



**Corporate Real Estate Analysis:
Evaluating Telecom Branch Efficiency in Greece**

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For Peer Review

Corporate Real Estate Analysis: Evaluating Telecom Branch Efficiency in Greece*

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This paper proposes productivity analysis for evaluating the relative efficiency in corporate real estate usage across decision-making units. Using data from the Greek Telecommunications Organization (GTO), we measure the productivity of 127 branches using the number of employees and the total area covered per building as inputs and the number of telephony access lines as outputs. We apply three non-parametric Data Envelopment Analysis (DEA) models assuming: constant returns to scale (CRS), variable returns to scale (VRS) and slacks-based measures (SBM), respectively. We discuss how the proposed approach can provide real estate managers and analysts a multi informational tool that allows the quantification of targets and may serve as a guide tool for the efficient employment of real estate assets.

Keywords: Real Estate, Productivity Analysis, Data Envelopment Analysis (DEA)

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This paper proposes productivity analysis for evaluating the relative efficiency in corporate real estate usage across decision-making units. Using data from the Greek Telecommunications Organization (GTO), we measure the productivity of 127 branches using the number of employees and the total area covered per building as inputs and the number of telephony access lines as outputs. We apply three non-parametric Data Envelopment Analysis (DEA) models assuming: constant returns to scale (CRS), variable returns to scale (VRS) and slacks-based measures (SBM), respectively. We discuss how the proposed approach can provide real estate managers and analysts a multi informational tool that allows the quantification of targets and may serve as a guide tool for the efficient employment of real estate assets.

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1. INTRODUCTION

Real estate is one of the major factors of production, cost and profit in most industries and may provide significant competitive advantages (Roulac, 2001). Notwithstanding, a number of studies suggest that firms do not generally exploit their real estate assets in the most efficient manner (eg., Zeckhauser and Silverman, 1983; Veale, 1989). Although some approaches have been developed for measuring corporate real estate effectiveness (see, for example, Pittman and Parker, 1989; Apgar, 1995), most real estate managers rely on benchmarking via *ad hoc* comparative ratio analysis for evaluating real estate efficiency within the firm and against competition.¹ However, there is little consensus in the academic and professional literature as to what measures are correct and why (eg., see Duckworth, 1993; Noha, 1993; Nourse, 1994). Roulac (2001) summarizes the concerns in the industry and literature by saying that: “*a conceptual linear programming approach is necessary to implement multiple complementary and competing strategic objectives in corporate property economics functions*”. The present paper attempts to address these concerns.

This paper proposes the application of productivity analysis in assessing how efficiently real estate assets are used within the units of a firm or across competing firms. Productivity analysis is broad methodological framework which can be used to distinguish two types of efficiency: technical efficiency, which determines whether a production unit (DMU) achieves maximum output using the given factors of production, and, allocative efficiency, which determines whether the factors of production are used in proportion that ensure maximum output at given market prices (for review of this literature see Coelli et al., 2005). While a variety of

¹ A number of professional organizations, such as the Industrial Development Research Council (IDRC), LaSalle Partners, Royal Institute of Chartered Surveyors (RICS), collect and publish “benchmark” measures of corporate real estate performance. These measures are mainly ad hoc ratios and are reported across countries and industries.

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3 approaches have been developed in order to measure inefficiency empirically, this paper adopts
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5 Data Envelopment Analysis (DEA), a popularly used family of nonparametric techniques (for a
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7 review see Ray, 2004).
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10 The remainder of the paper is organized as following. The next section makes a brief
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12 introduction to the methodology. Section 3 describes the data, the empirical application and the
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14 results. The final section summarizes our major findings and concludes the paper.
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18 *Figure 1. Technical, Allocative, Overall Efficiency and Congestion.*
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21 22 23 **2. METHODOLOGY**

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27 In this paper we adopt the well-established methodological framework of technical efficiency
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29 analysis as defined by Farrell (1957): a DMU is said to be technically efficient if a reduction in
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31 any input requires an increase in the other input or decrease of output. In order to introduce the
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33 terminology and demonstrate how measures of DEA are applied we provide an illustrative
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35 example with five DMUs denoted by A, B, C, D and E. The empirically derived efficient frontier
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37 consists of the convex combination of A, B, C and D. Figure 1 shows the four efficient DMUs, A,
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39 B, C and D; the solid line segment connecting points ABCD constitutes an isoquant or level line
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41 that represents the different amounts of two inputs (x_1, x_2) which can be used to produce the same
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43 amount. This line represents the efficient frontier of the production possibility set. By reason of
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45 Q, which exists on the line between A and B, E is inefficient. This is because Q uses less input to
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47 produce the same output as the efficient DMUs. The dashed line that intersects the isoquant at B
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49 is a minimum cost line since the pairs (x_1, x_2) on this line yield the same total cost when unit costs
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51 are c_1 and c_2 , respectively. However, shifting this dashed line upwards in parallel fashion until it
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53 reaches a point of intersection with E would increase cost. In fact, point B is the minimum total
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55 cost needed to produce the specified output. This is because any parallel shift downwards below
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4 B would yield a line that fails to intersect the production possibility set. The ratio $0 \leq \frac{OQ}{OE} \leq 1$
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7 is said to provide a radial measure of technical efficiency (TE) with $0 \leq 1 - (\frac{OQ}{OE}) \leq 1$ yielding
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10 a measure of technical inefficiency. Technical inefficiency measures the proportion with which E
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12 could be replaced to maintain the same quantity of output. Now, consider the point P at the
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14 intersection of this cost line through B with the ray from the origin to E. The ratio $0 \leq \frac{OP}{OQ} \leq 1$
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17 is referred to as price efficiency or allocative efficiency (AE). The corresponding measure
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19
20 $1 - \frac{OP}{OQ}$ represents allocative inefficiency and denotes a possible reduction in cost by using
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22 appropriate input mixes. It provides a measure of the extent to which the technical efficiency
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24 point, Q, falls short of achieving minimal cost because of failure to make the substitutions, or
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26 reallocations, involved in moving from Q to B along the efficiency frontier.
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30 We can also obtain a radial measure of overall efficiency (OEF) from the ratio
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32 $0 \leq \frac{OP}{OE} \leq 1$. Since $OEF = \frac{OP}{OE} = (\frac{OQ}{OE}) \cdot (\frac{OP}{OQ}) = TE \cdot AE$, we can express overall
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34 efficiency as the product of “allocative” and ‘technical efficiency’, ie., $OEF = TE \cdot AE$ (see
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36 Sengupta , 2002). The measure $(1 - \frac{OP}{OE})$ represents overall inefficiency and denotes the possible
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38 reduction in cost due to changing from B (observed input quantities) to P (cost minimizing input
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40 quantities). Point D is efficient only when we allow for congestion.² However, it will be
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42 inefficient under the standard assumption of no backward bending segment. The isoquant shown
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44 by the dashed line from point C represents the non-congested benchmark. The ratio $\frac{OD'}{OD}$
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47 represents the reduction in input x_1 required in order to reach the uncongested frontier from the
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49 congested frontier; that is we calculate the reduction that is achieved if congestion is eliminated.
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57 ² Congestion refers to the situation whereby increasing (decreasing) one or more inputs decreases
58 (increases) some outputs without improving (worsening) other inputs or outputs.
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The present paper adopts the DEA approach in evaluating efficiency across DMUs. DEA refers to a mathematical programming family of techniques which are flexible and have the advantage of making very few assumptions (for a description see Cooper, Seiford and Tone, 2000). The method, developed by Charnes et al. (1978), has been widely used at numerous applications measuring the performance of decision-making units (DMU) in the public and private sector (e.g., see Boussofiane *et al.*, 1997; Giuffrida and Gravelle, 2001, *inter alia*). DEA is used so widely because of its simplicity and the useful interpretation of results it yields even with limited data sets. The determination of the efficiency score of the a DMU in a sample of n DMUs in the Constant Returns to Scale (CRS) model is equivalent to the optimization of the following linear programming problem (Charnes et al., 1978; hereafter CCR):

$$\begin{aligned}
 \max_u z_0 &= \sum_{r=1}^s u_r y_{r0} \\
 \text{subject to} \\
 \sum_{r=1}^s u_r y_{rj} - \sum_{i=1}^m v_i x_{ij} &\leq 0, j = 1, 2, \dots, n \\
 \sum_{i=1}^m v_i x_{i0} &= 1 \\
 u_r &\geq 0, r = 1, 2, \dots, s \\
 v_i &\geq 0, i = 1, 2, \dots, m
 \end{aligned} \tag{1}$$

For the above linear programming problem, the dual can be written for a given DMU as:

$$\begin{aligned}
 \min_{\lambda} z_0 &= \Theta_0 \\
 \text{subject to} \\
 \sum_{j=1}^n \lambda_j y_{rj} &\geq y_{r0}, r = 1, 2, \dots, s
 \end{aligned}$$

$$\Theta_0 x_{io} - \sum_{j=1}^n \lambda_j x_{ij} \geq 0, i = 1, 2, \dots, m$$

$$\lambda_j \geq 0, j = 1, 2, \dots, n \quad (2)$$

Θ_0^* is the efficiency score and λ a $n \times 1$ vector of constants. Assuming that the DMU uses m inputs and s outputs, X and Y represent $m \times n$ input and $s \times n$ output matrices, respectively. The x_{ij} represents the input of the i -th type of the j -th DMU and y_{rj} the observed amount of output of the r -th type for the j -th DMU. A DMU is said to be efficient if technical efficiency is equal to one. A technical efficiency score less than one indicates the extent by which a DMU should reduce inputs while maintaining the same output in order to produce the output of a technically efficient DMU.

To determine efficiency measures under the Variable Returns to Scale (VRS) model (see Banker et al., 1984; hereafter BCC), a further convexity constraint $\sum_{j=1}^n \lambda_j = 1$ has to be considered. The input-oriented BCC model for a DMU can be written formally as:

$$\min_{\lambda} z_0 = \Theta_0$$

subject to

$$\sum_{j=1}^n \lambda_j y_{rj} \geq y_{r0}, r = 1, 2, \dots, s$$

$$\Theta_0 x_{io} - \sum_{j=1}^n \lambda_j x_{ij} \geq 0, i = 1, 2, \dots, m$$

$$\sum_{j=1}^n \lambda_j = 1$$

$$\lambda_j \geq 0, j = 1, 2, \dots, n \quad (3)$$

Running the above model for each DMU, the BCC-efficiency scores are obtained. The model eliminates the scale part of the efficiency from the analysis. It is an interesting subject to investigate the sources of inefficiency that a DMU might have. The CCR approach suggests that DMUs are flexible to adjust their size to the optimal firm size. On the other hand, the BCC method is less restrictive because it compares the productivity of companies only within similar sample sizes. The comparison between the two approaches also provides some information about the underlying technology: if the results of the CCR and the BCC approaches are similar, then returns to scale do not play an important role in the process.

The CCR model score is called global technical efficiency because it is postulated that the radial expansion and reduction of all observed DMUs and their nonnegative combinations are possible. A DMU is said to display total technical efficiency if it produces on the best practice observed boundary of the production possibility set, i.e. maximizes output with given inputs and after having chosen technology. The BCC scores are called local pure technical efficiency because the model assumes the convex combinations of the observed DMUs as the production possibility set. Scale efficiency measure can be calculated by dividing the total technical efficiency by pure technical efficiency. Using these concepts, the total technical efficiency can be further decomposed into pure technical efficiency and scale efficiency (Cooper et al., 2000). The following relationship demonstrates the decomposition of Global Technical Efficiency (TE):

$$\text{Technical efficiency} = (\text{Pure Technical efficiency}) \times (\text{Scale Efficiency})$$

Generally speaking, for each DMU the CCR model efficiency score will not exceed the BCC efficiency score. An efficiency score obtained using the CCR-model comprises both scale efficiency and pure technical efficiency. In a case where a DMU is found to be inefficient, one

can decompose this total inefficiency to see in what degree this due to scale inefficiency or technical inefficiency. The efficiency scale can be defined as:

$$SE = \frac{\theta_{CCR}^*}{\theta_{BCC}^*}$$

where the θ_{CCR}^* , and θ_{BCC}^* are the CCR and BCC scores, respectively. SE cannot exceed one, if it assumes a value of 1, the DMU is efficient both under CCR and BCC. If SE is less than 1 then the DMU is not scale efficient.

The above-described approach does not allow identifying whether a DMU operates under increasing returns to scale (IRS) or decreasing returns to scale (DRS). This problem can be solved using the non-increasing returns to scale (NIRS) expression of DEA by setting the constraint

$\sum_{j=1}^n \lambda_j \leq 1$ in (3). On the one hand, if $\frac{TE_{CCR}}{TE_{NIRS}} = 1$, the DMU operates under IRS and it is scale

inefficient since it has the potential to achieve bigger output. On the other hand, if $\frac{TE_{CCR}}{TE_{NIRS}} < 1$,

the DMU operates under DRS and inefficiency is due to excess output.

Cooper et al. (2000) introduced a non - radial measure of efficiency called SBM (slacks-based measure of efficiency). The input orientation of the SMB model is equivalent to the optimization of the following equation considering five conditions:

$$\min p_{in} = 1 - \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{io}}$$

subject to

$$\begin{aligned}
 x_0 &= X\lambda + s^- \\
 y_0 &= Y\lambda - s^+ \\
 \lambda &\geq 0, s^- \geq 0, s^+ \geq 0
 \end{aligned}
 \tag{4}$$

s^- is the input excesses of inputs and s^+ is the output shortfalls.

Based on the SBM efficiency score, Cooper et al (2000) defines the Mix efficiency score by $MIX = \frac{p_{in}^*}{\theta_{CCR}^*}$. This definition drives to the decomposition of the non-radial technical efficiency into MIX, pure technical efficiency and scale efficiency.

$$p_{in}^* = MIX \cdot PTE \times SE \tag{5}$$

This decomposition contributes to interpret sources of inefficiencies for each non-radial inefficient DMU. A more comprehensive decomposition of cost efficiency considers the input congestion as a piece of the decomposition of the cost inefficiency into technical inefficiencies, which is non-price related and allocative inefficiency, which is price related (Färe and Grosskopf, 2000). Technical efficiency requires pure technical efficiency to be computed by relaxing the strong input disposability restriction (Byrnes et al., 1984) to allow for an input congestion component. (Junoy, 2000). Then, the Technical efficiency (TE) is defined as the product of the scale efficiency, input congestion, and pure technical efficiency components in the condition of weak disposal (Färe et al., 1994):

$$TE(x,y) = SE(x,y) \times C(x,y) \times PTE(x,y) \tag{6}$$

The theoretical discussion identifies some shortcoming of procedures for measuring congestion see, for example Cooper et al (2001), and Cherchye et al. (2001). The work of Brockett et al.

(1998) improves upon the work of Färe et al. (1994) Nonetheless, the Färe's et al. (1994) approach is still useful if one's aim to assess the impact of congestion on the overall technical efficiency. In the recent paper, Färe and Grosskopf (2000) discuss the connection between slacks and congestion. We note, however, that precise measurement of congestion is not yet conclusive.

In (3), we measure the efficiency of a specific DMU₀ (Charnes et al.,1978) The model in (3) confronts to the condition of strong disposal. If we replace the first m inequalities in (3) by equations the model exhibits weak (input) disposal so there is no possibility of positive inputs slacks that may have to be disposed of:

$$\begin{aligned}
 \beta^* &= \min \beta \\
 &\text{subject to} \\
 &\sum_{j=1}^n \lambda_j x_{ij} = \beta x_{i0}, i = 1, 2, \dots, m \\
 &\sum_{j=1}^n \lambda_j y_{rj} \geq y_{r0}, r = 1, 2, \dots, s \\
 &\sum_{j=1}^n \lambda_j = 1 \\
 &\lambda_j \geq 0, j = 1, \dots, n
 \end{aligned} \tag{9}$$

The input congestion measure is then defined as the following ratio:

$$0 \leq C(\theta^*, \beta^*) = \frac{\theta^*}{\beta^*} \leq 1 \tag{10}$$

if and only if $C(\theta^*, \beta^*) < 1$ the congestion is presence.

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3 In the manner described above, DEA allows the partition technical efficiency in pure technical
4 efficiency, congestion, and scale efficiency and investigate the different types of inefficiency
5 across DMUs. The analysis can be done assuming constant returns to scale (CRS) or variable
6 returns to scale (VRS) approach. In addition to these two radial measures of efficiency, it is
7 possible to adopt a non-radial slacks-based measure of efficiency (SBM) in the input orientation.
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9 The decomposition of the non-radial technical efficiency can contribute in interpreting the
10 sources of inefficiencies (see Cooper et al., 2000). In this paper we apply the CRS and VRS
11 model for the calculation of technical efficiency using the CCR approach of Charnes et al. (1978)
12 and the BCC approach of Banker et al. (1984), respectively. Moreover, we apply a non-radial
13 slacks-based measure of efficiency (SBM) in the input orientation which allows us to interpret the
14 sources of inefficiencies (see Cooper et al., 2000).
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29 *Table 1. Distribution of DEA radial measure scores*
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33 **3. EVALUATING TELECOM BRANCH RELATIVE PERFORMANCE**

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38 In the empirical application we evaluate the technical efficiency of the Greek
39 Telecommunications Organization (GTO) DMUs with respect to real estate usage. More
40 specifically, we apply the input oriented DEA, as we are interested in examining the efficient
41 usage of the real estate input. The data set used corresponds to year 2002 for each one of the 127
42 branches of GTO spread over the 52 municipalities of Greece. The output variable was set as the
43 number of fixed telephony access lines. Although traffic volumes or revenues could also be used
44 as outputs, such data were not available for this study. The number of access lines has the
45 advantage of providing an exact figure of the installed client base irrespective of the frequency of
46 usage. Using traffic volumes or revenues as outputs could produce biased results in our
47 application. This is because of the fact that for the same level of inputs, branches in more affluent
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3 regions, which correspond to clients which make heavier usage of telecommunication services,
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5 will unfairly appear to be more efficient than branches operating in poorer regions. Since Greece
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7 has a wide variation of living standards and economic activity across rural and urban areas, large
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9 differences in traffic volume per customer between branches are to be expected. Regulatory
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11 constraints mean that the GTO is obliged to provide telecommunication services to all regions
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13 irrespective of the variations in profitability. This means that for the case of Greece and the
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15 purposes of this study telephony access lines constitute a more appropriate measure of output. As
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17 input variables we used the number of employees and the total area in m^2 covered by each branch.
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19 These are the two main cost centers for each branch. Although capital expenses could also be
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21 included as an input variable, these cannot be easily allocated to each branch. Moreover, the
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23 nature and homogeneity of the technology within the GTO means that it is unlikely that variations
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25 in capital expenses can lead to significant relative differences in efficiency. In any case, such data
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27 were not available. The number of employees includes all technical, administrative and support
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29 personnel. The total area includes all types of real estate used: offices, technical support and
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31 commercial. It is reasonable to assume that the GTO can adjust the levels of the two inputs in use
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33 and hence aims to achieve the maximum potential decrease in inputs while remaining in the
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35 production possibility set. It is also reasonable to assume that output is fixed in a market with the
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37 obligation to serve all customers in a predefined region that demand a telephone line. The number
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39 of access lines for 2002 totaled to just under 3 million, while the number of employees and the
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41 corporate real estate area amounted to about 8,400 and 278,000 m^2 , respectively. Finally, it must
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43 be noted that all the data used in this study was provided by the GTO administration.
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Figure 2: DEA analysis with CRS

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55 The DEA models discussed in the previous section were applied in order to compute relative
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57 measures of technical (TE), pure technical (PTE), scale (SE) and congestion (C) efficiencies,
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3 respectively. As shown in Table 1, the average efficiency for the CCR model is just under 40%
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5 with three branches on the efficiency frontier and only five branches with efficiency above 90%
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7 (see also Figure 2). That means that the average branch, if producing its output on the efficient
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9 instead of at its current (virtual) location, would have needed only 38.36% of the inputs currently
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11 being used. In the terms of average inefficiency, it would have needed 160.6% more inputs to
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13 produce the same outputs as an efficient branch. Units would need to lower inputs by 61.64% if
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15 all were operating on the production efficiency frontier. Pure technical inefficiency scores show
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17 a lower level of inefficiency, the average being 34.87%. Average scale inefficiency is 40.58%
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19 while congestion efficiency is 4.5%. With respect to technical efficiency, 2.4% of the branches
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21 are operating on the frontier. The average efficiency score for non-frontier branches is 36.8%,
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23 implying that non-efficient branches use, on average, 171.7 % more inputs per unit of output than
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25 efficient branches do. According to the pure technical efficiency criterion, 13 of the branches
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27 (10.2%) operate efficiently, with an average efficiency score of 61.1 % for non-frontier branches.
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29 This implies that non-efficient units use, on average, 63.6 % more inputs per unit of output than
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31 efficiency units do. The distribution of all scores is summarized in Table 1.
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Table 2. *Distribution of technical efficiency scores of the branches grouped by area occupied*

Table 2 gives the average technical efficiency score for branches grouped by the area they cover. The results according to both CCR and BCC suggest that branches occupying less (more) space are more (less) efficient. Branches occupying less than 2,000 m² appear to be the most efficient with an average score assuming constant (variable) returns to scale of about 41% (79%). As shown in Figure 3, there is a weak negative relationship between

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3 the branch surface and its efficiency score. The Pearson correlation coefficient (correl) between
4 these two variables is estimated at -15.4% which is marginally significant at the 10% level with
5 the relevant two-tailed t-statistic equal to -1.74. Branches with scores between 15-25 % present a
6 closing up at 1000 m². The best performing braches occupy surface less than 2,000 m². As can be
7 seen in Figure 4, there is also a negative correlation between the number of personnel of branches
8 and its efficiency score. The relevant correlation coefficient is estimated at -27.4% which is
9 significant below the 1% level.
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19 *Figure 3: Correlation between the branch surface and its efficiency score*

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21 *Figure 4: Correlation between the number of personnel in branch and its efficiency score*

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23 *Figure 5: DEA analysis with VRS*

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27 *Figure 6: Differences in efficiency scores between VRS and CRS model*

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32 If one uses the VRS model, the efficiency scores rise significantly (see Figure 5) with 13 out of
33 the 127 branches on the frontier (100% efficiency) and an average efficiency of 65.13%. This can
34 be explained by the fact that now branches of similar size are compared with each other and not
35 with the best ones of the whole sample. Figure 6 depicts the differences in efficiency scores
36 between the VRS and the CCR model. It appears that the optimal size of branches, i.e. the one
37 where the VRS and CRS efficiency scores converge, is in the beginning which corresponds to the
38 region of Athens. It is also suggests that many branches do not have an optimal size and may gain
39 in efficiency by merging. Under the constant return to scale (CRS) assumption, wide variations
40 with respect to technical efficiency are found between branches. Only three branches were found
41 to be efficient and the average efficiency of the network was 38.36%. Under the pure technical
42 efficiency (VRS), i.e., allowing for variable returns to scale, a different situation emerges with the
43 number of efficient branches increasing. The returns to scale properties of a DMU are now
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determined by the shape of the VRS frontier. If the efficiency distributions obtained using the CRS and VRS models are similar scale inefficiency is nonexistent and branch activity exhibits VRS.

Figures 7 and 8 depict the relationship between the efficiency score differences following the two approaches, and, the surface of branches and the number of employees, respectively. It can be inferred that branches with surface between 1,000 m² to 2,000 m² and with employees between 1 and 70 are of optimal size. There is a closing up when the number of employees reach 50 and the branch surface is 2000 m². As can be seen in Figures 4 and 8, the pure technical efficiency improvements should be primarily sought on branches with a number of employees between 1 and 70. However, after achieving pure technical efficiency, the smaller branches will still exhibit significant scale inefficiencies, i.e., difference in efficiency between CRS and VRS. This indicates that after achieving pure technical efficiency, the resulting scale size of branches does not allow the maximization of productivity due to the inherent returns to scale properties of branches' activities. Similar conclusions can be drawn with respect to the second input concerning the area occupied by each branch. The pure technical efficiency improvements should be primary sought in branches occupying an area less than 2000 m², although branches will still exhibit significant scale inefficiencies (see Figure 7).

Figure 7: Size evaluation of branches over surface

Figure 8: Size evaluation of branches over number of personnel

In the input oriented DEA approach, input slacks would be associated with the assumption of strong or weak disposability of inputs which permits zero marginal productivity of inputs and

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3 hence extensions of the relevant isoquants to form horizontal or vertical facets. In this case, units
4 which are deemed to be radial efficient, that is no further proportional reductions in inputs is
5 possible without sacrificing output, may nevertheless be able to implement further reductions in
6 some inputs. Such additional potential input reductions are typically referred to as non-radial
7 input slacks, in contrast to the radial slacks associated with DEA inefficiency, i.e., radial
8 deviations from the efficient frontier.
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12 Table 3 summarizes the output of the slack variable analysis. The results suggest that if it
13 were possible for the inefficient branches to perform like the best practicing one's savings of
14 about 61% (34%) in the total surface and 89% (58%) in the number of personnel would be
15 possible according to the CRS (VRS) approach. At the same time, potentially increased outputs
16 can be observed with an average increment of 635 lines per branch. Moreover, all the branches
17 show zero input slack in the total area variable while most of them show non-zero slack in the
18 personnel variable. This means that most branches are mix inefficient since the reduction needed
19 to bring them to the frontier changes the input proportions. However, 28 inefficient branches
20 operate without altering the mix (proportions) they utilized. The average value of slacks is 20
21 units showing the further reduction in the number of personnel over the reduction determined by
22 the efficiency score.
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Table 3: *Slack variable analysis*

Table 4: *Decomposition of non-radial SBM Technical Efficiency for the most efficient
branches*

We also decomposed the non-radial SBM scores of the most efficient branches and the results are given in Table 4. It can be observed that, for example, for DMU No 21, the low SBM (76.3%) is caused by SE (79.1%). For DMU No 12, the SBM (61.8%) can be mainly attributed to the SE (76.5%) and to MIX (85.7%). Although DMU No 12 is efficient with respect to VRS (93.9%), its low SE (76.5%) and SBM (61.6%), force it to be inefficient overall. The average result of non-radial slacks based model confirms the low efficiency of the 127 branches. Congestion was also present among the branches with 40 units operating without congestion while 72 units showed a congestion score of around 90%. The average price was 95%, that is on average 5% of the inputs could be reduced to eliminate the congestion.

Table 5: Returns to scale analysis

Turning to the analysis of returns to scale (see Table 5), as identified by the input oriented CCR, BCC and NIRS model, three branches from 127 showed constant returns to scale, ninety branches increasing returns to scale (IRS) and 44 decreasing returns to scale, respectively. Interestingly, 90 branches have a possibility to improve their efficiency by scaling up their activities. This could be accomplished by, for example, merging low ranked branches into one branch. The returns to scale characteristics of the projected activity of branches can be identified on the basis of the reference set of branches. For example, the DMU No 127 reference set is composed by of 90, 31 and 23, all of them belonging to IRS. This means that the projected activity of the branch 127 belongs to IRS.

Finally, we also examined the robustness of the efficient branches. For an inefficient DMU_o, the positive values of λ determines the set of dominating units (reference set) placed in the border of efficiency against the unit that is evaluated. The magnitude of λ defines if DMU_o has more similarity to one from the other efficient DMUs. To discriminate between relatively efficient branches, we count the number of efficient branches that appeared in the reference sets

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3 of inefficient branches. This number indicates the robustness of the efficient branches. Indeed, we
4
5 found that DMU₁₉, DMU₆₅, DMU₇₂, and DMU₉₀ appear more than 35 times in the reference sets
6
7 of inefficient DMUs. On the other hand, five DMUs appear less than two times in any
8
9 comparison group of inefficient branches.
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11 12 13 14 **4. CONCLUSIONS**

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16 In this paper we propose productivity analysis to evaluate the efficiency in the
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18 exploitation of corporate real estate assets. This approach provides an objective and consistent
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20 way of assessment compared to ad hoc ratio measures which are largely subjective and atheoretic.
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22 Productivity analysis produces a wealth of empirical results which can be used by managers as a
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24 multi-informative framework to quantify targets and serves as a guide tool for the efficient
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26 employment of real estate assets. In an empirical application, we applied four popular DEA
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28 models (CRS, VRS, SBM, and NIRS) to study radial and non-radial measures of efficiency for
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30 127 branches of the Greek Telecommunications Organization. We used data for 2002 with the
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32 number of fixed telephony access lines as an output variable and the number of employees and
33
34 the total area in m² covered by each branch as the two input variables. The results suggest that
35
36 there is significant potential for efficiency improvements in the GTO. More specifically, we
37
38 found significant elements of technical inefficiency with respect to the employment of real estate
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40 in the production process. The comparison of mean efficiency of CCR and VRS models showed
41
42 that a significant difference is due to the scale inefficiency of branches. The analysis identified
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44 scale inefficiency as the main reason of overall inefficiency. In a nutshell, we found that branches
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46 operate in wrong scale. The correlation between branch surface to the difference in efficiency
47
48 scores between the VRS and CRS approach suggests that the branches with size from 1,000 to
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50 3,000 m² are in the region of the optimal scale. We found that there is a significant waste of
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52 branch surface (34.82%) indicating the need for strategic and technical allocation of the real
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3 estate portfolio. The analysis of returns to scale (80%, Increasing Returns to Scale) indicates the
4 possibility of improving the overall efficiency by merging low efficient branches into one branch.
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8 Additional sources of inefficiency can be recognized in the framework of a cost
9 efficiency analysis. The analysis of allocative efficiency, a basic component of cost efficiency, is
10 based on actual market prices for inputs and outputs and may produce a different picture.
11
12 Although productivity analysis is very useful in analyzing production unit efficiency without the
13 need to impose a pre-defined functional form for production, care must be taken to analyze the
14 results in conjunction with the inputs and outputs used. Future research will focus on providing a
15 more complete analysis by attributing not only the production performance but also the cost
16 performance and additional production mix variables.
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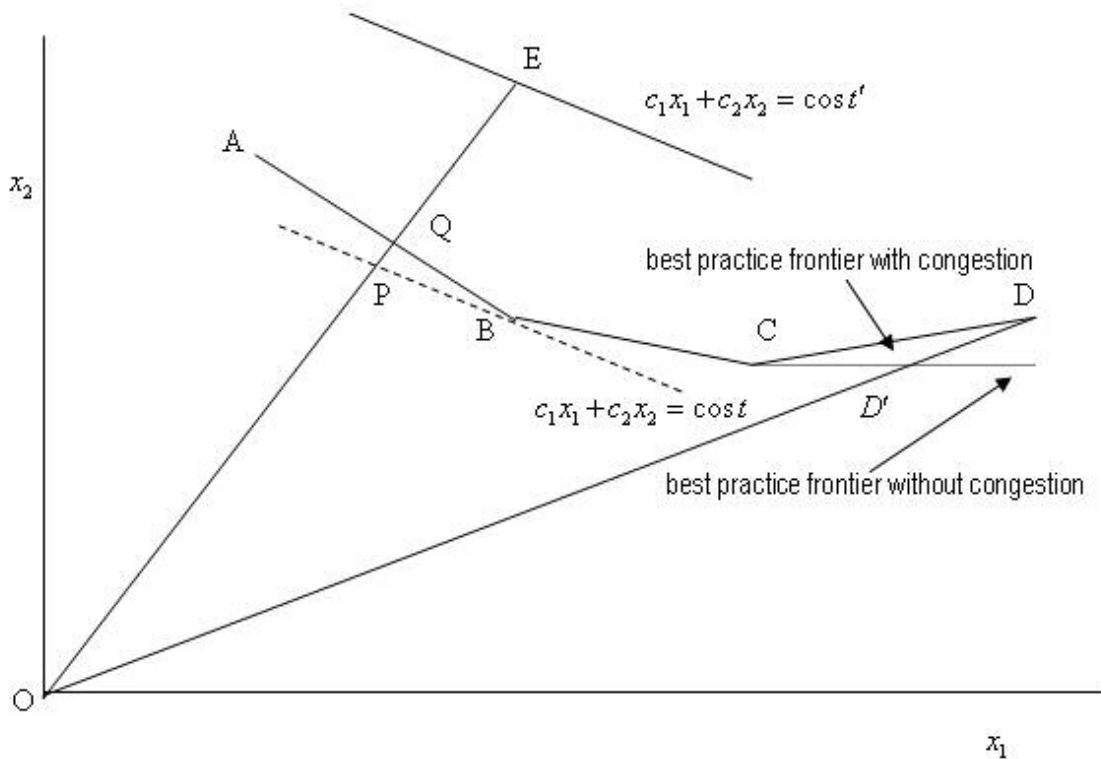


Figure 1: Technical, Allocative, Overall Efficiency and Congestion.

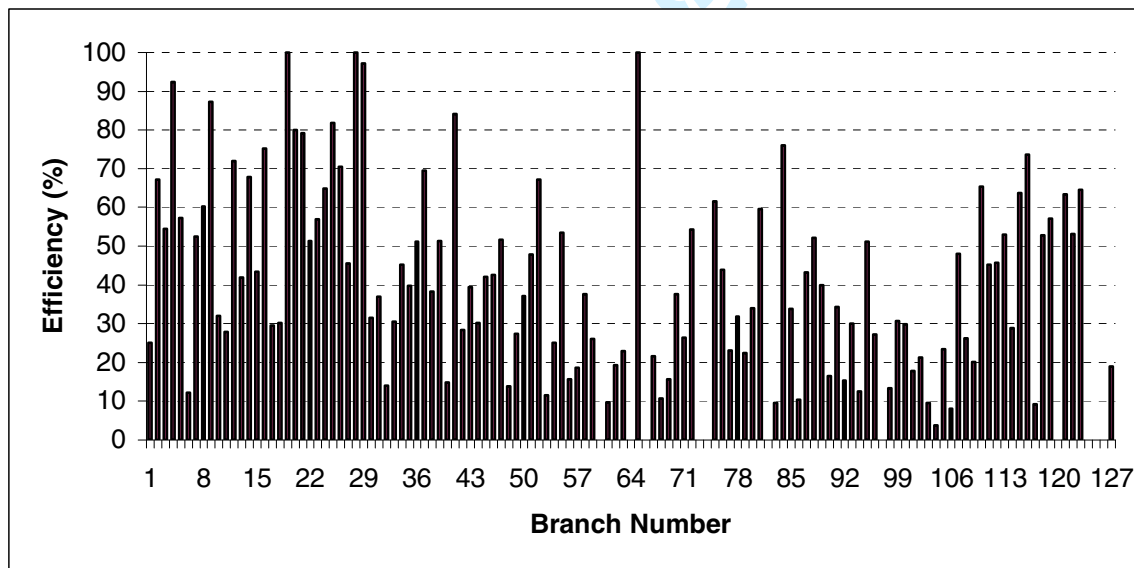


Figure 2: DEA analysis with CRS

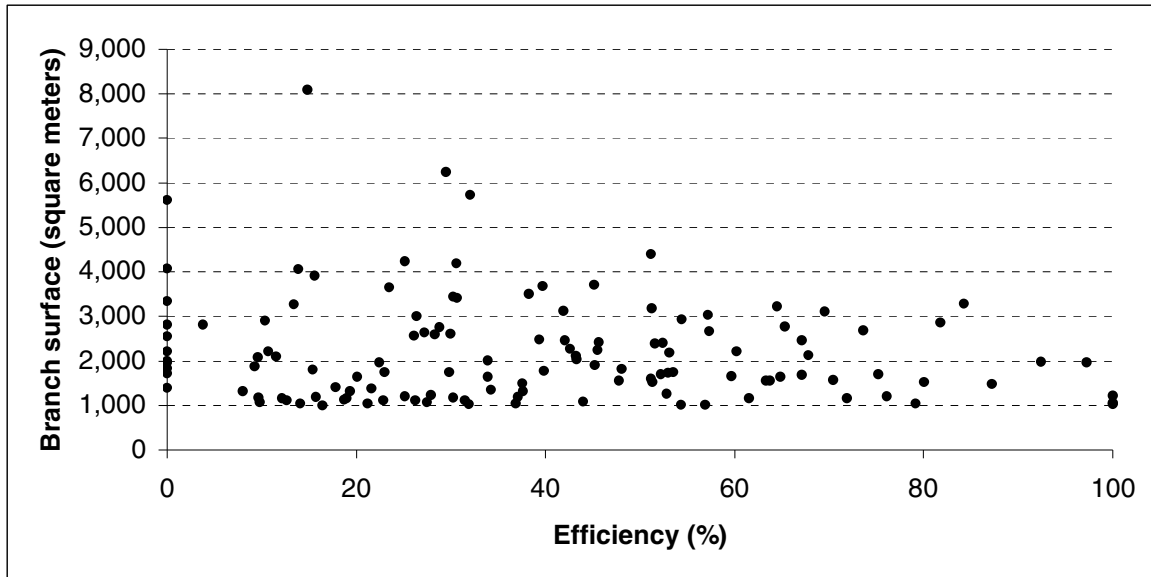


Figure 3: Correlation between the branch surface and its efficiency score

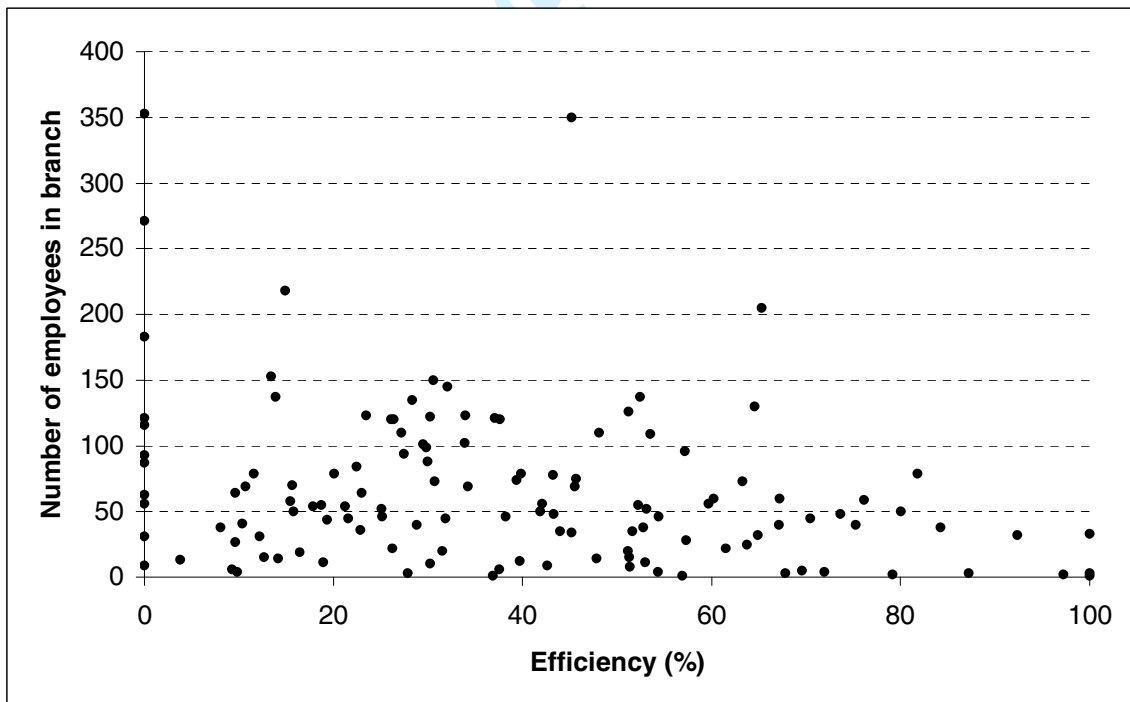


Figure 4: Correlation between the number of personnel in branch and its efficiency score

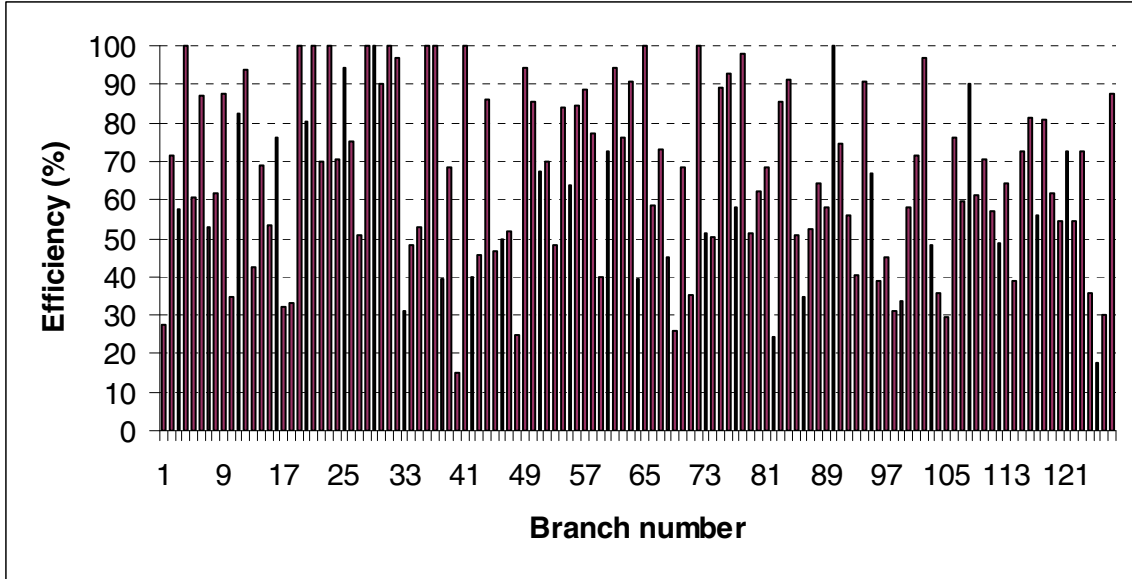


Figure 5: DEA analysis with VRS

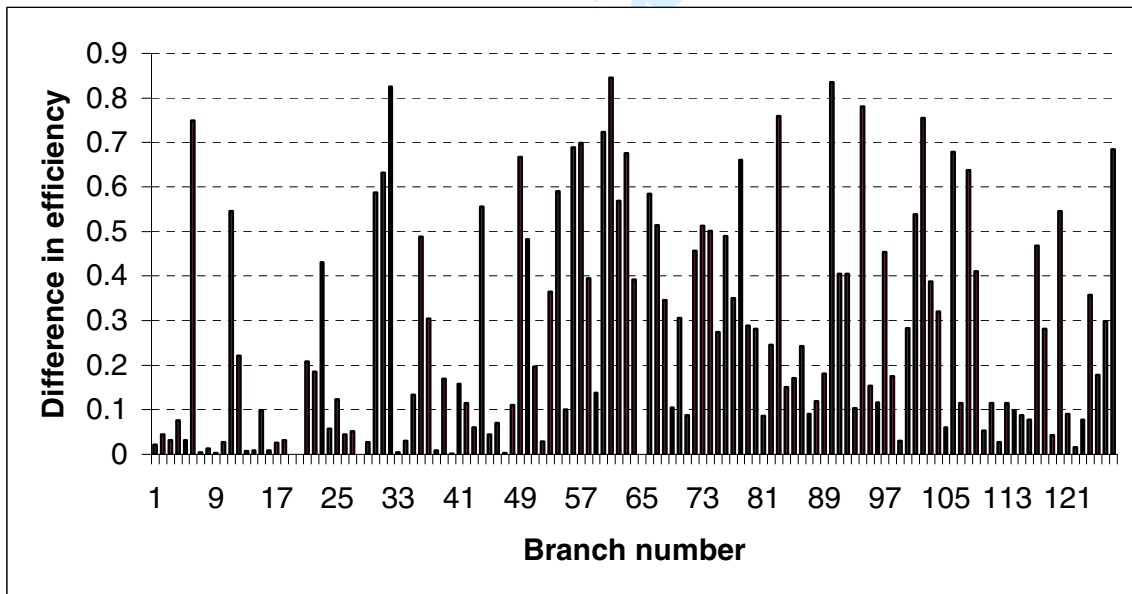


Figure 6: Differences in efficiency scores between VRS and CRS model

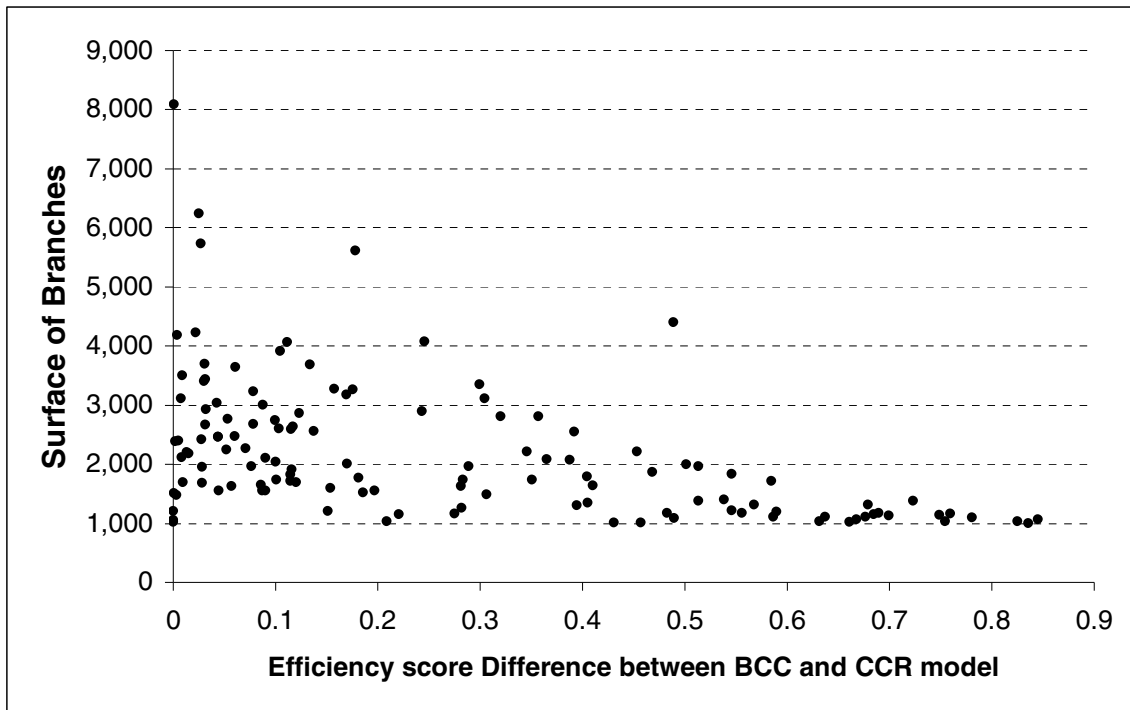


Figure 7: Size evaluation of branches over surface

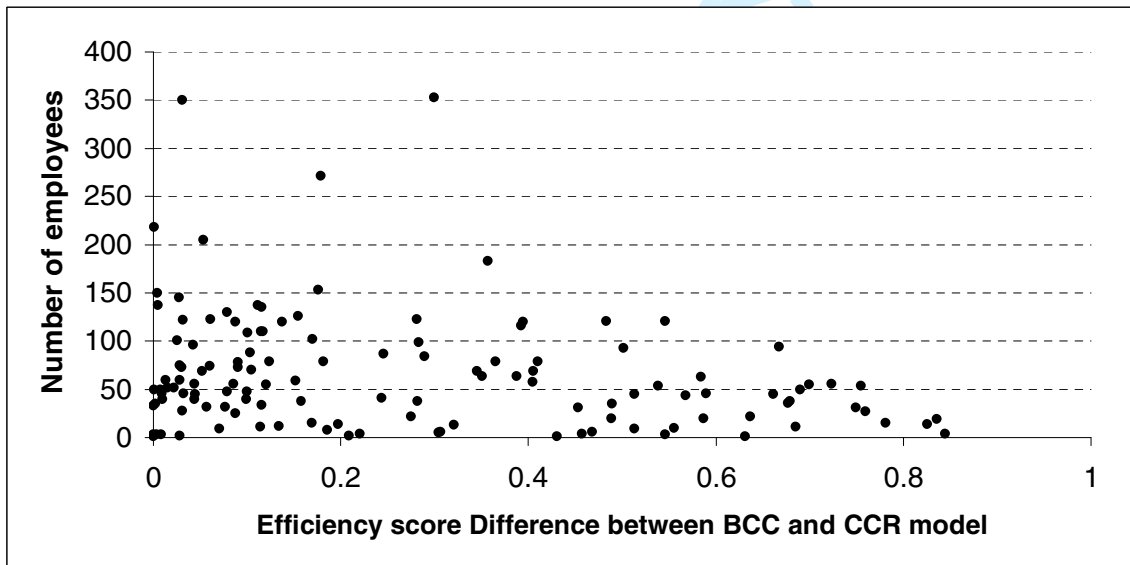


Figure 8: Size evaluation of branches over number of personnel

Table 1. Distribution of DEA radial measure scores

	TE		PTE		SE		C	
Mean	38.36%		65.13%		59.42%		95.42%	
Stdev	25.40%		23.07%		33.62%		9.13%	
Score Bin	#	%	#	%	#	%	#	%
Less than 50%	84	66.1%	35	27.6%	49	38.6%	2	1.5%
50% to 60%	17	13.4%	21	6.5%	8	6.3%	0	0.0%
60% to 70%	11	8.7%	15	11.8%	6	4.7%	0	0.0%
70% to 80%	6	4.7%	16	12.6%	14	11.0%	3	2.4%
80% to 90%	4	3.1%	14	11.0%	16	23.6%	10	7.9%
90% to 100%	2	1.6%	13	10.2%	30	24.4%	72	59.1%
100%	3	2.4%	13	10.2%	4	2.4%	40	29.1%
Total	127	100%	127	100%	127	100%	127	100%

Table 2. Distribution of technical efficiency scores of the branches grouped by area occupied

Group	# Branches	Area (m²)	CCR	BCC
1	4	5,001-	19.11%	24.90%
2	5	4,001 – 5,000	24.15%	41.58%
3	16	3,001 – 4,000	39.47%	50.24%
4	32	2,001 – 3,000	37.72%	51.17%
5	70	1,001 – 2,000	40.53%	78.70%

Table 3: Slack variable analysis

	CCR	BCC
Total surface	61.63%	34.82%
Number of personnel	89.33%	58.58%
Slacks	18.8	20.09

Table 4: Decomposition of non-radial SBM Technical Efficiency for the most efficient branches

DMU #	SBM	CRS	VRS	Mix Efficiency (MIX)	Scale Efficiency (SE)
19	100.0%	100.0%	100.0%	100.0%	100.0%
28	100.0%	100.0%	100.0%	100.0%	100.0%
2	97.1%	97.2%	100.0%	99.9%	97.2%
9	84.6%	87.2%	87.5%	97.0%	99.6%
21	76.3%	79.1%	100.0%	96.5%	79.1%
37	66.7%	69.5%	100.0%	95.9%	69.5%
14	65.3%	67.8%	68.6%	96.3%	98.7%
12	61.6%	71.9%	93.9%	85.7%	76.5%
23	56.8%	56.9%	100.0%	99.9%	56.9%
4	53.2%	92.3%	100.0%	57.6%	92.3%
Mean	24.3%	38.3%	65.1%	62.9%	59.4%

Table 5: Returns to scale analysis

DMU #	Efficiency Score	Reference Set	RTS
19	100.0%	-	CRS
28	100.0%	-	CRS
32	96.6%	(23, 90)	IRS
45	46.4%	(19, 65)	IRS
72	100.0%	-	IRS
75	89.0%	(19, 21, 65)	DRS
93	40.2%	(19, 65)	IRS
96	38.8%	(65, 72)	DRS
100	58.1%	(72, 90)	IRS
127	87.4%	(90, 31, 23)	IRS

Corporate Real Estate Analysis: Evaluating Telecom Branch Efficiency in Greece*

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This paper proposes productivity analysis for evaluating the relative efficiency in corporate real estate usage across decision-making units. Using data from the Greek Telecommunications Organization (GTO), we measure the productivity of 127 branches using the number of employees and the total area covered per building as inputs and the number of telephony access lines as outputs. We apply three non-parametric Data Envelopment Analysis (DEA) models assuming: constant returns to scale (CRS), variable returns to scale (VRS) and slacks-based measures (SBM), respectively. We discuss how the proposed approach can provide real estate managers and analysts a multi informational tool that allows the quantification of targets and may serve as a guide tool for the efficient employment of real estate assets.

Keywords: Real Estate, Productivity Analysis, Data Envelopment Analysis (DEA)

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Corporate Real Estate Analysis: Evaluating Telecom Branch Efficiency in Greece*

This paper proposes productivity analysis for evaluating the relative efficiency in corporate real estate usage across decision-making units. Using data from the Greek Telecommunications Organization (GTO), we measure the productivity of 127 branches using the number of employees and the total area covered per building as inputs and the number of telephony access lines as outputs. We apply three non-parametric Data Envelopment Analysis (DEA) models assuming: constant returns to scale (CRS), variable returns to scale (VRS) and slacks-based measures (SBM), respectively. We discuss how the proposed approach can provide real estate managers and analysts a multi informational tool that allows the quantification of targets and may serve as a guide tool for the efficient employment of real estate assets.

Keywords: Real Estate, Productivity Analysis, Data Envelopment Analysis (DEA)

1. INTRODUCTION

Real estate is one of the major factors of production, cost and profit in most industries and may provide significant competitive advantages (Roulac, 2001). Notwithstanding, a number of studies suggest that firms do not generally exploit their real estate assets in the most efficient manner (eg., Zeckhauser and Silverman, 1983; Veale, 1989). Although some approaches have been developed for measuring corporate real estate effectiveness (see, for example, Pittman and Parker, 1989; Apgar, 1995), most real estate managers rely on benchmarking via *ad hoc* comparative ratio analysis for evaluating real estate efficiency within the firm and against competition.¹ However, there is little consensus in the academic and professional literature as to what measures are correct and why (eg., see Duckworth, 1993; Noha, 1993; Nourse, 1994). Roulac (2001) summarizes the concerns in the industry and literature by saying that: “*a conceptual linear programming approach is necessary to implement multiple complementary and competing strategic objectives in corporate property economics functions*”. The present paper attempts to address these concerns.

This paper proposes the application of productivity analysis in assessing how efficiently real estate assets are used within the units of a firm or across competing firms. Productivity analysis is broad methodological framework which can be used to distinguish two types of efficiency: technical efficiency, which determines whether a production unit (DMU) achieves maximum output using the given factors of production, and, allocative efficiency, which determines whether the factors of production are used in proportion that ensure maximum output at given market prices (for review of this literature see Coelli et al., 2005). While a variety of

¹ A number of professional organizations, such as the Industrial Development Research Council (IDRC), LaSalle Partners, Royal Institute of Chartered Surveyors (RICS), collect and publish “benchmark” measures of corporate real estate performance. These measures are mainly *ad hoc* ratios and are reported across countries and industries.

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3 approaches have been developed in order to measure inefficiency empirically, this paper adopts
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5 Data Envelopment Analysis (DEA), a popularly used family of nonparametric techniques (for a
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7 review see Ray, 2004).
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10 The remainder of the paper is organized as following. The next section makes a brief
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12 introduction to the methodology. Section 3 describes the data, the empirical application and the
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14 results. The final section summarizes our major findings and concludes the paper.
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18 *Figure 1. Technical, Allocative, Overall Efficiency and Congestion.*
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21 22 23 2. METHODOLOGY

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27 In this paper we adopt the well-established methodological framework of technical efficiency
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29 analysis as defined by Farrell (1957): a DMU is said to be technically efficient if a reduction in
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31 any input requires an increase in the other input or decrease of output. In order to introduce the
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33 terminology and demonstrate how measures of DEA are applied we provide an illustrative
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35 example with five DMUs denoted by A, B, C, D and E. The empirically derived efficient frontier
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37 consists of the convex combination of A, B, C and D. Figure 1 shows the four efficient DMUs, A,
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39 B, C and D; the solid line segment connecting points ABCD constitutes an isoquant or level line
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41 that represents the different amounts of two inputs (x_1, x_2) which can be used to produce the same
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43 amount. This line represents the efficient frontier of the production possibility set. By reason of
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45 Q, which exists on the line between A and B, E is inefficient. This is because Q uses less input to
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47 produce the same output as the efficient DMUs. The dashed line that intersects the isoquant at B
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49 is a minimum cost line since the pairs (x_1, x_2) on this line yield the same total cost when unit costs
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51 are c_1 and c_2 , respectively. However, shifting this dashed line upwards in parallel fashion until it
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53 reaches a point of intersection with E would increase cost. In fact, point B is the minimum total
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55 cost needed to produce the specified output. This is because any parallel shift downwards below
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4 B would yield a line that fails to intersect the production possibility set. The ratio $0 \leq \frac{OQ}{OE} \leq 1$
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7 is said to provide a radial measure of technical efficiency (TE) with $0 \leq 1 - (\frac{OQ}{OE}) \leq 1$ yielding
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10 a measure of technical inefficiency. Technical inefficiency measures the proportion with which E
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12 could be replaced to maintain the same quantity of output. Now, consider the point P at the
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14 intersection of this cost line through B with the ray from the origin to E. The ratio $0 \leq \frac{OP}{OQ} \leq 1$
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17 is referred to as price efficiency or allocative efficiency (AE). The corresponding measure
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20 $1 - \frac{OP}{OQ}$ represents allocative inefficiency and denotes a possible reduction in cost by using
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22 appropriate input mixes. It provides a measure of the extent to which the technical efficiency
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24 point, Q, falls short of achieving minimal cost because of failure to make the substitutions, or
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26 reallocations, involved in moving from Q to B along the efficiency frontier.
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30 We can also obtain a radial measure of overall efficiency (*OEF*) from the ratio
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32 $0 \leq \frac{OP}{OE} \leq 1$. Since $OEF = \frac{OP}{OE} = (\frac{OQ}{OE}) \cdot (\frac{OP}{OQ}) = TE \cdot AE$, we can express overall
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34 efficiency as the product of “allocative” and ‘technical efficiency’, ie., $OEF = TE \cdot AE$. The
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36 measure $(1 - \frac{OP}{OE})$ represents overall inefficiency and denotes the possible reduction in cost due
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38 to changing from B (observed input quantities) to P (cost minimizing input quantities). Point D is
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40 efficient only when we allow for congestion.² However, it will be inefficient under the standard
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42 assumption of no backward bending segment. The isoquant shown by the dashed line from point
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44 C represents the non-congested benchmark. The ratio $\frac{OD'}{OD}$ represents the reduction in input
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46 x_1 required in order to reach the uncongested frontier from the congested frontier; that is we
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48 calculate the reduction that is achieved if congestion is eliminated.
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57 ² Congestion refers to the situation whereby increasing (decreasing) one or more inputs decreases
58 (increases) some outputs without improving (worsening) other inputs or outputs.
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The present paper adopts the DEA approach in evaluating efficiency across DMUs. DEA refers to a mathematical programming family of techniques which are flexible and have the advantage of making very few assumptions (for a description see Cooper, Seiford and Tone, 2000). The method, developed by Charnes et al. (1978), has been widely used at numerous applications measuring the performance of decision-making units (DMU) in the public and private sector. DEA is used so widely because of its simplicity and the useful interpretation of results it yields even with limited data sets. The determination of the efficiency score of the a DMU in a sample of n DMUs in the Constant Returns to Scale (CRS) model is equivalent to the optimization of the following linear programming problem (Charnes et al., 1978; hereafter CCR):

$$\begin{aligned}
 \max_u z_0 &= \sum_{r=1}^s u_r y_{r0} \\
 \text{subject to} \\
 \sum_{r=1}^s u_r y_{rj} - \sum_{i=1}^m v_i x_{ij} &\leq 0, j = 1, 2, \dots, n \\
 \sum_{i=1}^m v_i x_{i0} &= 1 \\
 u_r &\geq 0, r = 1, 2, \dots, s \\
 v_i &\geq 0, i = 1, 2, \dots, m
 \end{aligned} \tag{1}$$

For the above linear programming problem, the dual can be written for a given DMU as:

$$\begin{aligned}
 \min_{\lambda} z_0 &= \Theta_0 \\
 \text{subject to} \\
 \sum_{j=1}^n \lambda_j y_{rj} &\geq y_{r0}, r = 1, 2, \dots, s \\
 \Theta_0 x_{i0} - \sum_{j=1}^n \lambda_j x_{ij} &\geq 0, i = 1, 2, \dots, m
 \end{aligned}$$

$$\lambda_j \geq 0, j = 1, 2, \dots, n \quad (2)$$

Θ_0^* is the efficiency score and λ a $n \times 1$ vector of constants. Assuming that the DMU uses m inputs and s outputs, X and Y represent $m \times n$ input and $s \times n$ output matrices, respectively. The x_{ij} represents the input of the i -th type of the j -th DMU and y_{rj} the observed amount of output of the r -th type for the j -th DMU. A DMU is said to be efficient if technical efficiency is equal to one. A technical efficiency score less than one indicates the extent by which a DMU should reduce inputs while maintaining the same output in order to produce the output of a technically efficient DMU.

To determine efficiency measures under the Variable Returns to Scale (VRS) model (see Banker et al., 1984; hereafter BCC), a further convexity constraint $\sum_{j=1}^n \lambda_j = 1$ has to be considered. The input-oriented BCC model for a DMU can be written formally as:

$$\min_{\lambda} z_0 = \Theta_0$$

subject to

$$\sum_{j=1}^n \lambda_j y_{rj} \geq y_{r0}, r = 1, 2, \dots, s$$

$$\Theta_0 x_{i0} - \sum_{j=1}^n \lambda_j x_{ij} \geq 0, i = 1, 2, \dots, m$$

$$\sum_{j=1}^n \lambda_j = 1$$

$$\lambda_j \geq 0, j = 1, 2, \dots, n \quad (3)$$

Running the above model for each DMU, the BCC-efficiency scores are obtained. The model eliminates the scale part of the efficiency from the analysis. It is an interesting subject to investigate the sources of inefficiency that a DMU might have. The CCR approach suggests that DMUs are flexible to adjust their size to the optimal firm size. On the other hand, the BCC method is less restrictive because it compares the productivity of companies only within similar sample sizes. The comparison between the two approaches also provides some information about the underlying technology: if the results of the CCR and the BCC approaches are similar, then returns to scale do not play an important role in the process.

The CCR model score is called global technical efficiency because it is postulated that the radial expansion and reduction of all observed DMUs and their nonnegative combinations are possible. A DMU is said to display total technical efficiency if it produces on the best practice observed boundary of the production possibility set, i.e. maximizes output with given inputs and after having chosen technology. The BCC scores is called local pure technical efficiency because the model assumes the convex combinations of the observed DMUs as the production possibility set. Scale efficiency measure can be calculated by dividing the total technical efficiency by pure technical efficiency. Using these concepts, the total technical efficiency can be further decomposed into pure technical efficiency and scale efficiency (Cooper et al., 2000). The following relationship demonstrates the decomposition of Global Technical Efficiency (TE):

$$\text{Technical efficiency} = \text{Pure Technical efficiency} \times \text{Scale Efficiency}$$

Generally speaking, for each DMU the CCR model efficiency score will not exceed the BBC efficiency score. An efficiency score obtained using the CCR-model comprises both scale efficiency and pure technical efficiency. In a case where a DMU is found to be inefficient, one can decompose this total inefficiency to see in what degree this due to scale inefficiency or technical inefficiency. The efficiency scale can be defined as:

$$SE = \frac{\theta_{CCR}^*}{\theta_{BCC}^*}$$

where the θ_{CCR}^* , and θ_{BCC}^* are the CCR and BCC scores, respectively. SE cannot exceed one, if it assumes a value of 1, the DMU is efficient both under CCR and BCC. If SE is less than 1 then the DMU is not scale efficient.

The above-described approach does not allow identifying whether a DMU operates under increasing returns to scale (IRS) or decreasing returns to scale (DRS). This problem can be solved using the non-increasing returns to scale (NIRS) expression of DEA by setting the constraint

$\sum_{j=1}^n \lambda_j \leq 1$ in (3). On the one hand, if $\frac{TE_{CCR}}{TE_{NIRS}} = 1$, the DMU operates under IRS and it is scale

inefficient since it has the potential to achieve bigger output. On the other hand, if $\frac{TE_{CCR}}{TE_{NIRS}} < 1$,

the DMU operates under DRS and inefficiency is due to excess output.

Cooper et al. (2000) introduced a non - radial measure of efficiency called SBM (slacks-based measure of efficiency). The input orientation of the SMB model is equivalent to the optimization of the following equation considering five conditions:

$$\min p_{in} = 1 - \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{io}}$$

subject to

$$x_0 = X\lambda + s^-$$

$$y_0 = Y\lambda - s^+ \quad (4)$$

$$\lambda \geq 0, s^- \geq 0, s^+ \geq 0$$

s^- is the input excesses of inputs and s^+ is the output shortfalls.

Based on the SBM efficiency score, Cooper et al (2000) defines the Mix efficiency score by $MIX = \frac{p_{in}^*}{\theta_{CCR}^*}$. This definition drives to the decomposition of the non-radial technical efficiency into MIX, pure technical efficiency and scale efficiency.

$$p_{in}^* = MIX \cdot PTE \cdot SE \quad (5)$$

This decomposition contributes to interpret sources of inefficiencies for each non-radial inefficient DMU. A more comprehensive decomposition of cost efficiency considers the input congestion as a piece of the decomposition of the cost inefficiency into technical inefficiencies, which is non-price related and allocative inefficiency, which is price related (Färe and Grosskopf, 2000). Technical efficiency requires pure technical efficiency to be computed by relaxing the strong input disposability restriction (Byrnes et al., 1984) to allow for an input congestion component. (Junoy, 2000). Then, the Technical efficiency (TE) is defined as the product of the scale efficiency, input congestion, and pure technical efficiency components in the condition of weak disposal (Färe et al., 1994):

$$TE(x,y) = SE(x,y) * C(x,y) * PTE(x,y) \quad (6)$$

The theoretical discussion identifies some shortcoming of procedures for measuring congestion see, for example Cooper et al (2001), and Cherchye et al. (2001). The work of Brockett et al. (1998) improves upon the work of Färe et al. (1994) Nonetheless, the Färe's et al. (1994) approach is still useful if one's aim to assess the impact of congestion on the overall technical efficiency. In the recent paper, Färe and Grosskopf (2000) discuss the connection

between slacks and congestion. We note, however, that precise measurement of congestion is not yet conclusive.

In (3), we measure the efficiency of a specific DMU₀ (Charnes et al., 1978) The model in (3) confronts to the condition of strong disposal. If we replace the first m inequalities in (3) by equations the model exhibits weak (input) disposal so there is no possibility of positive inputs slacks that may have to be disposed of:

$$\begin{aligned}
 \beta^* &= \min \beta \\
 &\text{subject to} \\
 &\sum_{j=1}^n \lambda_j x_{ij} = \beta x_{i0}, i = 1, 2, \dots, m \\
 &\sum_{j=1}^n \lambda_j y_{rj} \geq y_{r0}, r = 1, 2, \dots, s \\
 &\sum_{j=1}^n \lambda_j = 1 \\
 &\lambda_j \geq 0, j = 1, \dots, n
 \end{aligned} \tag{9}$$

The input congestion measure is then defined as the following ratio:

$$0 \leq C(\theta^*, \beta^*) = \frac{\theta^*}{\beta^*} \leq 1 \tag{10}$$

if and only if $C(\theta^*, \beta^*) < 1$ the congestion is presence.

In the manner described above, DEA allows the partition technical efficiency in pure technical efficiency, congestion, and scale efficiency and investigate the different types of

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3 inefficiency across DMUs. The analysis can be done assuming constant returns to scale (CRS) or
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5 variable returns to scale (VRS) approach. In addition to these two radial measures of efficiency, it
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7 is possible to adopt a non-radial slacks-based measure of efficiency (SBM) in the input
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9 orientation. The decomposition of the non-radial technical efficiency can contribute in
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11 interpreting the sources of inefficiencies (see Cooper et al., 2000). In this paper we apply the CRS
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13 and VRS model for the calculation of technical efficiency using the CCR approach of Charnes et
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15 al. (1978) and the BCC approach of Banker et al. (1984), respectively. Moreover, we apply a non-
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17 radial slacks-based measure of efficiency (SBM) in the input orientation which allows us to
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19 interpret the sources of inefficiencies (see Cooper et al., 2000).
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25 *Table 1. Distribution of DEA radial measure scores*

26 27 28 29 **3. EVALUATING TELECOM BRANCH RELATIVE PERFORMANCE**

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33 In the empirical application we evaluate the technical efficiency of the Greek
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35 Telecommunications Organization (GTO) DMUs with respect to real estate usage. More
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37 specifically, we apply the input oriented DEA, as we are interested in examining the efficient
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39 usage of the real estate input. The data set used corresponds year 2002 for each one of the 127
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41 branches of GTO spread over the 52 municipalities of Greece. The output variable was set as the
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43 number of fixed telephony access lines. The number of access lines provides us with an exact
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45 figure of the installed client base irrespective of the frequency of usage. As input variables we
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47 used the number of employees and the total area in m² covered by each branch. The number of
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49 employees includes all technical, administrative and support personnel. The total area includes all
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51 types of real estate used: offices, technical support and commercial. It is reasonable to assume
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53 that the GTO can adjust the levels of the two inputs in use and hence aims to achieve the
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55 maximum potential decrease in inputs while remaining in the production possibility set. It is also
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3 reasonable to assume that output is fixed in a market with the obligation to serve all customers in
4 a predefined region that demand a telephone line. The number of access lines for 2002 totaled to
5 just under 3 million, while the number of employees and the corporate real estate area amounted
6 to about 8,400 and 278,000 m², respectively.
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14 **Figure 2: DEA analysis with CRS**
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17 The DEA models discussed in the previous section were applied in order to compute relative
18 measures of technical (TE), pure technical (PTE), scale (SE) and congestion (C) efficiencies,
19 respectively. As shown in Table 1, the average efficiency for the CCR model is just under 40%
20 with three branches on the efficiency frontier and only five branches with efficiency above 90%
21 (see also Figure 2). That means that the average branch, if producing its output on the efficient
22 instead of at its current (virtual) location, would have needed only 38.36% of the inputs currently
23 being used. In the terms of average inefficiency, it would have needed 160.6% more inputs to
24 produce the same outputs as an efficient branch. Units would need to lower inputs by 61.64% if
25 all were operating on the production efficiency frontier. The average efficiency score for non-
26 frontier units is 61.6% (VRS), implying that nonefficient units use, on average, 63.6% more
27 inputs per units of output than efficient units do.
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43 **Table 2. Distribution of technical efficiency scores of the branches grouped by area occupied**
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50 Table 2 gives the average technical efficiency score for branches grouped by the area they cover.
51 The results according to both CCR and BCC suggest that branches occupying less (more) space are
52 more (less) efficient. Branches occupying less than 2,000 m² appear to be the most efficient with
53 an average score assuming constant (variable) returns to scale of about 41% (79%). As shown in
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Figure 3, there is a weak negative relationship between the branch surface and its efficiency score. Branches with scores between 15-25 % present a closing up at 1000 m². The best performing branches occupy surface less than 2,000 m². As can be seen in Figure 4, there is also a negative correlation between the number of personnel of branches and its efficiency score.

Figure 3: Correlation between the branch surface and its efficiency score

Figure 4: Correlation between the number of personnel in branch and its efficiency score

Figure 5: DEA analysis with VRS

Figure 6: Differences in efficiency scores between VRS and CRS model

If one uses the VRS model, the efficiency scores rise significantly (see Figure 5) with 13 out of the 127 branches on the frontier (100% efficiency) and an average efficiency of 65.13%. This can be explained by the fact that now branches of similar size are compared with each other and not with the best ones of the whole sample. Figure 6 depicts the differences in efficiency scores between the VRS and the CCR model. It appears that the optimal size of branches, i.e. the one where the VRS and CRS efficiency scores converge, is in the beginning which corresponds to the region of Athens. It is also suggests that many branches do not have an optimal size and may gain in efficiency by merging.

Figures 7 and 8 depict the relationship between the efficiency score differences following the two approaches, and, the surface of branches and the number of employees, respectively. It can be inferred that branches with surface between 1,000 m² to 2,000 m² and with employees between 1 and 70 are of optimal size. There is a closing up when the number of employees reach 50 and the branch surface is 2000 m².

Figure 7: Size evaluation of branches over surface

Figure 8: Size evaluation of branches over number of personnel

In the input oriented DEA approach, input slacks would be associated with the assumption of strong or weak disposability of inputs which permits zero marginal productivity of inputs and hence extensions of the relevant isoquants to form horizontal or vertical facets. In this case, units which are deemed to be radial efficient, that is no further proportional reductions in inputs is possible without sacrificing output, may nevertheless be able to implement further reductions in some inputs. Such additional potential input reductions are typically referred to as non-radial input slacks, in contrast to the radial slacks associated with DEA inefficiency, i.e., radial deviations from the efficient frontier.

Table 3 summarizes the output of the slack variable analysis. The results suggest that if it were possible for the inefficient branches to perform like the best practicing one's savings of about 61% (34%) in the total surface and 89% (58%) in the number of personnel would be possible according to the CRS (VRS) approach. At the same time, potentially increased outputs can be observed with an average increment of 635 lines per branch. Moreover, all the branches show zero input slack in the total surface variable and in the personnel variable so the most of them are mix inefficient because the reduction to bring them to the frontier change the input proportions. However, 28 inefficient branches operate without altering the mix (proportions) they utilized. The average value of slacks is 20 units showing the further reduction in the number of personnel over the reduction determined by the efficiency score.

Table 3: Slack variable analysis

Table 4: Decomposition of non-radial SBM Technical Efficiency for the most efficient branches

We also decomposed the non-radial SBM scores of the most efficient branches and the results are given in Table 4. It can be observed that, for example, for DMU No 21, the low SBM (76.3%) is caused by SE (79.1%). For DMU No 12, the SBM (61.8%) can be mainly attributed to the SE (76.5%) and to MIX (85.7%). Although DMU No 12 is efficient with respect to VRS (93.9%), its low SE (76.5%) and SBM (61.6%), force it to be inefficient overall. The average result of non-radial slacks based model confirms the low efficiency of the 127 branches. Congestion was also present among the branches with 40 units operating without congestion while 72 units showed a congestion score of around 90%. The average price was 95%, that is on average 5% of the inputs could be reduced to eliminate the congestion.

Table 5: Returns to scale analysis

Turning to the analysis of returns to scale (see Table 5), as identified by the input oriented CCR, BCC and NIRS model, three branches from 127 showed constant returns to scale, ninety branches increasing returns to scale (IRS) and 44 decreasing returns to scale, respectively. Interestingly, 90 branches have a possibility to improve their efficiency by scaling up their activities. This could be accomplished by, for example, merging low ranked branches into one branch. The returns to scale characteristics of the projected activity of branches can be identified on the basis of the reference set of branches. For example, the DMU No 127 reference set is composed by of 90, 31 and 23, all of them belonging to IRS. This means that the projected activity of the branch 127 belongs to IRS.

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Finally, we also examined the robustness of the efficient branches. For an inefficient DMU_o, the positive values of λ determines the set of dominating units (reference set) placed in the border of efficiency against the unit that is evaluated. The magnitude of λ defines if DMU_o has more similarity to one from the other efficient DMUs. To discriminate between relatively efficient branches, we count the number of efficient branches that appeared in the reference sets of inefficient branches. This number indicates the robustness of the efficient branches. Indeed, we found that DMU₁₉, DMU₆₅, DMU₇₂, and DMU₉₀ appear more than 35 times in the reference sets of inefficient DMUs. On the other hand, five DMUs appear less than two times in any comparison group of inefficient branches.

4. CONCLUSIONS

In this paper we propose productivity analysis to evaluate the efficiency in the exploitation of corporate real estate assets. This approach provides an objective and consistent way of assessment compared to ad hoc ratio measures which are largely subjective and atheoretic. Productivity analysis produces a wealth of empirical results which can be used by managers as a multi-informative framework to quantify targets and serves as a guide tool for the efficient employment of real estate assets. In an empirical application, we applied four popular DEA models (CRS, VRS, SBM, and NIRS) to study radial and non-radial measures of efficiency for 127 branches of the Greek Telecommunications Organization. We used data for 2002 with the number of fixed telephony access lines as an output variable and the number of employees and the total area in m² covered by each branch as the two input variables. The results suggest that there is significant potential for efficiency improvements in the GTO. More specifically, we found significant elements of technical inefficiency with respect to the employment of real estate in the production process. The comparison of mean efficiency of CCR and VRS models showed that a significant difference is due to the scale inefficiency of branches. The analysis identified scale inefficiency as the main reason of overall inefficiency. In a nutshell, we found that branches

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3 operate in wrong scale. The correlation between branch surface to the difference in efficiency
4 scores between the VRS and CRS approach suggests that the branches with size from 1,000 to
5 3,000 m² are in the region of the optimal scale. We found that there is a significant waste of
6 branch surface (34.82%) indicating the need for strategic and technical allocation of the real
7 estate portfolio. The analysis of returns to scale (80%, Increasing Returns to Scale) indicates the
8 possibility of improving the overall efficiency by merging low efficient branches into one branch.
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16 Additional sources of inefficiency can be recognized in the framework of a cost
17 efficiency analysis. The analysis of allocative efficiency, a basic component of cost efficiency, is
18 based on actual market prices for inputs and outputs and may produce a different picture.
19 Although productivity analysis is very useful in analyzing production unit efficiency without the
20 need to impose a pre-defined functional form for production, care must be taken to analyze the
21 results in conjunction with the inputs and outputs used. Future research will focus on providing a
22 more complete analysis by attributing not only the production performance but also the cost
23 performance and additional production mix variables.
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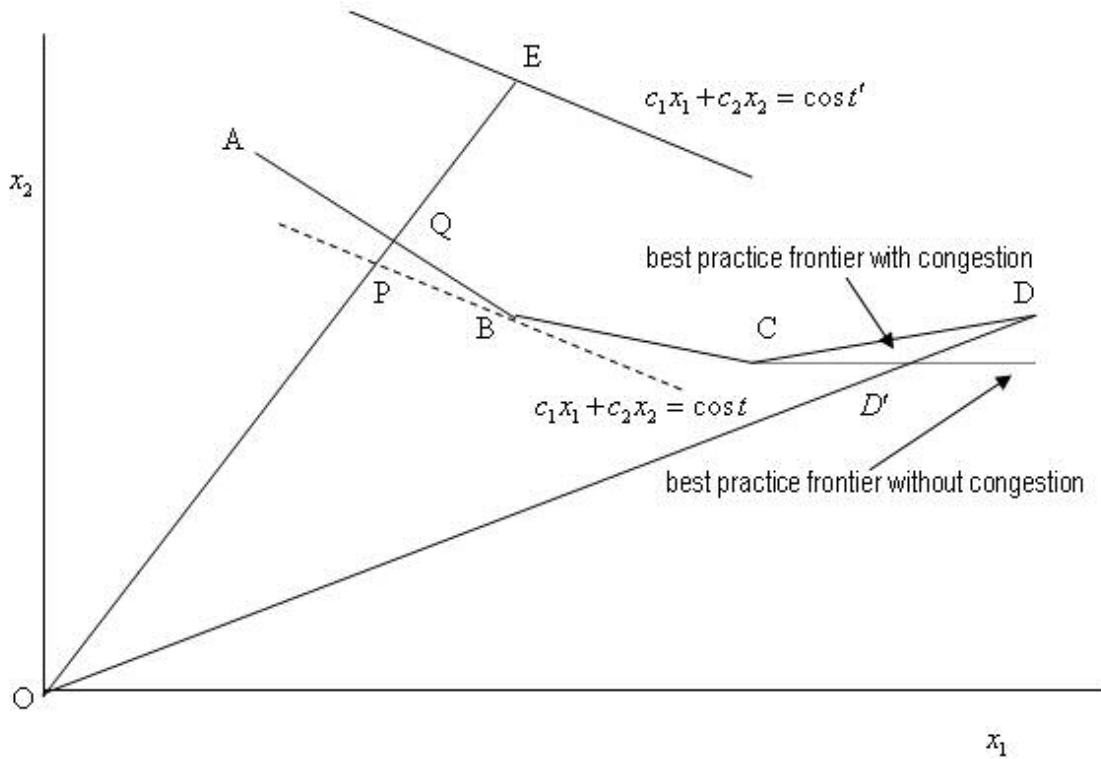


Figure 1: Technical, Allocative, Overall Efficiency and Congestion.

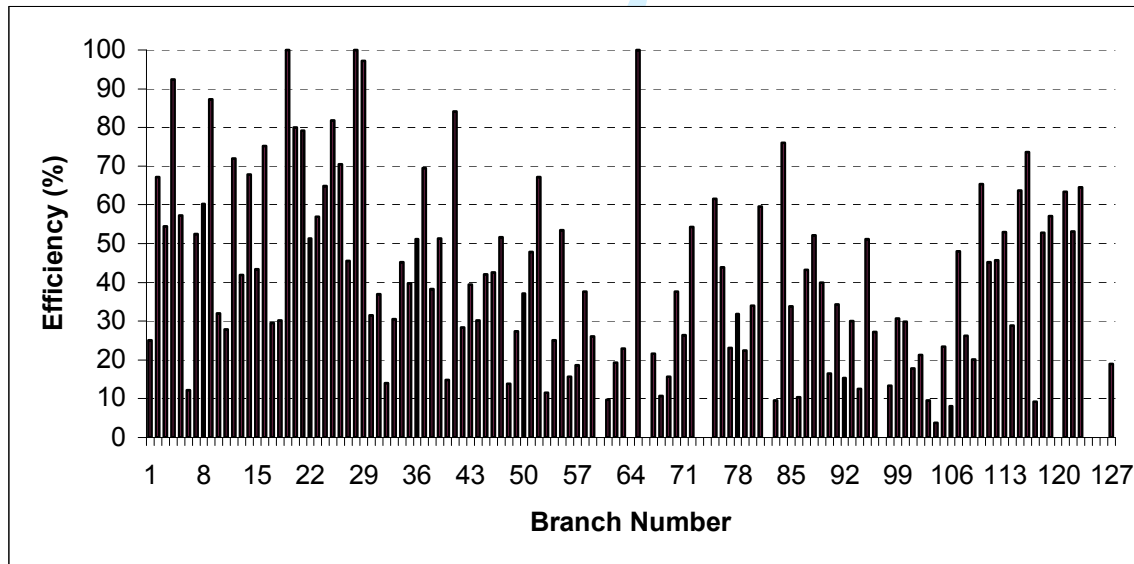


Figure 2: DEA analysis with CRS

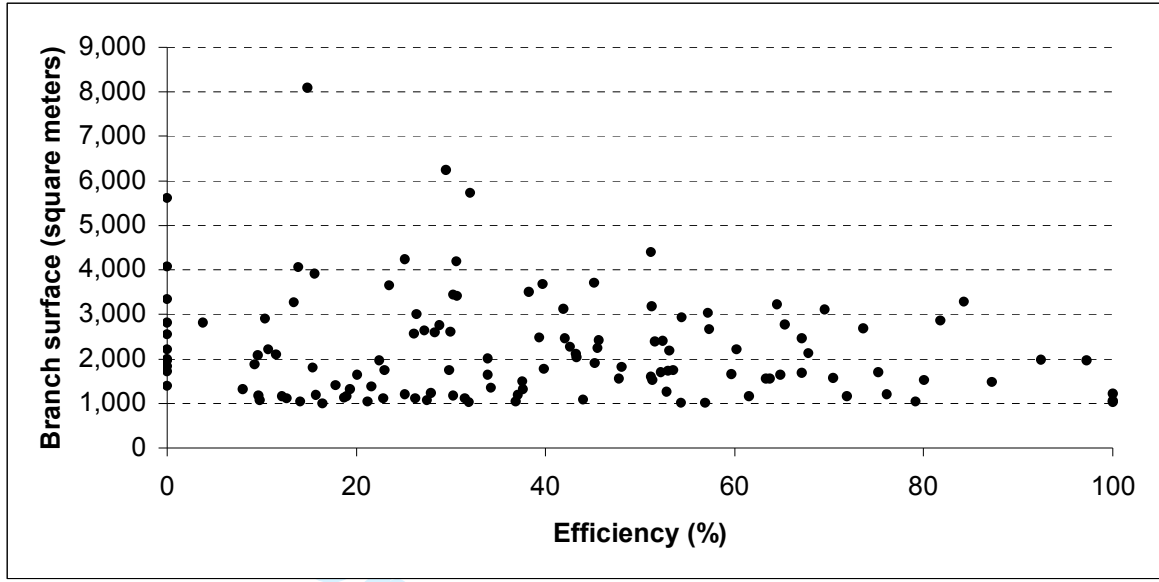


Figure 3: Correlation between the branch surface and its efficiency score

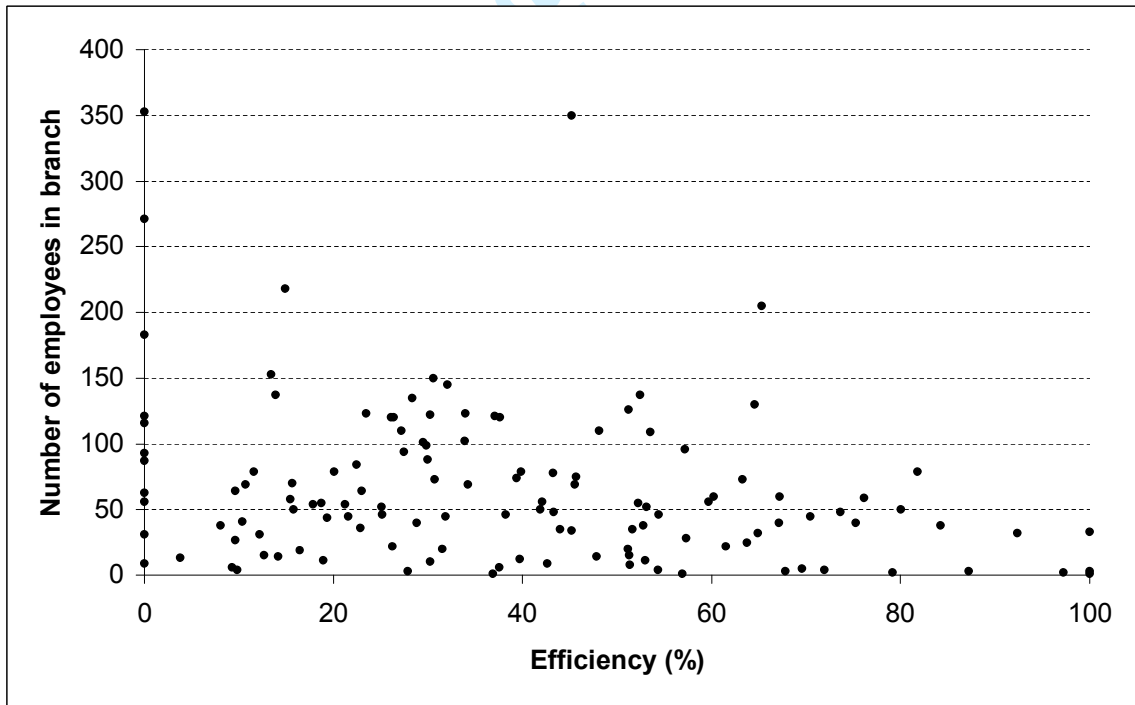


Figure 4: Correlation between the number of personnel in branch and its efficiency score

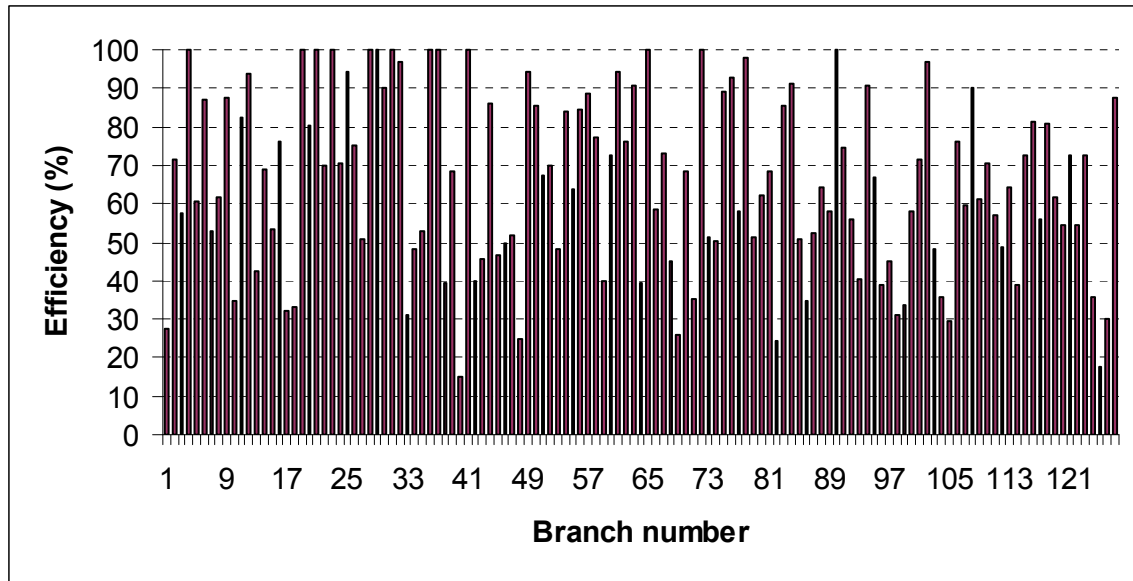


Figure 5: DEA analysis with VRS

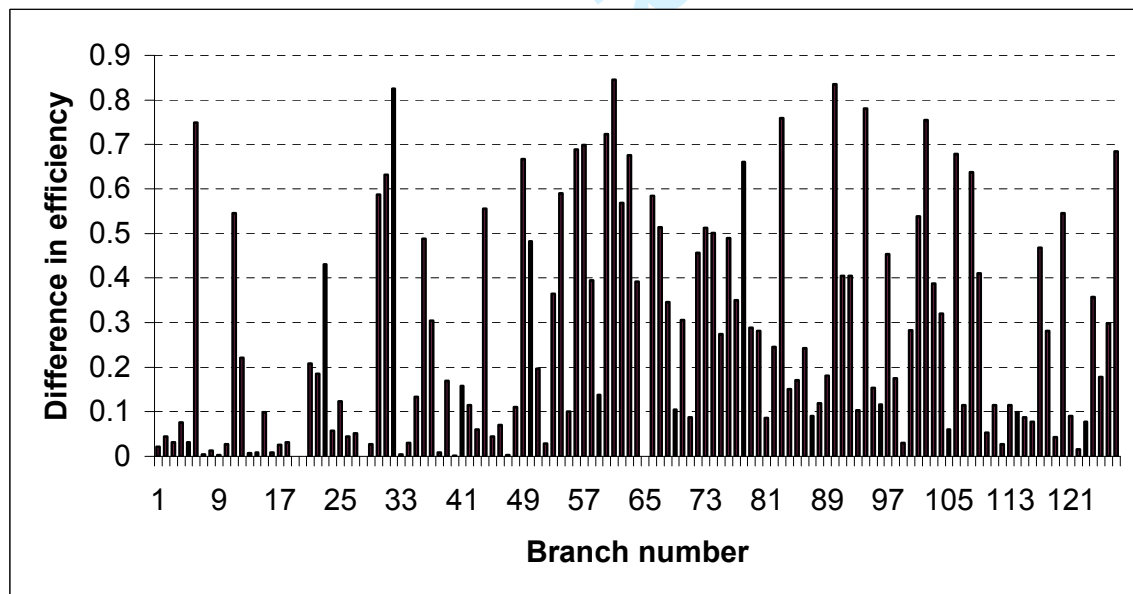


Figure 6: Differences in efficiency scores between VRS and CRS model

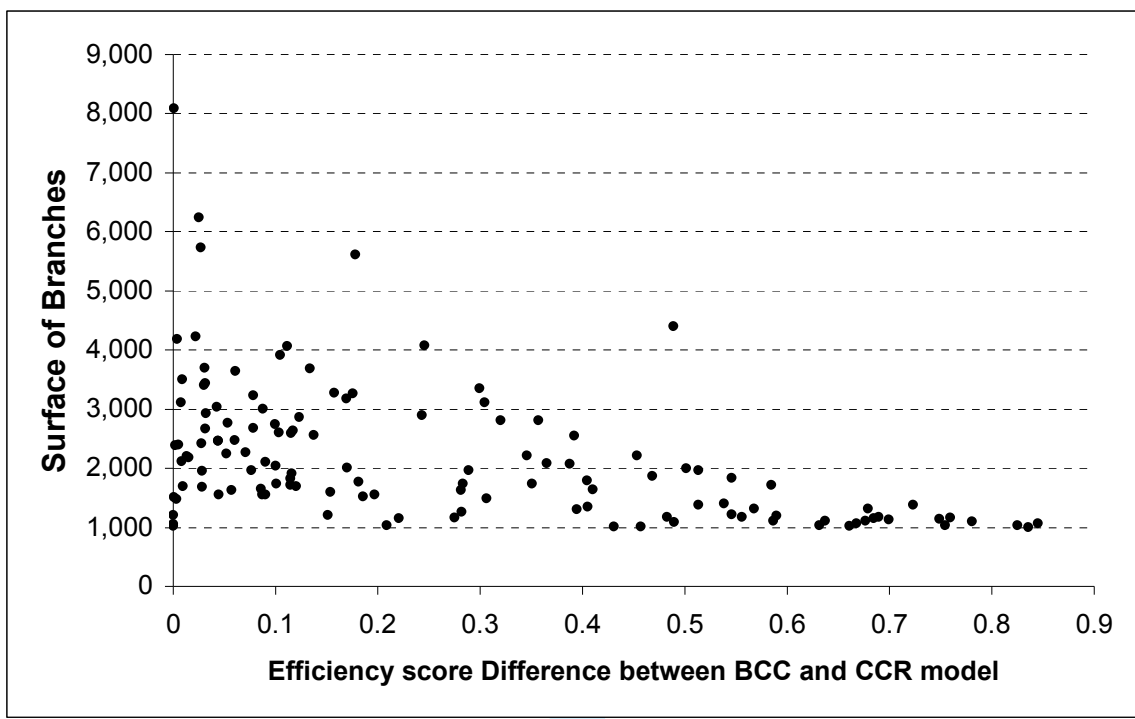


Figure 7: Size evaluation of branches over surface

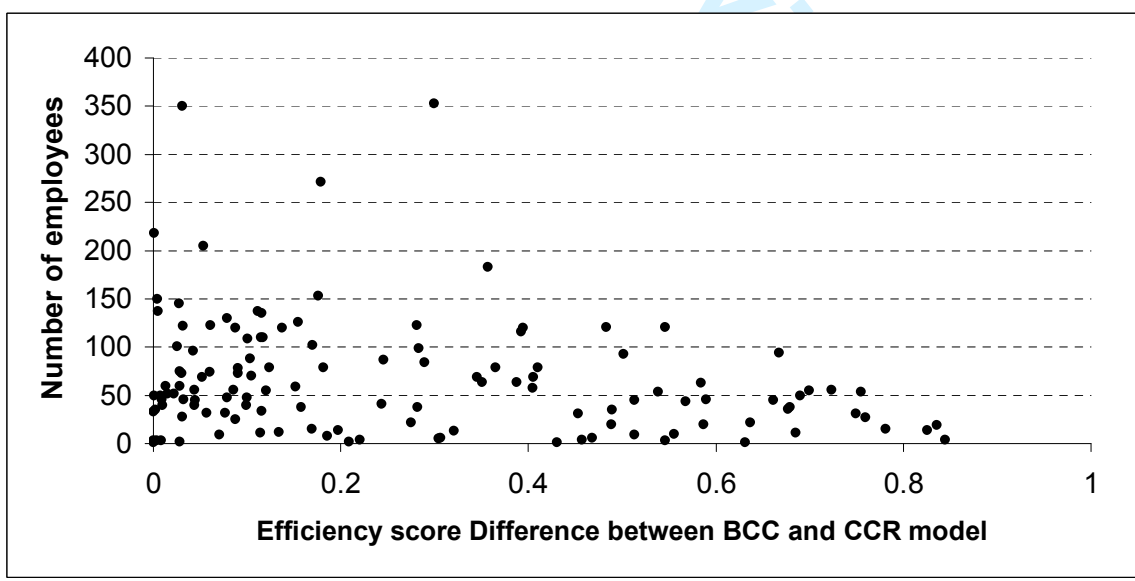


Figure 8: Size evaluation of branches over number of personnel

Table 1. Distribution of DEA radial measure scores

	TE		PTE		SE		C	
Mean	38.36%		65.13%		59.42%		95.42%	
Stdev	25.40%		23.07%		33.62%		9.13%	
Score Bin	#	%	#	%	#	%	#	%
Less than 50%	84	66.1%	35	27.6%	49	38.6%	2	1.5%
50% to 60%	17	13.4%	21	6.5%	8	6.3%	0	0.0%
60% to 70%	11	8.7%	15	11.8%	6	4.7%	0	0.0%
70% to 80%	6	4.7%	16	12.6%	14	11.0%	3	2.4%
80% to 90%	4	3.1%	14	11.0%	16	23.6%	10	7.9%
90% to 100%	2	1.6%	13	10.2%	30	24.4%	72	59.1%
100%	3	2.4%	13	10.2%	4	2.4%	40	29.1%
Total	127	100%	127	100%	127	100%	127	100%

Table 2. Distribution of technical efficiency scores of the branches grouped by area occupied

Group	# Branches	Area (m²)	CCR	BCC
1	4	5,001-	19.11%	24.90%
2	5	4,001 – 5,000	24.15%	41.58%
3	16	3,001 – 4,000	39.47%	50.24%
4	32	2,001 – 3,000	37.72%	51.17%
5	70	1,001 – 2,000	40.53%	78.70%

Table 3: Slack variable analysis

	CCR	BCC
Total surface	61.63%	34.82%
Number of personnel	89.33%	58.58%
Slacks	18.8	20.09

Table 4: Decomposition of non-radial SBM Technical Efficiency for the most efficient branches

DMU #	SBM	CRS	VRS	Mix Efficiency (MIX)	Scale Efficiency (SE)
19	100.0%	100.0%	100.0%	100.0%	100.0%
28	100.0%	100.0%	100.0%	100.0%	100.0%
2	97.1%	97.2%	100.0%	99.9%	97.2%
9	84.6%	87.2%	87.5%	97.0%	99.6%
21	76.3%	79.1%	100.0%	96.5%	79.1%
37	66.7%	69.5%	100.0%	95.9%	69.5%
14	65.3%	67.8%	68.6%	96.3%	98.7%
12	61.6%	71.9%	93.9%	85.7%	76.5%
23	56.8%	56.9%	100.0%	99.9%	56.9%
4	53.2%	92.3%	100.0%	57.6%	92.3%
Mean	24.3%	38.3%	65.1%	62.9%	59.4%

Table 5: Returns to scale analysis

DMU #	Efficiency Score	Reference Set	RTS
19	100.0%	-	CRS
28	100.0%	-	CRS
32	96.6%	(23, 90)	IRS
45	46.4%	(19, 65)	IRS
72	100.0%	-	IRS
75	89.0%	(19, 21, 65)	DRS
93	40.2%	(19, 65)	IRS
96	38.8%	(65, 72)	DRS
100	58.1%	(72, 90)	IRS
127	87.4%	(90, 31, 23)	IRS