

# A Data Envelopment Analysis of the Operational Efficiency of Bank Branches

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We performed a multiperiod data envelopment analysis (DEA) study of the efficiencies of selected branches of a large US bank (which we will call Big Bank) over six consecutive quarters (second quarter of 1992 to the third quarter of 1993). We developed a number of innovative application tools, including budgeting and target-setting modules, within a DEA framework that we subsequently customized for Big Bank. Within the performance-evaluation framework, we developed the ability to identify different potential groupings of branches that supported the multiple user views of the system. We also developed procedures to evaluate trends over time and differences in performance across user-defined aggregations of branches. We paid attention to the interface with the end users and, in particular, developed presentation tools to make the outcomes of the analysis available to managers at different levels of the bank.

Evaluating the performance of bank branches has been a subject of growing interest in recent years. Deregulation, followed by major banking crises and growing global competitive pressures, has

led banking institutions to look for new cost-cutting activities (as evident from the wave of mergers that swept the US banking industry in the early 1990s).

Historically banks measured the effi-

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ciency of their branches separately at the strategic and tactical levels. In strategic settings, they defined branch efficiency by simple operational ratios (for example, transactions per teller) or by financial ratios (for example, deposits to loans or return on assets). At the tactical level, they used industrial-engineering methods to measure time-and-motion efficiency (that is, micromanaging teller operations and optimizing work procedures or queuing systems). Traditionally they measured each of these aspects separately. Today, on the other hand, banks generally realize that simultaneous assessment, incorporating multiple quantitative and qualitative data sources, is necessary to evaluate branch operations. However, banks largely avoided addressing such concerns in an overall efficiency framework because of the complexity of the task.

Some of the difficulties in obtaining overall efficiency measures in banking applications stem from data availability. First, banks' databases are often organized to accommodate traditional accounting procedures and do not lend themselves easily to the combined analysis of marketing, financial, and operational data. Second, competitor banks are not eager to share comparative data. Benchmarking among branches of different banks is virtually impossible in this environment. Finally, although one can obtain some data from central banks or from independent market-research agencies, these data allow, at best, comparisons of the bank's overall position vis-a-vis national or regional averages. In the absence of detailed local trade data for the branch area market, one cannot perform detailed efficiency

evaluations.

Researchers found that data envelopment analysis (DEA) was an appropriate method for confronting these difficulties [Parkan 1987; Sherman and Gold 1985; Vassiloglou and Giokas 1990] because of its modeling flexibility and its ability to address quantitative and qualitative data and discretionary and nondiscretionary inputs. We extended the earlier banking applications and added innovative tools to enhance the managerial value of the analysis.

We used DEA to evaluate the relative efficiencies of selected Big Bank branches. Big Bank is basically a holding company that, over the years, has acquired many regional banks, mainly in the Midwestern states of the United States. Together, these banks operate a network with thousands of branches; Big Bank is among the largest of its kind in the US. Since Big Bank acquired the banks gradually, they differ markedly in management structures and styles. In addition, bank management practices often differ by geographic region to comply with different state banking regulations. For example, at the time of this study, Texas banks could not sell home equity loans, a practice that was legal and common in many other states.

The study was initiated by a headquarters unit whose task was to provide Big Bank management with ongoing evaluation criteria that it could use across individual banks. Prior to the study, headquarters relied on an elaborate reporting system to share data among its banks. Each bank reported quarterly on hundreds of individual measures, which headquarters analyzed, aggregated in various ways,

and edited in a voluminous report.

Representatives of the banks gathered each quarter to listen to highlights of the current report. Senior managers believed that these reports would help individual bank managers to identify successful patterns and subsequently follow them. Since top performance is a basis for individual and group bonuses, managers have the motivation to do just that. However, extracting useful information out of the large quantities of data assembled in these reports proved to be difficult. Only some of the data were reported at the branch level; most measures were aggregated to the bank level. In addition, one often found a unit (a bank or a branch) ranked at the top of the list for one factor and near the bottom with respect to another. Consequently, Big Bank officers felt that they lacked a mechanism to reconcile such conflicting signals and to integrate them into a meaningful measure.

Early in the study, we tested many model formulations, using over 40 data items relevant to the performance of the branches. We analyzed the data both from a general banking perspective and, more specifically, from Big Bank's point of view. After we selected the model formulations for this application, we then devised alternative means of presentation according to the varied needs and interests of the different managers for whom the model was built. We designed graphical presentations to identify sources of inefficiency and point out possible corrective actions. During the development stage of the study, we incorporated innovative analysis tools to address specific needs of Big Bank management.

### Data

The primary steps in constructing a DEA model are selecting decision-making units (DMUs), input and output factors, and the mathematical formulation of the model. The subsequent steps, such as establishing limits on factor weights and grouping the DMUs into meaningful subsets, cannot be taken until the building blocks of the model are defined.

The DMUs in this study were a sample of about 200 Big Bank branches. We chose branches, rather than banks, because our objective was to find ways to improve operations at the branch level. The selected branches were affiliated with four banks (in four major cities), three of which were located in Midwestern states, and the fourth in a Western state. The selected DMUs spanned a wide spectrum of sizes and types of activities. Some were large downtown branches, while others were small units (for example, an airport branch). We soon found that some of the branches were acting as outliers, performing unique activities that other branches did not perform. We eliminated these branches from the sample, leaving us with 182 branches to study.

To identify and isolate potential performance differences among branches that might be attributed to group associations rather than to the branch itself, we categorized the branches by their accumulated loans and deposit accounts, by their geographical locations (in one of four cities), by the type of location, by the number of days their lobbies were open, by the existence of a personal income center, and by the number of ATMs in them (Table 1). These categories became the basis for con-

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Measure	Categories
Total loans	four quartiles
Total deposits	five quintiles
City	four cities
Location	seven location types
Days lobby open	5, 6, 7
Personal income center	yes, no
Number of ATM machines	0, 1, 2, 3+

**Table 1: In this grouping of branches by seven performance measures (categories), the column on the right shows the possible values for each measure. For example, the branches were split into four groups by the total loans measure. Each group contained one fourth of the branches and the order in which branches were assigned to groups was by their size of total loans.**

ducting program evaluations and measuring the nature of the relationships between performance and group membership.

We aggregated branch operations by quarter because the bank used this period in its ordinary reporting and decision-making procedures. Thus, we had six data points for each branch over the 18 months for which we performed our analyses.

Two considerations guided us in selecting the DEA model for this application. First, since Big Bank was in the midst of a growth period, an output-oriented model (focusing on output enhancements) was more appropriate than an input-oriented one (focusing on savings in inputs). Second, since the branches in our sample fell in different size categories, it was important to account for variable scale effects. As a result, we chose the BCC output-oriented model [Banker, Charnes, and Cooper 1984] as the main platform for our analysis.

In applying DEA to banks, analysts have generally adopted one of two perspectives, seeing banks as intermediaries or as providers of financial services. As financial intermediaries, banks' primary function is to borrow funds from deposi-

tors and lend these funds to others for profit [Colwell and Davis 1992]. From this perspective, deposits are "inputs" and loans are "outputs."

As providers of financial services, banks use mainly capital and labor to produce loans, deposits, referrals to auxiliary services, and so forth. In this framework, deposits are included among the "outputs," since they are viewed as part of the services offered [Sherman and Ladino 1995]. We selected a variant of this approach for the Big Bank study.

We chose input and output factors based on our experience in previous DEA studies and on what data were available. The input factors reflected the resources the branches used, while the outputs represented a mix of quantitative and qualitative measures of results Big Bank expected from the branches.

We separated the inputs into two classes: discretionary and nondiscretionary factors. Discretionary inputs, such as teller hours or operating expenses, are those production factors whose values branch managers control directly. Nondiscretionary inputs, such as market size, economic status of the area, and competitive activ-

ity, are factors that influence the activity of the branch but are not under its direct control.

Following corporate-management objectives, the outputs consisted of both short- and long-term measures. The short-term measures were mainly volume indicators (total loans, deposits, and so forth), which show the immediate profit contribution of the branch. The long-term measures were mainly reflections of customer satisfaction and the branch's contributions to the reputation of Big Bank in its region.

We followed established DEA procedures in selecting the factors [Golony and Roll 1989]. We ran a special-purpose front-end statistical program to compute essential statistics on the data. We compared the mean of every parameter with various aggregate measures. We used the coefficient of variation to detect factors with large variance and computed the correlation coefficient between every pair of factors to detect coefficients that were close to  $\pm 1$  (indicating the possibility of eliminating one of the two factors without losing information) or close to zero (suggesting the elimination of factors that might be irrelevant to the "production" process). We ran simple and multiple linear regressions to clarify the overall relations between some of the inputs and outputs. Thus, after several iterations, we obtained a set of factors to use in the data envelopment analyses.

We viewed labor as a major input. Big Bank put its branch employees into three categories: officers (managers and their deputies), nonexempt employees (mainly tellers), and exempt employees (a US term that means that these are salaried employ-

ees who are not covered by the Fair Labor Act and therefore are exempt from limitations on such issues as overtime and work on holidays). The first and third groups were measured by full-time equivalents since, in some cases, a person could be assigned to more than one branch. The average workload was estimated as 10 hours a day for the officers, nine for exempt employees, and eight for nonexempt. Each group dedicates a certain percentage of its time to teller operations (close to a 100 percent for the nonexempt and almost zero percent for the officers) and the rest of the time to all other (nonteller) activities. After some testing, we decided to split the labor inputs into two parts, teller and nonteller operations, and to use the number of days the lobby was open to compute the total number of hours per week for these two inputs.

Next, we considered a number of factors that could describe branch facilities (parking space, number of ATMs, and so forth). The only factor to pass the filtering of the front-end data analysis was the size (in retail square feet).

We did extensive testing with the candidate factors to describe the marketing activities. Here we were limited by both data availability and data quality (for example, it was very difficult to obtain accurate figures on advertising). Consequently, we relied mainly on mail activities, using the ratio of direct marketing to the target population in the area as a measure of mailing expense per customer.

We did not incorporate most of the non-discretionary factors that we tested in the model because of poor data quality, inappropriate aggregation level, or lack of evi-

dence that they affected the performance of the branches. The only factor we found meaningful and conforming with other data sources was the unemployment statistic (whose complement, the employment rate, we actually used).

On the output side, we concluded with four factors, two representing volume indicators (short-term goals) and two measuring long-term commitment by the customers. Of the two volume indicators, loans had four components (direct, indirect, commercial, and equity) and deposits had three (checking, savings, and CDs). We measured the customers' loyalty to the branch by depth of relations (average number of accounts per customer) and satisfaction (based on a quarterly survey the bank runs).

Thus, the basic model formulation contained five inputs and four outputs, with the branches grouped into seven subsets.

### **Preliminary Results**

After we completed the various modeling steps and Big Bank management approved them, we ran the DEA model for all 182 branches in all six quarters. All told, we ran 1,092 linear-programming optimizations to generate the preliminary results. The model collected the results and automatically transferred them to an interactive display software that enabled Big Bank officials to interact with the problem in many different ways (Figures 1–6).

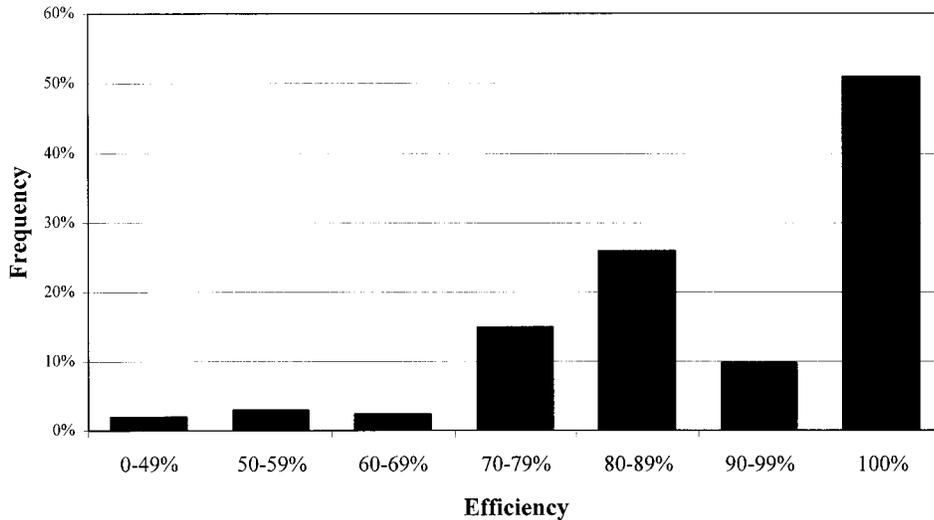
Our results showed that 92 branches were fully efficient in the third quarter of 1993 and only five fell below 70 percent efficiency (Figure 1).

Observing the results for a single period rarely leads to decisions in any real-world application. Management typically seeks

to identify trends over time before taking any action that involves financial risks. An important aspect of the Big Bank study was to group the branches into meaningful subsets with the objective of understanding the performance of each group (Figure 2). For example, we found that branches with large loans were more efficient than branches with small loans and, in particular, the branches holding the largest loan accounts were significantly more efficient than the branches in the other groups at the beginning of the project horizon. But the gap between this group and the other groups has gradually narrowed over the six quarters that we analyzed.

DEA contrasts each inefficient branch with its facet members (other efficient branches whose combined values create a reference point on the frontier of best performance for the inefficient branch) (Figure 3). The weights used for constructing the reference point are applied to all input-output factors, resulting in comparison values that are always smaller than or equal to the actual inputs, and larger than or equal to actual outputs. This does not necessarily mean that all the individual outputs (inputs) of the comparison branches will be above (below) the analyzed branch. As often happens in such comparisons, the deposit values for two out of the five efficient branches are smaller than the one under investigation, two are above it, and one is very close to it. In this way, DEA constructs for each branch its own individual benchmark composed of a specific subset of the efficient branches.

The enormous amount of detail DEA of-



**Figure 1:** This graph, taken from the software implemented at Big Bank, summarizes the efficiency scores for all branches in the third quarter of 1992. About half of the branches (92 out of 182) were efficient in that quarter, while the rest were mostly distributed around the 80–89 percent efficiency range with just five branches exhibiting low efficiencies (69 percent and below). This pattern of efficiency distribution was consistent with many previous DEA implementations in other application areas.

fers at the individual or subgroup levels can cause managers to lose sight of the forest for the trees. To prevent that from happening, we devised aggregations that help Big Bank managers to obtain meaningful statistics at any level that suits their objectives (Figure 4).

**Innovations in the DEA Application**

Our preliminary results followed the conventional DEA framework used in many application areas, in particular, in banking. These results were used to ensure management’s understanding of the methodology and their guidance for its potential uses at Big Bank. With management guidance we then adapted and used some innovative decision support tools in our study.

To allow bank managers to construct what-if scenarios that examined marginal changes in the output profile of a branch,

we used a DEA-based, resource-allocation model that was developed by Golany, Phillips, and Rousseau [1993]. We customized the model to find a (minimal) efficient input combination of existing branches that would meet the target vector of outputs, set by the user, while staying in the vicinity of the branch’s inputs—in particular, its nondiscretionary (ND) inputs. That efficient combination, based on a variant of the additive DEA model [Charnes et al. 1985], served to determine the amount of discretionary (D) resources required to meet the target vector of outputs in the most efficient way. The procedure is based on constructing a dummy branch with the desired outputs and an inefficient input profile. Then, we let DEA “improve” the dummy branch pattern by suggesting an efficient input mix that meets the target outputs (Figure 5).

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The resource-allocation model minimizes the weighted sum of the projected discretionary inputs, where the weights are driven by the input costs, that is, a minimum cost objective. This model is not guaranteed to find a feasible efficient solution for the (larger than original) target output vector. In particular, when  $DMU_0$  is efficient, the target outputs may go beyond the observed efficiency frontier. In these cases, the dummy DMU is modified again to make it inefficient on the output side, as well as the input side, and an extrapolation technique is used to find the required inputs for the target outputs.

When the original  $DMU_0$  is inefficient, the resource allocation model allows the user to enter an "inefficiency reduction"

estimate to scale up the projected discretionary inputs. For example, suppose its first input,  $X_{10}$ , is equal to 100, its efficiency is 80 percent, and the resource level determined for it to achieve desired outputs is 90. We assume that if the DMU will continue to perform as inefficiently as it has done before, it would actually need  $90/0.8 = 112.5$  units of its first input. The inefficiency reduction parameter is a means for the user to introduce external information that estimates how much of the gap between 90 to 112.5 the DMU can close.

The resource-planning procedure can also be applied to an efficient branch (Figure 6).

The bank can employ the same proce-

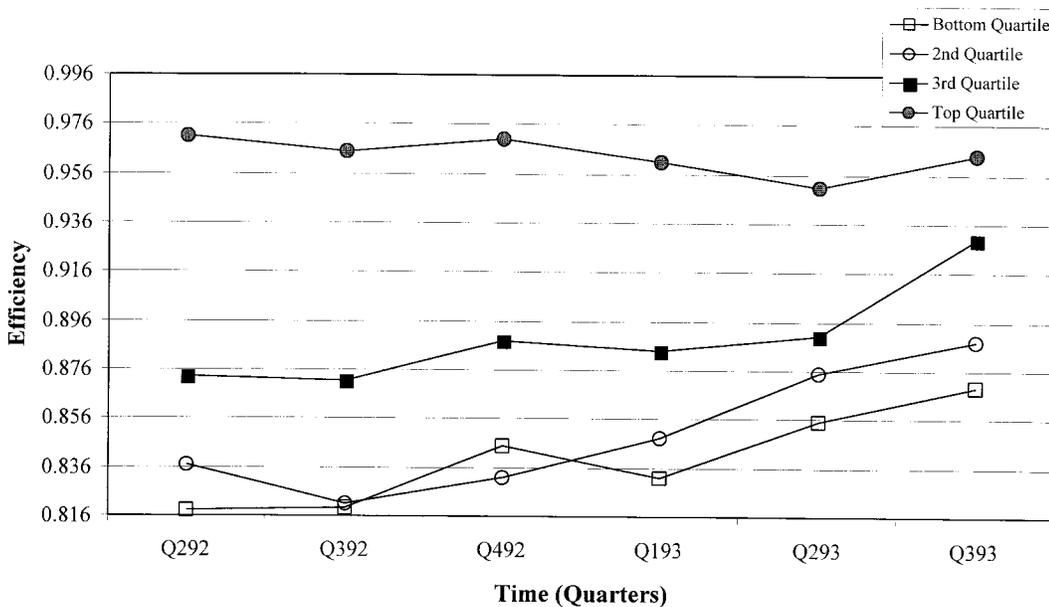


Figure 2: Analysis of the efficiency trends, where the branches were broken down to four quartiles by the size of the total loans output, revealed a positive correlation between size and efficiency. The top quartile (45 branches with the largest loan accounts) were consistently evaluated as nearly efficient with an average score of 0.96, while the bottom quartile exhibited significantly smaller efficient performance. This analysis also showed that the differences among the four groups were rather robust across the six quarters of the analysis.

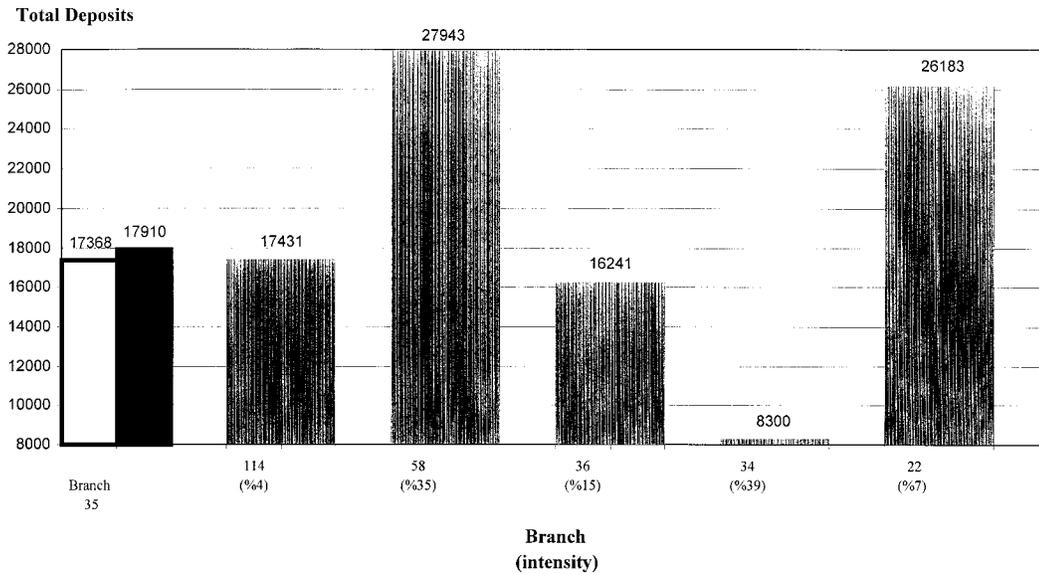


Figure 3: In a comparison of branch 35 to its benchmark branches for total deposits, DEA indicates that it could have increased its deposits from \$17,368,000 to \$17,910,000. The latter value is a (convex) linear combination of total deposits obtained from the five efficient branches graphed on the right of the chart. The actual deposit value for each branch appears on top of the bar, and the intensity weight used to combine it with the other values appears (in parentheses) under the branch label.

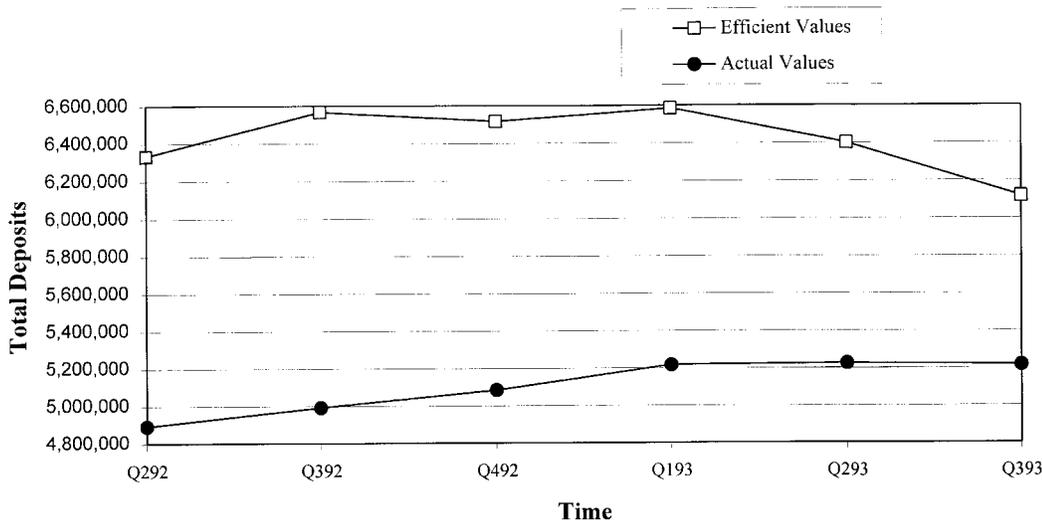
ture in the opposite direction. That is, a manager may set a given level of inputs (including, possibly, the ND inputs) and look for the maximal (efficient) outputs that can be expected from the branch. The inputs set by the manager could be dictated from above (for example, due to budgeting decisions at the corporate level), or they might represent what-if scenarios to help managers determine objective and attainable targets.

In a number of situations, we needed to identify the sources of the operating inefficiency of bank branches. The question was often whether the inefficiencies measured arose from the way operating programs were managed or the nature of the operating program itself. To capture this distinction, we used a decomposition framework

suggested by Byrnes [1985] for distinguishing between managerial and program efficiencies. The latter term refers to the inefficiency levels due to between-program differences; the former term refers to inefficiency levels due to within-program differences.

For example, we found efficiency differences between branches with personal investment centers (PICs) and branches without PICs in one of the cities of our sample. The general premise we investigated was whether these two groups of branches differed in productive efficiency. Thus, we wanted to measure the extent of operating-efficiency differences in these groups and then to identify the source of those differences. In this type of analysis, bank managers have two primary ques-

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**Figure 4:** Analysis of aggregate performance in total deposits shows that the gap between potential and actual values has narrowed during the six quarters by over 30 percent (from 1,600 to 900). Notice that the narrowing effect is only marginally due to improvements in actual performance. Most of the effect is due to sharp drops in the aggregate potential level of total deposits. One conjecture that may explain this phenomenon is that, during the first few quarters, some branches enjoyed particularly favorable conditions that enabled them to achieve relatively large deposits without investing too much in extra resources. These branches then determined the “ceiling” of best performance at a relatively high level. In the latter quarters, these conditions disappeared, and consequently the aggregate level of potential total deposits fell.

tions: To what extent are the observed differences in operating efficiency due to management of the branch, whether PIC or non-PIC? To what extent are the differences due to the existence of the PIC program?

In looking at the average managerial and program efficiency levels for PIC and non-PIC branches in one city during the second quarter of 1992, we found that the PIC branches tended to be, on average, much more efficient than the non-PIC branches (72.4 percent versus 44.9 percent). This difference was due primarily to the program itself (Table 2). The relatively similar managerial efficiency averages for the PIC (79.6 percent) and non-PIC (72.9 percent) groups, coupled with the highly

disparate program averages, suggest that the primary source of operating-efficiency advantage for PIC branches was in the adoption of the PIC program. The significance of these differences in the efficiency decompositions can be determined by means of nonparametric tests, such as the Mann-Whitney or Kruskal-Wallis tests for differences in means [Byrnes 1985]. The focus of these tests is to ask whether or not the samples could have been drawn from a population with the same distribution, regardless of its form [Hartman and Storbeck 1995; Ward et al. 1997]. Thus, one avoids the hazards of making assumptions about the distribution of DEA efficiency scores. For more details as to the organization of these nonparametric tests, see

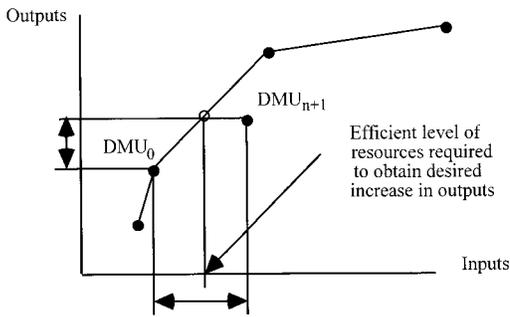


Figure 5: This figure provides an abstract illustration of the construction of a dummy branch ( $DMU_{n+1}$ ) to evaluate the amount of resources that need to be allocated to an efficient  $DMU_0$  to increase its outputs by a specified proportion. The double-arrow line on the left indicates the desired output enhancement and the double-arrow line at the bottom shows the initial inputs expansion in constructing  $DMU_{n+1}$ . When  $DMU_0$  is inefficient, the inputs expansion needed to construct  $DMU$  is naturally smaller than the expansion needed for efficient  $DMUs$ . Similar procedure applies for a desired reduction in outputs.

Brockett and Golany [1995]. Our evaluation, however, did not take into account other financial considerations (such as the

initial cost of setting up the PICs) that might influence management’s assessment of their success.

Beyond questions of statistical significance, this decomposition of operating efficiency into its component parts could have many implications for bank managers interested in reengineering business processes. Allen [1994] has suggested that the banking industry could benefit greatly from the reengineering movement by attempting to disentangle the web of historical cost structures. Allen has pointed out a number of management and infrastructure “levers” that drive bank costs. The former are factors linked with customer, product, and geography; the latter are such structural factors as process, function, physical plant, systems, and “pure” overhead. In their analysis of managerial and program efficiency in a Swedish savings and loan institution, Hartman and Storbeck [1995] drew parallels between Allen’s typology

These Resources Should Produce				These Results			
Resource	Value	Percent Change	Cost	Result	Value	Percent Change	Margin
Teller Labor	93	5.6 %	10.0	Total Loans	6,737	1.0 %	1.00
Non-Teller Labor	88	6.6 %	20.0	Total Deposits	20,097	1.0 %	1.00
Retail Sq. Feet	6,052	2.2 %	3.0	Depth	9.73	0.0 %	0.00
Marketing	8.28	-1.0 %	0.0	Satisfaction	0.50	3.0 %	0.00
Employment Rate	0.95	0.0 %					
Total Resource = \$20,851				Total Result = \$26,834			

Figure 6: The resource planning procedure was applied to an efficient branch (branch 2 in 1993) with desired changes (result targets) of +1 percent in total loans and deposits. The procedure indicated that the branch could use a minimal cost mix of added resources, increasing three inputs (teller labor by 5.6 percent, nonteller labor by 6.6 percent, and square footage by 2.2 percent), and decreasing a fourth input, marketing, by 1.0 percent. The cost and margin parameters in the figure are again masked, but one can get the idea of how these can serve to build the budget for the analyzed branch on one hand, or to estimate total value of expected results on the other.

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Branch Type	Overall	Managerial	Program
All	65.1	77.9	83.0
PIC	72.4	79.6	90.5
Non-PIC	44.9	72.9	62.6

**Table 2: This efficiency decomposition for PIC and non-PIC branches shows that while the managerial efficiency is about the same in the two groups, the program efficiency is dramatically different, causing a large difference in the overall efficiency.**

of “levers” or cost drivers and the distinctions between managerial-program efficiencies in DEA. Specifically, they tried to demonstrate the utility of this distinction in pinpointing the need for managerial versus infrastructure adjustments in operating procedures in branch banks.

For the city whose branches we analyzed, the calculations of program efficiency clearly demonstrate the dominance of the PIC branches over the non-PIC in terms of best practices. But the low levels of managerial efficiency in both programs reveal a great deal of variance in operating efficiencies and consequently the need to adjust managerial procedures.

### Concluding Remarks

Our experience with private-sector applications of management science techniques led us to recognize that the managers at the different levels of Big Bank have different focuses and objectives. Consequently, they require presentations that address the various aspects of the bank’s operations. Accordingly, we devised alternative means of display. We tailored each means of display to the needs of the specific bank management level—branch, regional, or corporate.

A recent article in *Business Week* [Holland and Melcher 1995] is devoted to the rapidly changing nature of bank-branch operations due to unprecedented

leaps in technology. With more and more financial services that are marketed through computer, phone, and facsimile lines, and a continuous increase in the number of customers able and willing to do their banking business through these media, the future of bank branching is unclear. The authors quote Edward E. Crutchfield, CEO of First Union Corp.: “This industry is on its way to eliminating the branch as a delivery system.”

Some of these changes were already present at the time of our Big Bank study. Indeed, additional insights into the operations of the branches would be possible if we were to do such a study now. In particular, with the advance information technologies that are now available at Big Bank (including a recently installed recording system that reports on the number of customers referred by each branch to corporate financial services units), one could expand the evaluation to include the newly emerging areas of operations in the branches.

Future efficiency evaluations of bank branches will have to account for their new roles. We believe that DEA is the right tool to use in this dynamic environment because it can easily be modified to address the changing needs of management. Moreover, the DEA application procedure forces managers to define the way

they view their business—not necessarily a single perspective across different management echelons—and decide on the best ways to measure how well operating units are performing according to prescribed strategy.

#### Acknowledgment

We express our gratitude to Thomas M. Heffner (Columbus, Ohio) and Patrick D. Parker (Austin, Texas) of the Magellan Group, who worked with us on in this project and provided great assistance in writing this paper.

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