Detecting Intrinsic Inefficiency on Process Level: Benchmarking of Transactions in Banking

Andreas Burger and Jürgen Moormann

Frankfurt School of Finance & Management / ProcessLab
Sonnemannstraße 9-11, 60314 Frankfurt am Main, Germany
{a.burger,j.moormann}@frankfurt-school.de
http://www.processlab.info

Abstract. Banks are looking for ways to close their operational performance gap. This paper proposes a new approach for the detection and analysis of process inefficiency. The Benchmarking of Transactions reveals insights concerning the performance of a business process and offers new opportunities for process improvement. The article delivers an overview of the concept as well as the results of an application in a large organization. The benchmarking approach is based on Data Envelopment Analysis. The approach is applied to a prototypical banking process using actual operational data. This real life application documents the large variance in performance found on transaction level and the existence of inefficiency. Furthermore, the pattern of inefficiency differs across the three proposed views of performance. This research raises issues in relation to the process execution performance. The analysis provides deep insights that can be helpful for understanding and improving business processes.

Keywords: Business Process Intelligence, Performance Measurement of business processes, Monitoring of business processes.

1 Introduction

Banks are constantly trying to improve their operational performance and profitability [1]. Operational performance has a high relevance for banks, as empirical studies indicate that it leads to increased profitability [2]. In banking, significant differences with regard to operational performance can be identified [3]. Operational performance is strongly linked to processes and the way they are designed and executed. There is consensus in the literature that there is a need for strengthening process level analysis in operations management [4].

Inefficiency in general can be defined as the performance gap in comparison to the best practice. In general, the performance gap can be closed in two distinct ways: Firstly, the process flow can be changed and the *design-related inefficiency* can be eliminated. This means that a process is improved through changing its structure and design. Secondly, *intrinsic inefficiency* can be eliminated by improving the quality of the process execution. This means that variation in the process execution caused by manual and automatic processing activities is reduced by adjusting the execution quality to a best practice level.

D. Ardagna et al. (Eds.): BPM 2008 Workshops, LNBIP 17, pp. 146–157, 2009.

This paper introduces a promising approach for process analysis based on Data Envelopment Analysis (DEA). Benchmarking of Transactions offers new insights into the pattern of intrinsic inefficiency of a given process. This in itself can be seen as a research endeavor [5]. Thus, it provides a rich basis for generating new ideas for business process improvement. The target of our research is to reveal the pattern of inefficiency for a given process, to provide additional insights into the performance of the process while incorporating multiple factors simultaneously and, finally, to derive proposals for improvement.

The contribution of the work is threefold. Firstly, it delivers an innovative approach for process performance analysis via Benchmarking of Transactions. Secondly, it adds alternative input-output-models for application of DEA on a disaggregated process level. Thirdly, it enriches the process-related research in Banking with a single case study based on actual operating data.

The paper is structured as follows: It starts with an outline of the background and the initial reasons for this research. Then related literature is reviewed in section 2. In the following section the Benchmarking of Transactions approach and the underlying methodology, Data Envelopment Analysis, is outlined. Section 4 delivers details on the case study as such and data used. Section 5 gives an overview of the results and key findings of the empirical analysis. Finally, the conclusion provides an outlook and outlines aspects for discussion.

2 Related Work

This research is in line with the need to intensify the development and use of analytical models for measuring performance and conducting experiments on a process level [6]. Empirical studies on the basis of actual operating data from the daily business are seen as an important research approach in operations management [7].

The proposed concept of Benchmarking of Transactions as an instrument for performance measurement on process level is unique. The approach is interdisciplinary in its character and touches various research fields. In the following paragraphs the related work is briefly outlined and differences compared to the proposed approach are pointed out.

Business Process Intelligence: This research relates to the need to increase the effort in the area of process analysis and optimization [8]. In this work case-related transaction logs form the basis for the process analysis with respect to intrinsic inefficiency. In contrast to *Process Mining* approaches [9] that aim to construct formal process models on the basis of process logs, this research proposes an approach for using input and output data for detecting inefficiencies and deriving new insights into the performance pattern of the process.

Efficiency measurement on disaggregated level: Researchers so far have not shown a great deal of interest in the topic and measuring efficiency on a disaggregated process level remains one of the main challenges [10]. Banking is probably the sector with the highest number of efficiency analyses in general and DEA is widely used in this sector [11]. Despite these efforts, processes have been very been seldom in the focus of the analysis. The procedure proposed here adds a new approach for efficiency measurement in banking with an application at a disaggregated process level.

Additionally, our research project should be viewed in relation to other *Business Process Management* (BPM) techniques. This is vital, because only little research has thus far focused on process analysis in this area [12]. The work shown here stands in contrast to traditional process analysis techniques that a) have a strong focus on activities rather than on transactions, b) only capture single aspects (e.g. costs, time) and are not capable of capturing multiple aspects simultaneously, and c) tend to relate to average performance rather than to best practice standards. Experience reports in the area of process analysis show that examining one aspect at a time makes interpretation and diagnosis difficult and could leave important information undetected [13].

3 Benchmarking of Transactions – Introduction and Methodology

Practical experience suggests that there are performance differences in transaction processing. Although transactions are similar in principle, some require more effort or take longer; some cause breaks in the process or even lead to an error from a client's point of view. There is quite a discussion about the inefficiency of processes, but no appropriate measurement, from a scientific point of view, is performed.

The *Benchmarking of Transactions* approach proposed here describes a specific form of performance measurement on process level. In order to analyze the intrinsic inefficiency of a process, single transactions of a process are benchmarked. More specifically, the individual performance of a transaction is assessed by calculating a single measure of efficiency, including multiple aspects such as time, costs, quality. The performance gap is determined by benchmarking each single transaction against a *best practice* transaction. The aggregation of the individual efficiency of the transactions describes the performance pattern of a process.

The proposed approach for detecting intrinsic inefficiency applies three different views on performance. The views are independent from each other and each is based on a specific research question. But bringing the results of the views together can provide additional insights into the process. Superior insights can be obtained by analyzing objects in relation to efficiency from various angles simultaneously, rather than looking at the information obtained from benchmarking the dimensions separately. The performance views are as follows:

Productive efficiency: This view focuses on the relationship between production effort and output quantity. A transaction would be classified as efficient when it is produced with minimal effort. This view on performance equals a productivity analysis with multiple variables. Usually, production effort on a disaggregated level is measured as time spent for processing. The output is measured in pieces. In practice, the determination of the actual costs for production on disaggregated levels or on an activity basis is tied to various problems or might not be possible at all.

Performance efficiency: The second view tries to capture the performance from a more theoretical point of view. The term *performance* is used to underline the fact that multiple aspects can be considered in one analysis only. It analyzes on a transaction level the relationship between production effort and the performance achieved. A transaction would be classified as efficient if it achieves the focused performance with minimal effort. The production effort is measured as time spent for processing. The definition of this model is quite flexible and depends on the individual application.

Profitability efficiency: The third view looks at the performance from an economic standpoint. It analyzes the relationship between costs spent and revenues generated. A transaction would be classified as efficient if it reaches the maximum profitability. This view on performance equals a simple ratio-based profitability analysis.

The methodological basis for the proposed *Benchmarking of Transactions* is the *Data Envelopment Analysis* (DEA). The underlying concept goes back to Farrell [14] and the first practical application was done by Charnes, Cooper, and Rhodes [15]. DEA is a non-parametric, non-stochastic efficiency measurement method [16]. The efficiency measurement for the object of analysis, also called *Decision making unit* (DMU), is accomplished via the construction of an empirically based production frontier [the "best practice frontier"] and the evaluation of the DMU against a peer object [17]. It allows for an efficiency measurement of multidimensional problem settings on the basis of very limited assumptions. This is achieved by the linear programming-based conversion of multiple input and output measures into a single comprehensive measure of efficiency. The *throughput* of a process is treated as a *black box* in the analysis, but Triantis [10] argues that the attempt to capture performance purely from an input and output perspective can lead to potentially useful insights. DEA is the natural choice for analyzing input-output-relations in cases where the transformation process is unknown and cannot be formulated via *a priori* functional relationship [18].

The flexible definition of the DMU allows for multiple applications of DEA on different levels of abstraction. Transactions of a process constitute a valid DMU as they meets all homogeneity requirements [19].

When applying DEA the following issues need further attention and need to be considered when interpreting the results of DEA studies. DEA gives the "*benefit of the doubt*" to all DMU in the benchmarking [20]. The methodology makes every DMU look as efficient as possible in comparison to other units.

DEA objectively determines individual weights across the inputs and outputs for every DMU. The performance assessment or efficiency measurement is based on the *extended Pareto-Koopmans* efficiency definition [18]. This definition is operationalized by a *radial* efficiency measure. The major problem with this is that the radial measure does not reflect all identifiable potentials for improvement [21], as it assumes for example the simultaneous and proportional reduction of all input factors. The remaining potential for improvement is called *slack*. In line with Lovell [22] all slacks are made transparent and reported separately.

DEA offers strong diagnostic capabilities by providing data reductions, alternative classification schemes, cues to causality, and comparison standards; together with statistical analysis it enables to gain awareness of relationships and trends and provokes interest, raises issues, and reveals preferences [17]. A discussion of the strengths and weaknesses of performance analysis with DEA can be found at Coelli [23].

4 Case Study – Description and Data

The analysis is conducted on the basis of a single case study. Our research can be classified as *theory-building* [24] and involves explorative elements. It is based on limited assumptions and the perceived problem of having performance differences on a transaction level. The case study approach seems appropriate as it is understood as the first step for completely new and exploratory investigations [25]. This work overcomes the bias in operations management towards research on manufacturing [26].

The research project is conducted in co-operation with *Commerzbank*, the second largest bank of Germany. The process under analysis in this research is the *Securities settlement and clearing* process. From a bank's business model point of view, the securities business has high significance for a bank and provides a high potential for revenue generation. Due to its semi-automatic character, its high transaction volume, the mandatory separation of duties along the process life cycle, and various internal and external parties involved the chosen process represents a prototypical banking process.

An introduction to the Securities operations in general and the Securities processing in particular can be found at Simmons [27]. The Securities settlement and clearing process covers all activities necessary for executing the purchases and sales of Securities. Conceptually the processing lifecycle can be broken down into five steps, such as trade capture, transaction enrichment, validation, clearing and settlement, posting. The operational data as well as transactions logs are stored in various data bases along the process chain. The data collection in empirical studies is usually linked to difficulties in identifying, extracting and transforming the data into a ready-to-use format [28].

The scope of the research presented here is limited to a specific business, a part of the process, and type of transaction. Specifically it covers the process steps of trade capture and transaction enrichment and focuses on transactions resulting from the purchases and sales of new issued bonds that were rejected for settlement by the *Central Securities Depository* (CSD). All transactions are subject to a manual intervention in order to resume processing.

Main reason for the process break is a time delay in updating static data on the side of the CSD. Performance differences for the transactions in this specific case can result from (a) differences in handling the exception manually and (b) differences in performing the automatic processing.

The size of the sample is 274 transactions and comprises all transactions of its kind within the bank for the month of January 2008. As outlined, all transactions are homogenous with respect to the type of product, processing route, and reason for the manual exception handling. Despite the homogeneity of the transactions, there are significant performance differences to be noted. Table 1 gives an overview of the descriptive statistics for the input and output variables for all 274 transactions.

Table 1. Descriptive Statistics for Inputs and Outputs

Variables	Input	Input	Input	Output	Output	Output	Output	Test basis
N=274	**Man time (h)**	**Auto time (h)**	**CpTx (€)**	**Revenue (€)**	**CpTx index (%)**	**Revenue-index (%)**	**STP-index (%)**	**TIME-index (%)**
Min:	**0:00:08**	**1:00:09**	**4,23 €**	**498,42 €**	**8,7%**	**0,5%**	**4,9%**	**16,9%**
Max.	**3:32:48**	**5:38:14**	**48,52 €**	**101.728,55 €**	**100,0%**	**100,0%**	**100,0%**	**100,0%**
Mean:	**0:26:12**	**2:00:10**	**13,80 €**	**14.474,56 €**	**44,1%**	**14,2%**	**46,3%**	**41,0%**
Median:	**0:13:28**	**1:17:45**	**11,57 €**	**7.621,82 €**	**36,6%**	**7,5%**	**40,0%**	**32,2%**

The DEA calculation was performed with *DEA-Solver PRO60e*, a commercial DEA software package. Calculations were based on the input-oriented CCR-model [15]. Additional statistical analyses were conducted with *Minitab 15.1.1.0.*

DEA analyses in general are based on analyzing input-output relations. It is important to note that DEA entails the principle not to remove highly correlated variables as this might affect the results of the measurement [29]. The following input and output variables are defined:

Inputs are the *manual time* as well as the *automatic time* needed for processing; both are calculated on the basis of *timestamps* and include working and waiting times. In addition, a calculative *Costs per Transaction* (CpTx) is determined by assuming that manual time costs trice the automatic time.

Outputs are as follows: The *STP-Index* is calculated by taking the proportion of automatic time in relation to the total time that is then divided once more by the total time of the transaction. A theoretical *revenue* contribution for every transaction is calculated by assuming a small and fixed margin on the *consideration* amount, i.e. the amount of a trade including accrued interest; this figure is also used in an indexed form. The above described *CpTx* is also used as an output in indexed form.

5 Results

This section outlines the results and key findings of the benchmarking of transactions. The analysis itself is conducted in two steps: In step one, the benchmarking of transactions is performed by calculating the efficiency scores for the three performance views (EFF 1, EFF 2, EFF 3). DEA calculates a single score for each transaction. An efficiency score of 1.0 indicates that the transaction is efficient, whereas a score of 0.8 indicates that there is an inefficiency of 20% in comparison to best practice. In step two, the results of step one are brought together. Furthermore, selected statistical analyses are performed in order to derive hypotheses for process improvement.

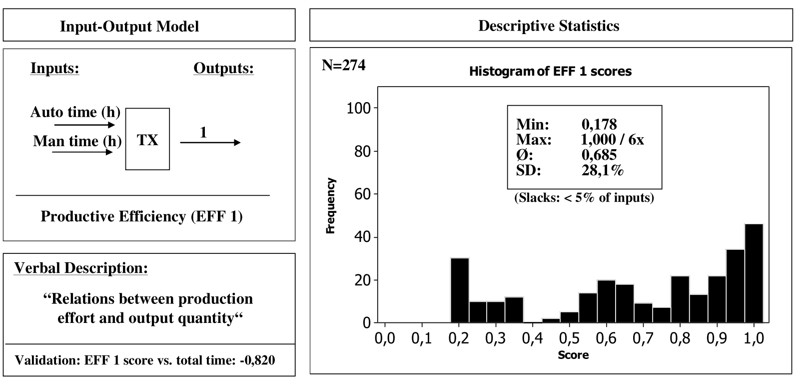
The results in general are presented through a set of descriptive statistics. In line with Bauer et al. [30] a validation of the efficiency scores against a typical operations performance ratio, in this case the *total time*, is performed for every performance view. The results of step one are as follows:

The *productive view* is based on two inputs (*manual time*, *automatic time*) and a single output set to 1. This assumes that every transaction has the same output produced without considering any differences in outcomes, such as quality aspects. Results of the efficiency measurement are given in Fig. 1. Six out of 274 transactions can be determined as *productive* efficient. The average productive inefficiency is 31.5%. The efficiency scores are highly correlated (-0.820) with the performance indicator *total time*. It can be stated that 90 transactions show a score between 0.9 und 1 which indicates a very good performance of almost 1/3 of the sample. Meanwhile, 67 transactions show a score of 0.5 or less which indicates a significant amount of inefficiency. Further analysis into the reasons could reveal helpful insights for improving the processing and remove intrinsic inefficiency. This is not in the scope of this paper. But it is important to realize, that all inefficiency against best practice on a transaction basis sums up to ~ 50% of the cycle time.

The *performance view* is based on one input (*Total Time Index*) and three outputs. The outputs cover the degree of automation achieved in processing (*STP Index*), the theoretical revenue generated (*Revenue Index*), and the calculative costs incurred (*CpTx Index*). This specific definition of performance tries to capture various aspects in a single analysis that are relevant from an operations manager's point of view. The interpretation of the result has to be made with care as the underlying relationships are of theoretical nature. Nevertheless, the efficiency score is a good basis for identifying best practice and rank all other transactions in line with this specific view of performance. An overview of the results is given in Fig. 2. The following insights can be gained. The average performance inefficiency is 66.3%. The weak correlations of the scores with total time indicate the need for strong arguments in order to defend the results in front of operations managers. Only four out of 274 transactions can be determined as efficient from a performance perspective. On the other hand, 194 transactions bear an inefficiency of > 50%. In contrast to the productive view, the efficiency scores are more evenly distributed across the full score range. The two transactions # 8700736881 and # 8700736882 are rated efficient in terms of a productive as well as a performance view.

The *profitability view* is based on one input (*CpTx*) and one output (*revenue*). Basically, this equals a straightforward ratio analysis. Nevertheless, DEA delivers additional information in comparison to simply calculating a profitability ratio. The view describes the calculative relationship between costs incurred and revenue generated. An overview of the results is given in Fig. 3. The average inefficiency is 91.3%. The efficiency scores show a high correlation of -0.723 with total time which is interesting in the light of the high average inefficiency measured. Only one transaction is rated efficient. It is fair to say that the score is highly driven by the value of the underlying trade.

Nevertheless, the efficient transaction # 8700440363 has also been determined efficient in line with the performance view. The distribution of the scores shows that the bulk of the transactions are relatively close with respect to the profitability ratio, but 14 transactions show a significantly higher ratio than the others. From an operations management point of view, a specific treatment for big ticket deals might be appropriate due to the high amount of revenue generated and the operational risk involved in processing.



Correlation of variables:

	Man time (h)	Auto time (h)	Output (=1)
Man time (h)		-0,0914	0,0000
Auto time (h)	-0,0914		0,0000
Output (=1)	0,0000	0,0000	

Efficient DMU / Benchmark
 # 8700890516 / 209x
 # 8700736881 / 172x
 # 8702519350 / 95x
 # 8700890515 / 11x
 # 8700633253 / 4x
 # 8700736882 / 0x (= # 8700736881)

Inefficient DMU: 268x

Fig. 1. Overview of the Descriptive Statistics of the Productive Efficiency Analysis

Input-Output Model

Inputs: TIME-Index [%] → **TX** → **Outputs:** CpTx-Index [%], Revenue-Index [%], STP-Index [%]

Performance Efficiency (EFF 2)

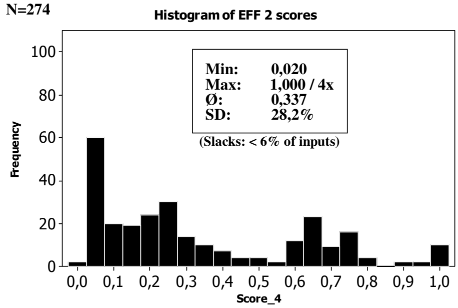
Verbal Description:

"Relations between production effort and performance achieved"

Validation: EFF 2 score vs. total time: -0,257

Descriptive Statistics

N=274



Correlation of variables:

	TIME-Index	CpTx-Index	Revenue-Index	STP-Index
TIME-Index		-0,7624	-0,0239	-0,7706
CpTx-Index	-0,7624		0,0162	0,9970
Revenue-Index	-0,0239	0,0162		0,0132
STP-Index	-0,7706	0,9970	0,0132	

Efficient DMU / Benchmark

 # 8700736881 / 224x
 # 8700822956 / 134x
 # 8700440363 / 46x
 # 8700736882 / 0x (= # 8700736881)

Inefficient DMU: 270x

Fig. 2. Overview of the Descriptive Statistics of the Performance Efficiency Analysis

Input-Output Model

Inputs: CpTx (€) → **TX** → **Outputs:** Revenue [€]

Profitability Efficiency (EFF 3)

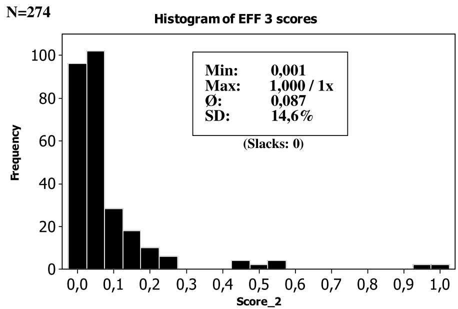
Verbal Description:

"Relations between cost spent and revenue generated"

Validation: EFF 3 score vs. total time: -0,723

Descriptive Statistics

N=274



Correlations of variables:

	CpTx (€)	Revenue (€)
CpTx (€)		-0,0452
Revenue (€)	-0,0452	

Efficient DMU / Benchmark

 # 8700440363 / 273x

Inefficient DMU: 273x

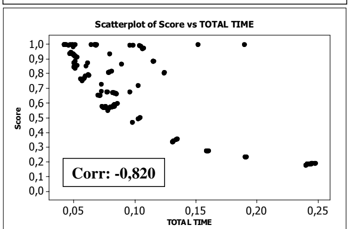
Fig. 3. Overview of the Descriptive Statistics of the Profitability Efficiency Analysis

Step 2 of the analysis shows some additional results by bringing together the results from the three performance perspectives. Examples are displayed in Fig. 4. Correlation analysis indicates that total time is generally a good indicator (e.g. -0.820 with productive efficiency scores) for efficiency across the three views. The graph reveals a non-linear relationship between the two factors. A further breakdown of the productive efficiency scores by the currency of the underlying bonds shows that there are significant differences when it comes to inefficiency. Bonds denominated in *Czech Koruna* (CZK) show a relatively high efficiency score (Ø 0.884) and a very low standard deviation of the scores. Bonds denominated in *Japanese Yen* (JPY) show an average productive efficiency score of 0.511 with a significant standard deviation. A final data analysis reveals that the intra-day variation of the productive efficiency scores varies across the trade dates.

The analysis presented in this work is not conclusive. But all results show that new insights can be revealed that can lead to improving the performance of a process. The data body is very rich and requires further structured analysis.

For example, additional regression analysis could be run to identify the statistical relationship between the efficiency scores and other transaction-related variables [10]. Nevertheless, the here presented results underline the significant opportunities offered by this approach.

EFF 1 score vs. Total time



EFF scores vs. Performance indicators

	EFF 1 score	EFF 2 score	EFF 3 score	CpTx	Total time
EFF 1 score					
EFF 2 score	0,007				
EFF 3 score	0,617	0,497			
CpTx	-0,495	-0,300	-0,784		
Total time	-0,820	-0,257	-0,723	0,862	

EFF 1 scores by Currency

EFF 1

	#	# (%)	Avg	Max	Min	SD
CHF	12	4,4%	0,795	1,000	0,277	0,27
CZK	12	4,4%	0,884	0,887	0,873	0,26
EUR	204	74,5%	0,697	1,000	0,178	0,28
GBP	6	2,2%	0,479	0,581	0,277	0,27
JPY	10	3,6%	0,511	0,999	0,190	0,27
USD	30	10,9%	0,582	0,999	0,186	0,29
Total	274	100,0%	0,685	1,000	0,178	0,28

EFF 1 scores vs. Trade Date

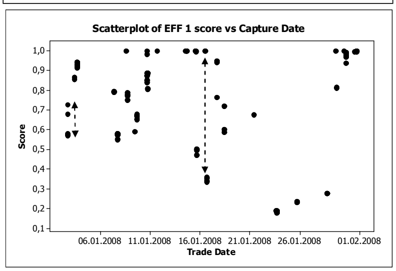


Fig. 4. Examples of Additional Analysis with Regards to Inefficiency Patterns

6 Conclusions and Aspects for Discussion

The here presented *Benchmarking of Transactions* delivers a new approach for performance analysis on process level. It detects the intrinsic process inefficiency and provides deep insights for deriving new aspects for process improvement. It is fair to note that the scope taken in the case study is narrow and it is not necessarily true that these results are universally applicable to complete process chains or other processes. Nevertheless the research is ongoing and the scope will be broadened.

Key characteristics of the approach are: (1) the focus on single transactions; (2) the benchmarking on the basis of a comparison against best practices rather than averages; (3) the model based calculation of a single performance measure including multiple variables; and (4) a process analysis on the basis of input-output models rather than process activities. Due to its strong methodological basis, the approach differs from other business analysis concepts that are criticized for being performed on the basis of subjective rather than objective analytical methods [12].

Key results of the prototypical banking process application are: (a) large variance in performance on transaction level exists; (b) significant intrinsic inefficiency can be detected (c) the pattern of inefficiency differs across the three proposed views of performance (d) critical areas for improving the performance can be identified.

Opportunities for further research can be identified: A promising field of research is the analysis of intrinsic inefficiency of other banking or service processes. It would be worthwhile to analyze whether there exists a systematic level of inefficiency across processes or even sectors. Further research is required that involve more sophisticated models for determining the inefficiency of the various views of performance. Finally, it needs to be assessed which impact a removal of intrinsic inefficiency has on service quality and the agility of the operations department. Roth and Jackson III [31] state that a further increase in efficiency in banking might lead to a reduction in service quality and reduces the agility to adapt to market changes.

The following aspects for discussion are proposed: Relevance and opportunities for applying this approach in practice, discussion of strength and weaknesses of this rather outside-in approach, based on analyzing input-output-relations, in comparison to traditional process analysis techniques. The practical relevance of a single performance measure on process level could also be discussed.

The introduced *Benchmarking of Transactions* is in line with the increasing sophistication in process management and the quest for *Business Process Intelligence*. Operations managers demand powerful tools to understand their specific processes, achieve transparency, and find ways to improve their operational performance constantly.

References

1. Soteriou, A., Zenios, S.A.: Operations, Quality, and Profitability in the Provision of Banking Services. Management Science 45, 1221–1238 (1999)
2. Casu, B., Molyneux, P.: Efficiency in European Banking. In: Goddard, J.A., Molyneux, P., Wilson, J.O.S. (eds.) European Banking: Efficiency, Technology and Growth, pp. 99–140. John Wiley & Sons, Chichester (2001)
3. Berger, A.N., Humphrey, D.B.: Efficiency of Financial Institutions: International Survey and Directions for Future Research. European Journal of Operational Research 98, 175–212 (1997)

4. Safizadeh, M.H., Field, J.M., Ritzman, L.P.: An empirical analysis of financial services processes with a front-office or back-office orientation. Journal of Operations Management 21, 557–576 (2003)
5. Färe, R., Grosskopf, S., Lovell, C.A.K.: Production Frontiers. Cambridge University Press, Cambridge (1994)
6. Gunasekaran, A., Kobu, B.: Modelling and analysis of business process reengineering. International Journal of Production Research 40, 2521–2546 (2002)
7. Swamidass, P.M.: Empirical Science: New Frontier in Operations Management Research. The Academy of Management Review 16, 793–814 (1991)
8. Grigori, D., Casati, F., Castellanos, M., Dayal, U., Sayal, M., Shan, M.-C.: Business Process Intelligence. Computers in Industry 53, 321–343 (2004)
9. van der Aalst, W.M.P., Reijers, H.A., Weijters, A.J.M.M., van Dongen, B.F., Alves de Medeiros, A.K., Song, M., Verbeek, H.M.W.: Business process mining: An industrial application. Information Systems 32, 713–732 (2007)
10. Triantis, K.P.: Engineering Applications of Data Envelopment Analysis: Issues and Opportunities. In: Cooper, W.W., Seiford, L.M., Zhu, J. (eds.) Handbook on Data Envelopment Analysis, pp. 401–441. Kluwer Academic, Boston (2004)
11. Paradi, J.C., Vela, S., Yang, Z.: Assessing Bank and Bank Branch Performance: Modelling Considerations and Approaches. In: Cooper, W.W., Seiford, L.M., Zhu, J. (eds.) Handbook on Data Envelopment Analysis, pp. 349–400. Kluwer Academic, Boston (2004)
12. Valiris, G., Glykas, M.: Critical review of existing BPR methodologies: The need for a holistic approach. Business Process Management Journal 5, 65–86 (1999)
13. Kourti, T., MacGregor, J.F.: Process analysis, monitoring and diagnosis, using multivariate projection methods. Chemometrics and Intelligent Laboratory Systems 28, 3–21 (1995)
14. Farrell, M.J.: The Measurement of Productive Efficiency. Journal of the Royal Statistical Society 120, 253–281 (1957)
15. Charnes, A., Cooper, W.W., Rhodes, E.: Measuring the efficiency of decision making units. European Journal of Operational Research 2, 429–444 (1978)
16. Cooper, W.W., Seiford, L.M., Tone, K.: Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software. Kluwer Academic, Boston (2007)
17. Epstein, M.K., Henderson, J.C.: Data Envelopment Analysis for Managerial Control and Diagnosis. Decision Sciences 20, 90–119 (1989)
18. Cooper, W.W., Seiford, L.M., Zhu, J.: Data Envelopment Analysis: History, Models and Interpretations. In: Cooper, W.W., Seiford, L.M., Zhu, J. (eds.) Handbook on Data Envelopment Analysis, pp. 1–39. Kluwer Academic, Boston (2004)
19. Golany, B., Roll, Y.: An Application Procedure for DEA. Omega 17, 237–250 (1989)
20. Sherman, H.D., Zhu, J.: Service Productivity Management - Improving Service Performance using Data Envelopment Analysis (DEA). Springer, New York (2006)
21. Ray, S.: Data Envelopment Analysis: Theory and Techniques for Economics and Operational Research. Cambridge University Press, Cambridge (2004)
22. Lovell, C.A.K.: Production Frontiers and Productive Efficiency. In: Fried, H.O., Lovell, C.A.K., Schmidt, S.S. (eds.) The Measurement of Productive Efficiency: Techniques and Applications, pp. 3–67. Oxford University Press, New York (1993)
23. Coelli, T.J., Rao, D.S.P., O'Donnell, C.J., Battese, G.E.: An Introduction to Efficiency and Productivity Analysis. Springer, New York (2005)
24. Flynn, B.B., Sakakibara, S., Schroeder, R.G., Bates, K.A., Flynn, E.J.: Empirical research methods in operations management. Journal of Operations Management 9, 250–284 (1990)

25. Meredith, J.: Building operations management theory through case and field research. Journal of Operations Management 16, 441–454 (1998)
26. Karmarkar, U.S., Apte, U.M.: Operations management in the information economy: Information products, processes, and chains. Journal of Operations Management 25, 438–453 (2007)
27. Simmons, M.: Securities Operations: A Guide to Trade and Position Management. Wiley & Sons, Chichester (2001)
28. Genrich, M., Kokkonen, A., Moormann, J.: Challenges for Business Process Intelligence. In: ter Hofstede, A.H.M., Benatallah, B., Paik, H.-Y. (eds.) BPM Workshops 2007. LNCS, vol. 4928, pp. 5–10. Springer, Heidelberg (2008)
29. Dyson, R.G., Allen, R., Camaho, A.S., Podinovski, V.V., Sarrico, C.S., Shale, E.A.: Pifalls and protocols in DEA. European Journal of Operational Research 132, 245–259 (2001)
30. Bauer, P.W., Berger, A.N., Ferrier, G.D., Humphrey, D.B.: Consistency Conditions for Regulatory Analysis of Financial Institutions: A Comparison of Frontier Efficiency Methods. Journal of Economics and Business 50, 85–114 (1998)
31. Roth, A.V., Jackson III, W.E.: Strategic Determinants of Service Quality and Performance: Evidence from the Banking Industry. Management Science 41, 1720–1733 (1995)