differentiation level in terms of efficiency scores reported – 10.66 percent and 9.98 percent respectively, measured by the standard deviation (see Appendix). We also found hat efficiency scores obtained in model 1 follow the direction of changes in the scores obtained in model 2. Likewise, results from model 1A follow the direction of changes in results derived from model 2A.

Figure 1: Average cost efficiency scores based on panel data



[10] The analysis has been conducted here using a special software package developed at the University of Dortmund known as *Efficiency Measurement System (EMS)*.

These pairs of models comprise the same set of inputs and differ only with respect to one output, i.e. gross profit on banking activities (see Table°1 for details). Models 3 and 4 in turn report the highest efficiency scores and are not particularly correlated with each other, unlike the others. This is mainly due to the different outputs in the latter two models. Fully efficient units range from 2 up to 25 out of 90 observations (i.e. 10 banks times 9 years), depending on the model applied.

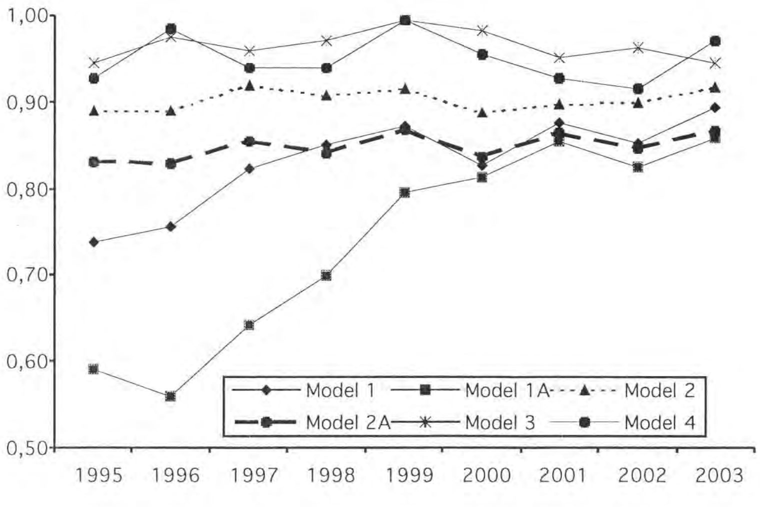
B: DEA window analyses – locally intertemporal data

The results reported above relied on DEA approach under static conditions, where the observations for the banks in different years are treated as separate observations, and all measured against each other on an intertemporal basis. As noted earlier, this may not be a reasonable assumption because of technological improvements over the nine-year period under scrutiny, possibly making the comparison of DMUs in different years inappropriate. To deal with this problem, we used a window DEA approach with a window width of three years: i.e.

Table 3: Average efficiency scores by bank and by model

	BG_	BPH	BRE	BZ WBK	HANDL.	ING B_	KB	MILLENN.	P	P K
Model 1	0,88	0,82	0,82	0,73	0,74	0,80	0,91	0,81	0,93	0,96
Model 1A	0,75	0,69	0,78	0,63	0,69	0,70	0,80	0,76	0,83	0,80
Model 2	0,90	0,91	0,93	0,80	0,88	0,88	0,92	0,87	0,96	0,97
Model 2A	0,88	0,82	0,91	0,75	0,82	0,80	0,86	0,84	0,92	0,88
Model 3	1,00	0,98	0,98	0,93	0,99	0,99	0,96	0,92	0,95	0,98
Model 4	0,94	0,91	0,97	0,91	0,96	0,94	0,98	0,92	0,99	0,99
	0,89	**0,86**	**0,90**	**0,79**	**0,85**	**0,85**	**0,91**	**0,85**	**0,93**	**0,93**
	8,12%	**10,09%**	**8,30%**	**11,37%**	**12,03%**	**10,53%**	**6,64%**	**6,28%**	**5,46%**	**7,39%**

Figure 2: Efficiency scores by model – averaged across all banks



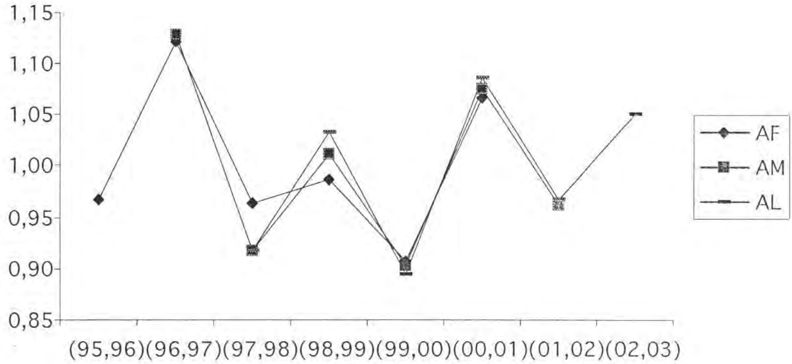
employing locally intertemporal data as defined in Section 2 so that the window covering the years 1995-1997 was coupled with 2001-2003 period.

We obtained results for DEA window analysis using locally intertemporal data for each bank based on each of the six performance models (as specified in Table 1). To be brief, we focused on selected findings only. Table 3 sets out the efficiency scores averaged across the seven windows for each bank and the basis of each of the six models. The findings show that PEKAO displays the least volatility in efficiency looking at the standard deviation results across all production models (5.46 percent) with an average efficiency score of 93 percent. In contrast, the most volatile efficiency results were obtained for HANDLOWY (12.03 percent) with an average efficiency score of 85 percent.

Finally, in contrast to the above results, we also report in Figure 2 below the changes in efficiency scores for each production model, averaged across all windows but this time averaged across all banks, year by year.

The graphs show that there have been tendencies for fluctuations in average efficiency to diminish over time. At the beginning of the study horizon, there was a considerable disparity between models reporting the highest and lowest efficiency scores using average across all seven windows and all ten banks. This disparity narrows considerably from 1999 onwards with a general upward trend in production efficiency – rising from an overall efficiency of 82% in 1995 to 91% in 2003, using again averages across the six models and all banks.

Figure 3: Geometric mean of Malmquist indices between adjacentperiods: model 1A



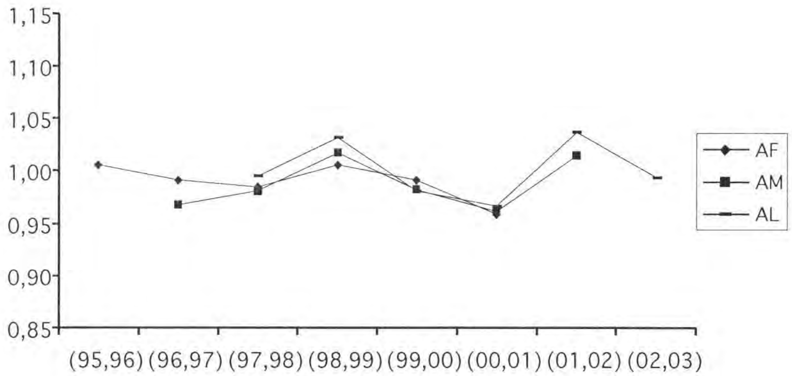
C: Malmquist productivity index

The large volume of information derived from window DEA may be difficult to summarize and evaluate. Therefore, it is often helpful to break down the information using the Malmquist index. We calculate Malmquist indices from the window DEA scores between adjacent (A) periods on the basis of *first* (F), *middle* (M) and *last* (L) year formulation – giving rise to the notation AF, AM, AL (for full details of this approach see Asmild *et al.*, 2004).

Our findings show that Malmquist indices on the basis of these three formulations within each production model are quite similar and indicate similar changes in average efficiency scores over the study horizon (a full set of results is not reported here but may be obtained from the authors). Results for model 1A for each Malmquist Index (related to AF, AM and AL) are shown in Figure 4 below – this being the model which demonstrates the greatest volatility in changes in efficiency. On the basis of geometric mean, the largest annual increase in efficiency is +13 percent for the years 1996-1997 (denoted 96.97 in Figure 3) while the largest annual decrease is –11 percent between 1999-2000.

In contrast to results in Figure 3, Figure 4 represents the results which generates the least volatility (namely results from model 3) over the study period. The change in efficiency from year to year ranges between +4 and –4%.

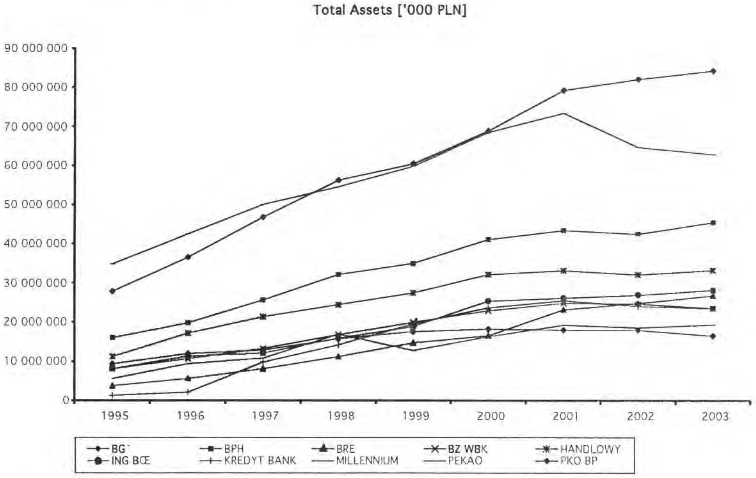
Figure 4: Geometric mean of Malmquist indices between adjacent periods: model 3



The results reported in the previous section and in the appendix offer opportunities for further analyses of the banking industry in the context of development affecting the Polish economy since 1989. Within this process, the banking sector has experienced both restructuring of financial institutions and re-capitalization of almost every single player in the banking industry. The scale of these changes has fundamentally changed the structure and performance of the sector. Figure 5 below shows the build up of total assets by the banks in our sample over the period 1995-2003. This simple measure illustrates how significant these changes have been. Nevertheless, the largest banks in Poland, as a group, have not only witnessed a reduction in the relative *dispersion* of their cost efficiencies but have also experienced an upward trend in the average *level* of efficiency during the period under investigation.

By contrast, for individual banks, the process of improving efficiency has not always been stable. In some cases, for example Bank MILLENNIUM.[11] changes in ownership structure were associated with significant volatility in efficiency scores. Two other banks have also experienced similar volatility, namely KREDYT BANK and BRE. One reason for such a variation in results could be unstable cost ratios associated with these banks – their cost ratios rose and fell significantly in the periods in line with volatility in the efficiency results. Naturally, explanation of the derived efficiency scores over time for any one bank would require further analyses and a greater focus on the individual characteristics and conditions confronting each of them.

Figure 5: Total assets by bank in the period 1995-2003



An examination of the efficiency scores obtained by banks and their core business activities (either retail or corporate focused) suggests that those operating in the retail sector tend to be more efficient than banks providing services for the corporate sector. Indeed, two retail banks – PEKAO and PKO – achieved the highest efficiency scores over the analyzed period, while BRE and HANDLOWY, which are traditionally corporate focused, are found to be relatively cost inefficient. One can only speculate that such a difference in efficiency is caused by the nature of these two types of bank customers. Individuals are likely to have weaker bargaining power than corporate clients. Corporate clients, however, may be more attractive targets for some banks – since they are likely to earn more in absolute terms from a single corporate client than would be expected from any single individual. But on the other hand, companies are likely to be more demanding with probably stronger negotiating positions.

[11] Formerly Big Bank Gda_ski, this bank is a unit derived from three other banks that merged over the years 1997-2001.

5. Conclusions

In this study, efficiency scores are reported from DEA analysis. We have shown how this approach allows for the calculation of efficiency scores even for a small number of different units within the context of a fairly large number of performance variables. The efficiency results for the Polish banking sector based on the methodologies indicate that the relative dispersion of efficiency for the ten banks declined between 1995 and 2003 with a general improvement in overall cost efficiency performance. This pattern, however, does not apply to every bank since, for a few cases, efficiency remained unstable over the time period.

This study supports a view that is already established – namely that DEA as well as other frontier analysis techniques in general essentially confirm the outcomes of qualitative analysis. In particular, efficiency estimates should serve as a foundation to interested bodies (banks themselves, investors, supervision institutions etc.) to encourage them to seek an answer to the question: why is a particular bank classified as being efficient or inefficient? Furthermore, DEA can serve as an early warning system for spotting emergent inefficient banks. Moreover, it is crucial to point out that DEA results are particularly sensitive to any variation in the dataset - the addition to or elimination of even one decision - making unit (bank) from the sample may have a significant impact on the relative efficiency measures of individual banks and for the sector as a whole. DEA results are also sensitive to false or inaccurately recorded data.

Limitations concerning the use of DEA in this study should not diminish the importance of DEA-based efficiency analysis. In Poland the measurement of banking sector efficiency is a relatively new topic. The first studies on the subject were only published in the country in the late 1990s. Previously, most of the studies concerning Polish banks were focused on profitability and general financial performance. Efficiency was only analyzed, to a large extent, on the basis of a one-dimensional approach (one output, one input), particularly in the context of labour efficiency using simple ratios such as profit per employee. Until the late 1990s, no complex efficiency analysis of Polish banks had been conducted with respect to technological efficiency and economies of scale (Rogowski, 1998). It is hoped that the results presented here serve as a foundation for further research concerning the efficiency and future competitiveness of the Polish banking industry – especially in the context of Poland's membership of the European Union and the dynamics of the European banking industry.

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APPENDIX

Results from panel data analysis for all 90 observations

model 1	1995	1996	1997	1998	1999	2000	2001	2002	2003	Av.
BG⁻	0,93	1,00	0,86	0,82	0,79	0,75	0,77	0,79	0,80	0,84
BPH	0,71	0,78	0,79	0,79	0,77	0,75	0,74	0,76	0,93	0,78
BRE	0,60	0,69	0,62	0,67	0,55	0,52	0,75	0,68	0,83	0,66
BZ WBK	0,65	0,66	0,68	0,73	0,73	0,70	0,60	0,64	0,75	0,68
HANDLOWY	0,66	0,59	0,61	0,66	0,68	0,62	0,67	0,65	0,69	0,65
ING BŒ	0,67	0,65	0,56	0,65	0,71	0,79	0,92	0,90	1,00	0,76
KREDYT BANK	0,35	0,48	0,99	0,90	1,00	0,97	0,93	0,90	0,84	0,82
MILLENNIUM	1,00	0,58	1,00	0,86	1,00	0,48	0,73	0,59	0,68	0,77
PEKAO	0,90	0,85	0,87	0,78	0,86	0,91	0,94	0,87	0,87	0,87
PKO BP	0,88	0,99	1,00	0,92	0,89	0,89	0,89	0,86	0,89	0,91
Av.	**0,74**	**0,73**	**0,80**	**0,78**	**0,80**	**0,74**	**0,79**	**0,77**	**0,83**	**0,77**
standard deviation	19,56%	17,56%	17,17%	9,90%	14,31%	16,33%	11,84%	11,62%	10,22%	14,28%
minimum	35,12%	47,97%	55,64%	64,97%	54,77%	47,57%	60,45%	59,26%	67,61%	54.82%
number of efficient banks	1	1	2	0	2	0	0	0	1	7
% of efficient banks	10%	10%	20%	0%	20%	0%	0%	0%	10%	7,78%
correlation	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	
Overheads / Total assets	-72,97%	-54,89%	-64,70%	-15,14%	-22,29%	7,20%	-42,88%	-29,85%	-35,15%	
Total Costs/Total Assets	-16,00%	1,58%	-42,05%	14,69%	-17,81%	7,67%	-1,19%	21,54%	-4,78%	
Overheads/Gross profit on BA	-14,60%	-15,09%	63,15%	61,12%	51,95%	-14,29%	-48,94%	-24,95%	-47,09%	
ROE	-25,35%	80,62%	14,43%	-33,70%	-36,21%	43,80%	26,58%	-11,47%	-1,01%	
ROA	35,65%	34,89%	-54,50%	-66,81%	-70,11%	-13,73%	13,56%	-17,25%	0,19%	

model 1A	1995	1996	1997	1998	1999	2000	2001	2002	2003	Av.
BG⁻	0,64	0,65	0,56	0,56	0,55	0,51	0,56	0,58	0,59	0,58
BPH	0,55	0,55	0,56	0,53	0,52	0,50	0,49	0,51	0,64	0,54
BRE	0,43	0,54	0,57	0,67	0,55	0,52	0,75	0,68	0,83	0,61
BZ WBK	0,49	0,49	0,48	0,52	0,51	0,49	0,45	0,44	0,48	0,48
HANDLOWY	0,66	0,57	0,59	0,57	0,55	0,43	0,48	0,44	0,43	0,53
ING BŒ	0,44	0,48	0,42	0,47	0,51	0,55	0,61	0,57	0,66	0,52
KREDYT BANK	0,28	0,39	0,77	0,54	0,61	0,54	0,59	0,62	0,59	0,55
MILLENNIUM	1,00	0,43	1,00	0,58	0,71	0,36	0,53	0,40	0,52	0,61
PEKAO	0,78	0,68	0,66	0,57	0,60	0,62	0,67	0,67	0,62	0,65
PKO BP	0,64	0,69	0,67	0,62	0,60	0,59	0,62	0,58	0,59	0,62
Av.	0,59	0,55	0,63	0,56	0,57	0,51	0,57	0,55	0,59	0,57
standard deviation	20,31%	10,45%	16,31%	5,44%	5,92%	7,53%	9,34%	9,77%	10,85%	10,66%
minimum	27,79%	38,56%	42,30%	46,76%	50,79%	35,98%	44,60%	40,26%	43,39%	41,16%
number of efficient banks	1	0	1	0	0	0	0	0	0	2
% of efficient banks	10%	0%	10%	0%	0%	0%	0%	0%	0%	2,22%
correlation	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	
Overheads / Total assets	-60,09%	-71,03%	-90,97%	-57,19%	-61,07%	-3,35%	-85,40%	-80,51%	-82,18%	
Total Costs/Total Assets	-29,61%	-33,85%	-74,23%	-33,30%	-48,52%	-6,99%	-43,34%	-18,37%	-23,79%	
Overheads/Gross profit on BA	-30,36%	-34,81%	83,73%	-11,39%	-3,24%	-32,68%	-52,75%	-11,50%	26,46%	
ROE	-46,47%	64,56%	-15,68%	-35,91%	-18,56%	56,81%	47,07%	-46,56%	0,19%	
ROA	34,13%	36,86%	-61,12%	-34,54%	-21,41%	28,06%	54,22%	-47,36%	-3,24%	

model 2	1995	1996	1997	1998	1999	2000	2001	2002	2003	Av.
BG⁻	0,93	1,00	0,97	0,85	0,83	0,78	0,80	0,80	0,81	0,86
BPH	0 ,88	0,94	0,90	0,88	0,80	0,84	0,81	0,82	0,94	0,87
BRE	0,96	0,90	0,72	0,82	0,92	0,64	0,81	0,74	0,83	0,82
BZ WBK	0,81	0,79	0,80	0,83	0,79	0,75	0,64	0,69	0,78	0,77
HANDLOWY	1,00	0,82	0,80	0,77	0,78	0,75	0,77	0,78	0,77	0,81
ING BŒ	1,00	0,85	0,70	0,70	0,80	0,88	0,93	0,93	1,00	0,86
KREDYT BANK	0,41	0,53	1,00	0,93	1,00	1,00	0,93	0,90	0,84	0,84
MILLENNIUM	1,00	0,74	1,00	0,88	1,00	0,64	0,75	0,67	0,68	0,82
PEKAO	1,00	0,93	0,93	0,81	0,87	0,94	1,00	0,99	0,91	0,93
PKO BP	0,89	1,00	1,00	0,92	0,89	0,92	0,91	0,88	0,91	0,92
Av.	**0,89**	**0,85**	**0,88**	**0,84**	**0,87**	**0,81**	**0,84**	**0,82**	**0,85**	**0,85**
standard deviation	18,07%	14,11%	11,79%	7,04%	8,33%	12,41%	10,71%	10,31%	9,37%	11,35%
minimum	40,76%	53,36%	69,74%	69,53%	77,79%	63,71%	64,09%	67,30%	68,34%	63,85%
number of efficient banks	4	2	3	0	2	1	1	0	1	14
% of efficient banks	40%	20%	30%	0%	20%	10%	10%	0%	10%	15,56%
correlation	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	
Overheads / Total assets	-89,48%	-79,08%	-64,63%	-30,17%	-63,21%	9,60%	-54,92%	-38,70%	-32,16%	
Total Costs/Total Assets	-44,62%	-31,80%	-40,47%	-1,42%	-37,77%	1,44%	-16,95%	8,19%	-15,98%	
Overheads/Gross profit on BA	-70,02%	-56,87%	50,70%	25,54%	-18,13%	-12,73%	-68,67%	-55,67%	-64,46%	
ROE	-27,90%	69,12%	26,52%	-28,35%	-5,03%	40,51%	32,75%	7,02%	7,45%	

model 2A	1995	1996	1997	1998	1999	2000	2001	2002	2003	Av.
BG⁻	0,68	0,94	1,00	0,81	0,74	0,65	0,70	0,67	0,69	0,77
BPH	0,79	0,79	0,74	0,75	0,64	0,65	0,64	0,66	0,72	0,71
BRE	0,97	0,69	0,72	0,90	1,00	0,63	0,81	0,74	0,83	0,81
BZ WBK	0,79	0,69	0,68	0,72	0,67	0,64	0,56	0,58	0,60	0,66
HANDLOWY	1,00	0,84	0,85	0,72	0,64	0,57	0,60	0,57	0,57	0,71
ING BŒ	0,82	0,69	0,58	0,55	0,62	0,66	0,71	0,72	0,80	0,68
KREDYT BANK	0,35	0,45	0,88	0,72	0,74	0,78	0,66	0,66	0,62	0,65
MILLENNIUM	1,00	0,73	1,00	0,70	0,79	0,56	0,64	0,53	0,56	0,72
PEKAO	0,97	0,85	0,83	0,71	0,72	0,81	0,91	0,89	0,79	0,83
PKO BP	0,92	1,00	0,78	0,69	0,69	0,74	0,77	0,72	0,72	0,78
Av.	0,83	0,77	0,81	0,73	0,73	0,67	0,70	0,68	0,69	0,73
standard deviation	20,03%	15,64%	13,41%	8,96%	11,10%	8,18%	10,56%	10,23%	9,75%	11,98%
minimum	35,18%	44,50%	58,43%	54,63%	61,53%	56,17%	56,10%	53,32%	56,38%	52,92%
number of efficient banks	2	1	2	0	1	0	0	0	0	6
% of efficient banks	20%	10%	20%	0%	10%	0%	0%	0%	0%	6,67%
correlation	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	
Overheads / Total assets	-77,73%	-80,72%	-83,41%	-65,10%	-65,07%	-14,96%	-73,45%	-69,56%	-71,40%	
Total Costs/Total Assets	-69,90%	-28,70%	-48,34%	-30,15%	-33,55%	-20,37%	-54,52%	-31,48%	-43,78%	
Overheads/Gross profit on BA	-83,12%	-51,63%	40,63%	-60,26%	-72,43%	-15,57%	-75,23%	-51,44%	-20,91%	
ROE	-72,01%	79,74%	50,24%	28,33%	48,22%	46,04%	67,69%	-4,36%	26,46%	
ROA	77,16%	60,76%	1,38%	20,59%	72,08%	5,26%	76,27%	-3,14%	26,28%	

model 3	1995	1996	1997	1998	1999	2000	2001	2002	2003	Av.
BG⁻	1,00	1,00	1,00	0,96	1,00	0,89	0,95	0,95	1,00	0,97
BPH	0,99	1,00	0,93	0,89	0,88	0,84	1,00	0,89	0,87	0,92
BRE	1,00	0,94	0,93	0,77	1,00	0,77	0,75	0,66	0,75	0,84
BZ WBK	0,99	1,00	0,99	0,90	0,86	0,76	0,66	0,75	1,00	0,88
HANDLOWY	1,00	0,89	0,83	0,79	0,81	1,00	1,00	1,00	1,00	0,93
ING BŒ	1,00	0,99	0,85	0,97	0,94	1,00	1,00	1,00	1,00	0,97
KREDYT BANK	0,73	0,81	0,84	1,00	1,00	1,00	0,92	0,84	0,89	0,89
MILLENNIUM	0,94	0,90	0,81	0,99	1,00	1,00	0,62	0,70	0,65	0,84
PEKAO	0,84	0,85	0,87	0,78	0,80	0,88	0,90	0,96	1,00	0,87
PKO BP	0,95	0,99	0,97	0,87	0,82	0,82	0,84	0,87	1,00	0,90
Av.	0,94	0,94	0,90	0,89	0,91	0,90	0,86	0,86	0,91	0,90
standard deviation	9,06%	7,13%	6,97%	8,85%	8,57%	9,76%	14,37%	12,35%	12,79%	9,98%
minimum	73,05%	81,07%	80,86%	76,61%	79,51%	75,98%	61,67%	65,79%	64,54%	73,23%
number of efficient banks	4	3	1	0	4	2	3	2	6	25
% of efficient banks	40%	30%	10%	0%	40%	20%	30%	20%	60%	27,78%
correlation	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	
Overheads / Total assets	-62,38%	-30,00%	49,79%	12,74%	-58,02%	-26,32%	-16,36%	-6,23%	38,04%	
Total Costs/Total Assets	-6,33%	17,37%	58,70%	45,63%	-0,67%	5,26%	20,57%	-8,48%	-16,69%	
Overheads/Gross profit on BA	-55,97%	-44,58%	-37,57%	33,48%	-54,38%	-20,80%	-55,72%	-43,45%	-69,93%	
ROE	12,16%	64,81%	50,51%	21,76%	57,21%	-29,38%	-10,07%	14,64%	11,29%	
ROA	87,86%	74,69%	41,87%	-0,81%	49,96%	-39,39%	-7,74%	16,21%	16,44%	

model 4	1995	1996	1997	1998	1999	2000	2001	2002	2003	Av.
BG⁻	0,98	1,00	0,87	0,85	0,86	0,76	0,79	0,87	0,93	0,88
BPH	0,76	0,79	0,80	0,80	0,78	0,76	0,74	0,80	1,00	0,80
BRE	0,76	0,81	0,74	0,84	1,00	0,68	0,92	0,90	1,00	0,85
BZ WBK	0,72	0,70	0,72	0,76	0,74	0,70	0,63	0,73	1,00	0,74
HANDLOWY	0,90	0,93	0,82	0,77	0,80	0,74	0,72	0,74	1,00	0,82
ING BŒ	0,89	0,79	0,64	0,69	0,76	0,88	0,94	0,92	1,00	0,83
KREDYT BANK	0,41	0,59	1,00	0,91	1,00	1,00	0,93	1,00	1,00	0,87
MILLENNIUM	1,00	0,87	1,00	1,00	1,00	0,89	0,74	0,63	0,73	0,87
PEKAO	1,00	0,95	0,93	0,81	0,93	0,95	1,00	0,99	1,00	0,95
PKO BP	0,91	1,00	1,00	0,92	0,92	0,90	0,90	0,93	1,00	0,94
Av.	0,83	0,84	0,85	0,83	0,88	0,82	0,83	0,85	0,97	0,86
standard deviation	18,02%	13,42%	13,06%	9,14%	10,51%	11,11%	12,14%	12,28%	8,54%	12,02%
minimum	41,34%	58,70%	63,74%	68,57%	73,93%	67,87%	63,17%	62,81%	73,09%	63,69%
number of efficient banks	2	2	3	1	3	1	1	1	8	22
% of efficient banks	20%	20%	30%	10%	30%	10%	10%	10%	80%	24,44%
correlation	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	ecrs	
Overheads / Total assets	-86,78%	-86,66%	-77,56%	-60,87%	-69,52%	-30,06%	-73,11%	-62,09%	-13,48%	
Total Costs/Total Assets	-23,98%	-35,92%	-59,46%	-18,22%	-54,57%	-7,23%	-26,15%	-1,61%	-27,92%	
Overheads/Gross profit on BA	-40,51%	-48,81%	56,13%	30,78%	-26,59%	-10,32%	-62,85%	-20,98%	-41,97%	
ROE	-15,88%	59,87%	7,18%	-27,80%	12,20%	28,51%	35,80%	-32,14%	-10,54%	
ROA	63,00%	50,93%	-48,68%	-50,25%	18,85%	-21,55%	36,15%	-35,65%	-6,06%	