DATA ENVELOPMENT ANALYSIS AND MALMQUIST TOTAL FACTOR PRODUCTIVITY (TFP) INDEX: AN APPLICATION TO TURKISH AUTOMOTIVE INDUSTRY

ALPER KARADUMAN

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I certify that this thesis satisfies all the requirements as a thesis for the degree of Master of Science.

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This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science.

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ABSTRACT

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This thesis shows how the relative efficiency of automotive companies can be evaluated and how the changes in productivity of these companies by time can be observed. There are 17 companies in the analysis which are the main automotive manufacturers of Turkish automotive industry. A method called stepwise approach is used to determine the input and output factors. The two input variables used are the company's Payment for Raw Materials and Components and Payment for Wages and Insurances of Employees; the three output variables are Domestic Sales, Exports

and Capacity Usage. The panel data that covers the time period between years 2001 and 2005 is obtained from OSD (Automotive Manufacturers Association).
The efficiency analysis is performed according to basic Data Envelopment Analysis (DEA) models which are Charnes, Cooper and Rhodes (CCR) models and Banker, Charnes and Cooper (BCC) models. The software LINGO 10 is used for solving the linear programming models. After finding the overall efficiency, technical efficiency and scale efficiency of each company for each year, the changes in the efficiencies are analyzed by using Malmquist Total Factor Productivity (TFP) Index.

The results are illustrated by the help of many tables and graphs for better understanding. When the results in tables and graphs are analyzed, the negative effect of 2001 economic crisis on automotive industry can be observed. Besides, it is seen that the efficiency changes by time show variance from company to company because they produce 7 types of vehicles and there are important differences between them such as production technology, market, demand, etc.

Keywords: Data Envelopment Analysis, Malmquist Total Factor Productivity Index, Automotive Industry, Efficiency, Linear Programming

ÖZ

VERİ ZARFLAMA ANALİZİ VE MALMQUIST TOPLAM FAKTÖR VERİMLİLİĞİ (TFV) ENDEKSİ: TÜRK OTOMOTİV ENDÜSTRİSİNDE BİR UYGULAMA

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Bu tez, otomotiv şirketlerinin göreli etkinlik ölçümlerinin nasıl yapılacağını ve bu şirketlerin etkinliklerinin zaman içerisindeki değişimlerinin nasıl inceleneceğini göstermektedir. Çalışmada Türk otomotiv endüstrisinin ana üreticileri olan 17 şirket kullanılmıştır. Girdi ve çıktı faktörlerini belirlemek üzere literatürde adımsal yaklaşım olarak geçen bir yöntem kullanılmıştır. Kullanılan iki girdi değişkeni şirketin ham madde ve yan sanayi için yaptığı ödemeler ve çalışanların ücret ve sigortaları için yaptığı ödemelerdir; üç çıktı değişkeni ise iç satışlar, ihracat ve

kapasite kullanımıdır. 2001 ve 2005 yılları arasına ait panel veri OSD (Otomotiv Sanayi Derneği)’den temin edilmiştir.
Verimlilik analizi, iki temel Veri Zarflama Analizi (VZA) modeli olan Charnes, Cooper ve Rhodes (CCR) ve Banker, Charnes ve Cooper (BCC) modellerine göre yapılmıştır. Doğrusal programlama modellerinin çözümü için LINGO 10 yazılımı kullanılmıştır. Her şirketin her yıla ait toplam etkinlik, teknik etkinlik ve ölçek etkinliği değerlerinin bulunmasından sonra etkinliklerin zaman içindeki değişimleri Malmquist Toplam Faktör Verimliliği (TFV) Endeksi kullanılarak incelenmiştir.

Sonuçlar, daha iyi anlaşılmaları amacıyla çok sayıda tablo ve grafik yardımıyla gösterilmiştir. Tablo ve grafiklerdeki sonuçlar analiz edildiğinde 2001 ekonomik krizinin otomotiv endüstrisi üzerindeki olumsuz etkisi görülebilmektedir. Ayrıca, zaman içindeki etkinlik değişimlerinin şirketten şirkete farklılık gösterdiği görülmektedir. Çünkü şirketler 7 değişik araç türü üretmekte dolayısıyla aralarında üretim teknolojisi, pazar ve talep gibi konularda farklılıklar bulunmaktadır.

Anahtar Kelimeler: Veri Zarflama Analizi, Malmquist Toplam Faktör Verimliliği Endeksi, Otomotiv Sanayi, Verimlilik, Doğrusal Programlama

To My Family

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TABLE OF CONTENTS

LIST OF TABLES

TABLES

LIST OF FIGURES

FIGURES

CHAPTER 1

INTRODUCTION

The industry of industries is the phrase used by Womack (1990) to define the automotive industry in “The Machine That Changed the World: The Story of Lean Production”. The value added that it produces, its direct and indirect contribution to employment and its pioneering to technological developments make automotive industry a key factor of the development of countries. In addition, because it takes inputs from many industries such as iron and steel, rubber and plastic, textile, glass, dye, electrics and electronics industries and causes large business volume in marketing, repairing, maintenance, spare parts sales, funding and insurance, automotive industry has an important role in economies (Bedir, 2002).

The most important event in the history of automotive industry is the transition from craft production to mass production developed by Henry Ford. The mass production reduced the costs by producing in great amounts. Then, in the 1990s a new production type called lean production was developed by Japanese automotive companies, especially by Toyota. The logic of that production type is decreasing the use of resources and increasing efficiency. One should apply to *The Machine that Changed the World: The Story of Lean Production* for more detailed information about the lean production.

Automotive industry is a locomotive sector in Turkey too. In the late 1980s, because of the liberal economy the conservation ratios were decreased and so the entrance of foreign capital into Turkish automotive industry was allowed. Today, there are approximately 40,000 people working in 17 main producers of Turkish automotive industry.

There are many financial and statistical indicators that show the importance of automotive industry in Turkish economy. One of the popular financial studies on the firms and sectors is the one carried out by ISO (Istanbul Chamber of Industry). ISO lists the top 500 industry firms of each year according to sales. The firms are also listed according their total turnover, gross value added, capital, equity capital, net assets, profit before tax or loss, export and the number of employees.

The list of ISO ranks the firms including the automotive companies according to one of the financial indicators like annual sales. However, it is a fact that only sales or another factor is not enough to compare and to rank the automotive companies because there are other concepts to be considered such as efficiency. An automotive company may get big turnover but it does not prove that the company is efficient in using its resources. For example, inadequate capacity usage is an important problem in Turkish automotive industry. Producers can not produce as much as they are able to produce due to insufficient demand in sector. Hence, a company with high turnover but low capacity usage is not really efficient. Therefore, the other factors like capacity usage should be taken into account in addition to one factor to rank the automotive companies. In other words, multiple inputs and outputs should be involved. This is one of the objectives of this study.

Considering more than one factor to compare companies requires the method of Data Envelopment Analysis (DEA). DEA measures the relative efficiency of decision units with respect to others. By the way, efficient and inefficient automotive companies can be detected. Besides, decision makers can see how inefficient companies may be improved that is an advantage of DEA.

However, DEA can measure the efficiencies of decision units for a specific time which means that it does not allow to analyze the changes in efficiencies by time. Therefore, Malmquist Total Factor Productivity TFP Index can be used to catch the changes in efficiencies and interpret the possible reasons of those changes.

In this study, first the DEA models are developed to measure the efficiencies of 17 automotive companies. Inputs and outputs in the model are determined by a method called stepwise approach in literature. Then, the efficiency changes of companies are observed by Malmquist TFP Index. Finally, it is tried to interpret the results company-based and sector-based.

The thesis report is organized as:

Chapter 2 starts with the definition of efficiency measurement in literature. The concept of production frontier and so the parametric and non-parametric frontiers are discussed. Then, DEA and its logic is explained. In other words, what DEA does and how it does are explained. The advantages and disadvantages of DEA are also presented. The examples of efficiency measurement in automotive industry are briefly given. Lastly, the mathematical DEA models and Malmquist TFP Index are shown.

In Chapter 3, the process of model construction is presented. The determination of the input and output factors by stepwise approach is explained. Then, the application of this approach to automotive companies for determining the factors to be used in DEA models is presented.

Chapter 4 includes the solutions of mathematical models used in this study. The results of DEA models such as CCR and BCC models and Malmquist TFP Index are given via tables. Most results are illustrated by figures and their interpretations are presented.

CHAPTER 2

LITERATURE SURVEY

2.1 EFFICIENCY MEASUREMENT IN THE LITERATURE

Production is an act of transforming inputs into outputs. Since resources are limited, producing a specific quantity of output with as little input as possible is the desirable objective. This is actually the origin of the efficiency concept. Before a detailed explanation of efficiency, some terminology should be clarified because there has been confusion in the use of the terms of efficiency and productivity of which both will be used in this study.

Haksever (2000) explains that productivity of a unit is the ratio of its output to input used to produce that output, so the productivity of a unit is unique. On the other hand, efficiency is the degree of achievement of a predetermined goal, an optimum outcome or the best practice. It can be said that the efficiency is not unique like productivity because it depends on the performance of the unit. Therefore, the efficiency of a unit is relative and different for each unit.

The production function is the function that shows the relationship between inputs and outputs. In other words, it shows how much output can be produced by given inputs or vice versa and the first empirical analysis of the production function as frontier was performed by Farrell (1957) who is a pioneer in this field. Then, the efficiency comparisons based on frontiers were called as Farrell efficiency score.

Farrell proved that 'overall efficiency' can be decomposed into allocative efficiency and technical efficiency. One of the objectives of Farrell's study was to answer the question “How much can inputs be reduced while maintaining the same level of output?” which is also known as input-oriented efficiency measure.

2.1.1 Input-Oriented Efficiency Measure

Farrell assumed that a company uses two inputs for producing one output because the production function for two inputs and one output can be shown in two dimensional space as in Figure 2.1 (Norman and Stoker, 1991).

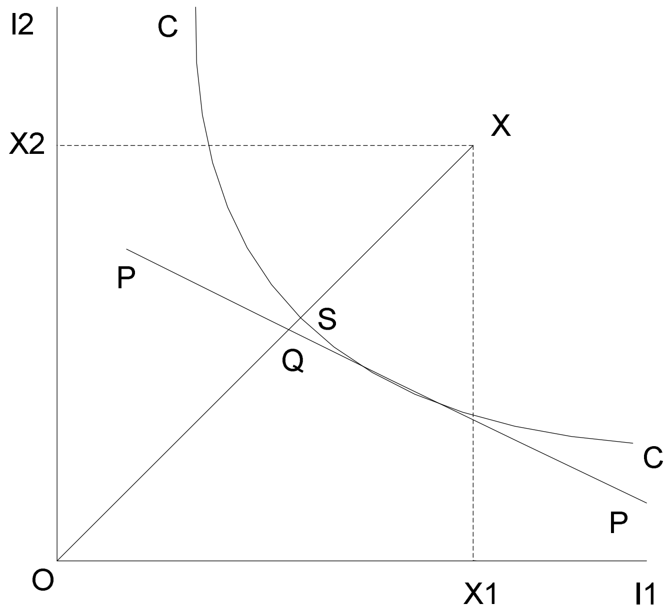

Figure 2.1 Technical and Allocative Efficiency (Input-oriented)

In Figure 2.1, I1 and I2 represent two inputs used for producing one output and CC curve is the output isoquant. It is seen that company X uses X1 units of input I1 and X2 units of I2 to produce 1 unit of output. X is inefficient because it lies above CC curve. The line PP represents the cost minimization line. Technical efficiency is the radial distance of X from CC curve (output isoquant) because technical efficiency is the degree of producing maximum output from given inputs. Besides, allocative efficiency is the radial distance from PP line (cost minimization line) because allocative efficiency is the degree of using the inputs in optimal proportions given their prices for minimizing the cost.

Technical efficiency $= \dfrac{OS}{OX}$ and Allocative efficiency $= \dfrac{OQ}{OS}$

If technical efficiency and allocative efficiencies are multiplied then overall efficiency is found as follows:

$$\text{Technical efficiency x Allocative efficiency} = \frac{OS}{OX} \text{ x } \frac{OQ}{OS} = \frac{OQ}{OX} = \text{Overall efficiency}$$

2.1.2 Output-Oriented Efficiency Measure

In the input-oriented efficiency measure, the technical inefficiency of the firm is the amount by which all inputs can be proportionally reduced without a reduction in the output. In other words, input-oriented measure tries to answer the question “How much can inputs be reduced while maintaining the same level of output?”, as mentioned above. However, the corresponding question “How much can output be increased while keeping the level of inputs constant?” Hence, the output-oriented efficiency measure tries to answer that question.

Similarly, a company Y can be considered such that two outputs are produced by using one input. The case is illustrated in Figure 2.2.

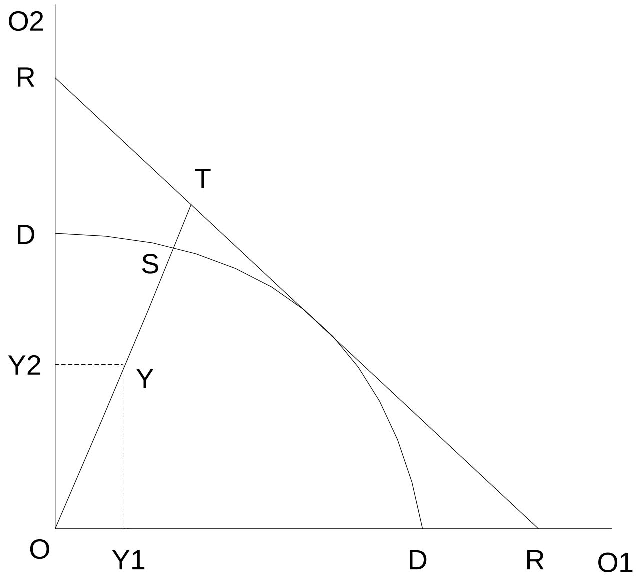

Figure 2.2 Technical and Allocative Efficiency (Output-oriented)

In Figure 2.2, O1 and O2 represents two outputs produced by using one output and DD curve is the input isoquant. It is seen that company Y produces Y1 units of output O1 and Y2 units of O2 by using 1 unit of input. Y lies below DD curve so it is inefficient. The line RR represents the cost minimization line. In Figure 2 the distance |YS| is the technical inefficiency because both two outputs can be increased until reaching point S. Therefore, from the output-oriented perspective the technical efficiency of Y is:

$$\text{Technical efficiency} = \frac{OY}{OS}$$

Besides, the allocative efficiency for output-oriented measure is the degree of producing the outputs in optimal proportions given their prices for maximizing the revenue. Hence, the allocative efficiency of Y is:

$$\text{Allocative efficiency} = \frac{OS}{OT}$$

As mentioned in input-oriented measure, the multiplication of technical efficiency and allocative efficiency gives the overall efficiency as follows:

$$\text{Technical efficiency x Allocative efficiency} = \frac{OY}{OS} \text{ x } \frac{OS}{OT} = \frac{OY}{OT} = \text{Overall efficiency}$$

2.1.3 Parametric vs. Non-parametric Frontiers

Both input and output oriented measures mentioned above show that efficiency is measured by the help of production functions. Also, it should be noted that in both illustrations of input and output-oriented measures the production functions (CC and DD curves) are assumed to be known. However, in real life production is a complex process that consists of many inputs and outputs so in many cases there is no known functional form for the production function. Therefore, the important thing is the method used for deriving the production functions.

In literature, there are two empirical approaches to the measurement of efficiency based on the above concepts of technical and allocative efficiency. The first, mostly used in economy, is parametric (either stochastic or deterministic). The form of the production function either is assumed to be known or is estimated statistically (in other words, theoretically). The advantages of this approach are that any hypotheses can be tested statistically and so the relationships between inputs and outputs can be shown as functional forms. However, because there is no known functional form for the production function in many cases, it may be inappropriate to talk about a production function.

In the non-parametric approach no assumptions are made about the form of the production function. Instead, a best practice function is formed empirically from observed inputs and outputs (Norman and Stoker, 1991). Another property of non-parametric programming is that the frontier is piecewise linear. On the other hand, the frontier is defined as linear in parametric programming. Fare, Grosskopf and Lovell (1985) can be studied regarding this topic. In non-parametric programming approach, all deviations from efficient frontier are evaluated as inefficiencies. However, in parametric statistical estimation approach it is accepted that the deviation has noise and inefficiency components. One can apply Ferrier and Lovell (1990), Lovell and Schmidt (1988) and Bauer (1990) for further information about the parametric statistical approach.

For non-parametric approach, the problem about the empirical production function is establishing the methodology that forms the frontier according the input and output values of the observed units. To understand the methodology the following postulates in literature can be reviewed. It should be noted that the postulates were compiled by Yolalan (1993).

Postulate 1. $(\vec{x}, \vec{y}) \in \Omega, \vec{y} \neq 0 \Rightarrow \vec{x} \neq 0$

Postulate 2. $(\vec{x}, \vec{y}) \in \Omega, \vec{x} < \infty \Rightarrow \vec{y} < \infty$

Postulate 3. $(\vec{x}, \vec{y}) \in \Omega, \vec{x}_I \geq \vec{x} \Rightarrow (\vec{x}_I, \vec{y}) \in \Omega$

Postulate 4. $(\vec{x}, \vec{y}) \in \Omega, \vec{y}_I \leq \vec{y} \Rightarrow (\vec{x}, \vec{y}_I) \in \Omega$

Postulate 5.

$$(\vec{x}_k, \vec{y}_k) \in \Omega, \forall k \in \{1,\ldots, p\} and \sum_{k=1}^{p} \lambda_k = 1, \lambda \geq 0 \Rightarrow \Omega = \left\{ (\vec{x}, \vec{y}) \mid \vec{x} = \sum_{k=1}^{p} \lambda_k \vec{x}_k, \vec{y} = \sum_{k=1}^{p} \lambda_k \vec{y}_k \right\}$$

Postulate 6. $(\vec{x}, \vec{y}) \in \Omega \Rightarrow (k\vec{x}, k\vec{y}) \in \Omega, k \in (0,1]$

Postulate 7. $(\vec{x}, \vec{y}) \in \Omega \Rightarrow (k\vec{x}, k\vec{y}) \in \Omega, k \in [1, \infty)$

Postulate 8. $\forall j = 1,\ldots, N, (\vec{x}_j, \vec{y}_j) \in \Omega$

Postulate 9. Ω is the smallest set that satisfies all postulates.

Postulate 1 explains that input must be used to observe output. Postulate 2 explains that finite amount of inputs produce finite amount of outputs. Postulate 3 explains that it is possible to produce a specific amount of output by using more amounts of inputs than the necessary amount. Postulate 4 explains that it is possible to produce less amounts of outputs by using the same amount of inputs. Postulate 5 explains that linear combinations of inputs and outputs can be realized under the existing conditions. A convex set is defined by this postulate. Postulate 6 and 7 explains that the scale can be decreased or increased without changing the input/output ratio.

Postulate 8 explains that N decision making units represent the production possibility set accurately. Postulate 9 explains that there are no other decision making units of which efficiencies are better than the present ones.

Figure 2.3 shows the sets defined by the help of the postulates above. In the figure, x represents one input and y represents one output. Also, there are 8 observed units.

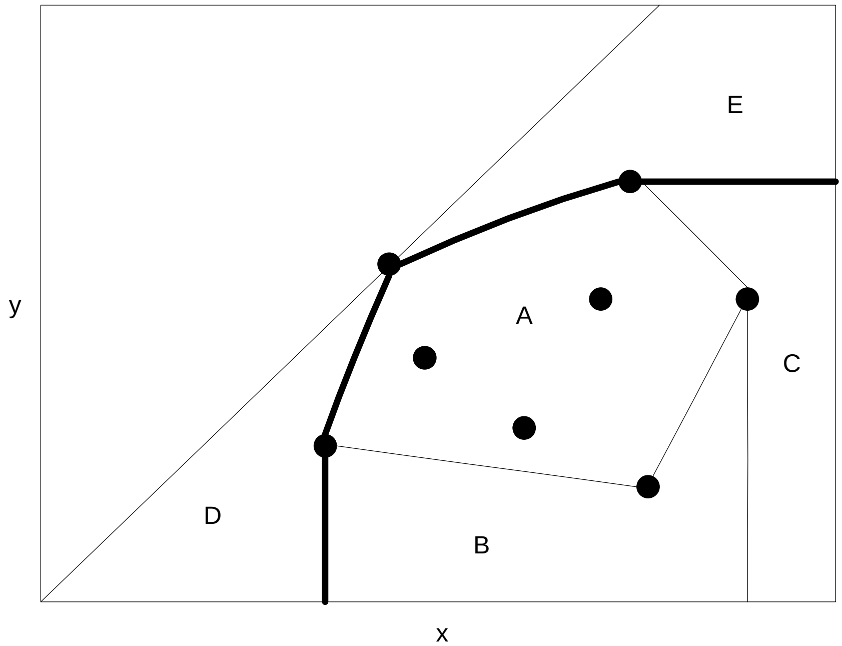

Figure 2.3 Illustrations of Postulates

If Postulates 1, 2, 5, 8, 9 are in use then the defined production set is A.

If Postulates 1, 2, 4, 5, 8, 9 are in use then the defined production set is A U B

If Postulates 1, 2, 3, 4, 5, 8, 9 are in use then the defined production set is A U B U C

If Postulates 1, 2, 3, 4, 5, 6, 8, 9 are in use then the defined production set is A U B U C U D

If Postulates 1, 2, 3, 4, 5, 7, 8, 9 are in use then the defined production set is A U B U C U E

If Postulates 1, 2, 3, 4, 5, 6, 7, 8, 9 are in use then the defined production set is A U B U C U D U E

The set A is not realistic because according in set A it is not possible to produce less outputs by using the same inputs. However, it is possible in real life and this situation is called as inefficiency. Therefore, set B is added to set A (Postulate 4) for making the frontier more realistic. Similarly, in real life it is possible to produce the same output by using more inputs. Hence, set C is added too (Postulate 3). In sum, the bold lines that enclose the set A U B U C form the production frontier.

If Postulate 6 is in use it means that the output can be decreased by decreasing the scale. In other words, there can be units in set D. Hence, the new production set is A U B U C U D. Similarly, if the output can be increased by increasing the scale set E should be added. The new set is A U B U C U D U E and this type of production frontier satisfies Constant Return to Scale (CRS). The directions of return to scale will be discussed in Data Envelopment Analysis section.

2.1.4 Data Envelopment Analysis

There are lacks in Farrell approach to measure the efficiency. One of lacks is that Farrell's approach is based on single output or input. However, there may be many inputs and outputs in practice. The other lack is the guiding to inefficient units for improvement. In other words, it does not show how to produce more output or to use less input. Therefore, a new method that improves the efficiency measurement of Farrell should be improved.

The term Data Envelopment Analysis (DEA) was firstly introduced in the literature by Charnes, Cooper and Rhodes (1978). DEA is a linear programming based non-parametric technique. Because of this property, Ganley and Cubbin (1992) called DEA as non-parametric programming. DEA measures the efficiency of a DMU (Decision Making Unit is the term first used by Charnes, Cooper and Rhodes in 1978 for determining the units of which relative efficiency scores are calculated by DEA) by its position relative to the frontier of best performance. Therefore, it can be said that DEA is a method that measures the relative efficiencies of DMUs Since there is not a known production function in many cases, DEA establishes the efficient frontier mathematically by the ratio of weighted sum of multiple outputs to weighted sum of multiple inputs. All DMUs can set their own weights independently in order to make themselves as efficient as possible. However, there are two constraints to prevent the subjectivity. One of the constraints states that if the weights of a DMU are used for other DMUs their efficiencies should not exceed 100%. According to other constraint, any weight should not be negative.

In order to understand the use of DEA, Fried and Lovell (1993) listed the following as questions that DEA can help to answer for managers:

- How are appropriate role models selected as possible benchmarks for performance improvement?
- Which production facilities are the most efficient in organization?
- If all operations were to perform according to best practice, how many more service outputs could be produces and how much resource inputs can be reduced by and in what areas?
- What are the characteristics of efficient operating facilities and how can they guide me in choosing locations for expansion?
- What is the optimum scale for operations and how much can be saved if all facilities were the optimum size?
- How can external circumstances be taken into account in evaluating the performance of individual operating facilities?

How DEA can help in those topics will be explained in next chapter in which the DEA mathematical programming model is mentioned in detail.

In sum, the simplicity and the reliability makes DEA one of the popular and mostly used methods. The popularity can be understood by reviewing the DEA bibliography update prepared by Gattoufi, Oral and Reisman (2004) because approximately 2000 references has been published between year 1951 and 2001. Moreover, one can apply to Seiford (1996) for the implementation examples in literature. DEA has been used in many areas such as schools (Charnes et al, 1981), hospitals (Banker et al, 1986), banks and branches (Ferrier and Lovell, 1990), electricity services (Fare et al, 1985) and the firms in stock exchange (Ulucan, 2000), (Al-Shammari, 1999).

The main advantages of DEA are that:

- One of the common methods, the regression analysis, can be used in either multiple inputs or multiple outputs cases. However, DEA can incorporate both multiple inputs and outputs. Cubbin and Tzanidakis (1998) and Thanassoulis (1993) can be observed for the comparison of DEA and regression analysis methods.
- DEA only requires information on output and input quantities (not prices) to calculate technical efficiency so it does not need any information about prices (Büyükkılıç and Yavuz, 2005).
- Possible reasons of inefficiency can be determined by DEA in addition to efficiency levels. Moreover, DEA also allows technical inefficiency to be decomposed into scale effects, the effects of unwanted inputs and a residual component. By identifying the "peers" (efficient DMUs) for inefficient DMUs, DEA provides a set of potential role models that the inefficient DMU can become efficient by behaving as role models (Charnes, Cooper and Rhodes, 1978).
- External factors which affect the outputs but that are not in the direct control of DMUs' managers can be included in the model in DEA. One can apply to Banker and Morey (1986), and Golany and Roll (1993) for more information about the use of external variables in DEA.
- Because an optimization model is used for each DMU in DEA, individual evaluations can be performed rather than the averages in regression analysis (Cubbin and Tzanidakis, 1998).

However, DEA has limitations which are as the following:

- DEA produces results that are particularly sensitive to measurement error because it is a deterministic technique rather than a statistical technique. It means that if one DMU's inputs are understated or its outputs overstated, then that DMU can become an outlier that significantly affects the shape of the frontier and reduces the efficiency scores of the DMUs closed to it. In regression analysis, the presence of error terms in the estimation tends to decrease the effect of outliers, but in DEA they are given equal weight to that of all other DMUs. It is important to check the potential outliers in the data. Analysis of the units whose output-to-input ratios lie more than about two-and-a-half standard deviations from the sample mean is a useful control.

- DEA only measures efficiency relative to best practice within the observed DMUs. Thus, it is not meaningful to compare the scores between two different studies because the best practices' differences between the samples are not known.
- DEA scores are sensitive to input and output specification and the size of the sample. Increasing the sample size reduces the average efficiency score because more DMUs mean greater scope for DEA to find similar comparison partners. Conversely, few DMUs relative to the number of outputs and inputs can artificially increase the efficiency scores. Increasing the number of outputs and inputs used in the model without increasing the number of DMUs increases the efficiency scores on average.

In literature, there are many rules regarding the minimum number of DMUs in the model. One of the rules is that the number of DMUs should be greater than M x S (where M = number of inputs and S = number of outputs). The logic of this rule is that there are M x S possibilities in which DMUs can be efficient, therefore at least M x S DMUs can be identified as efficient. (Dyson, Thanassoulis and Boussofiane, 1990). Besides, Soteriou and Zenios (1998) also stated that the appropriate number of DMUs in the model should exceed the product of the number of inputs and outputs in order to discriminate between DMUs.

Dyson et al. (2001) mentioned another suggested 'rule of thumb' which states that the number of DMUs should be at least 2(M x S) where M x S is the product of the number of inputs and number of outputs.

The other rule regarding the maximum number of variables or the minimum number of DMUs in the DEA model is that the number of DMUs in the sample should be at least three times greater than the sum of the number of outputs and inputs included in the model (Nunamaker, 1985). This rule of thumb has been used or mentioned in many studies in the literature such as Saez and Achaerandio (2004), Ureta, Rivas and Thiam (2001), Akhtar and Bokhari (2005), Ajodhia (2006) and Banker (1989). In this study, the third rule of thumb is used and the number of variables is determined according to that rule.

Besides, there are other methods such as PCA (Principal Component Analysis) and super-efficiency method that can be used when there are excessive number of inputs and outputs. One can apply to Adler and Golany (2001) and Zhu (1998) for more information about the PCA method, Andersen and Petersen (1993) about super-efficiency method.

- Lastly, since there is not an assumption about the probability distribution of the observation errors in DEA Sengupta (1987) stated that DEA is not suitable for statistical analysis.

2.1.5 Efficiency Measurement in Automotive Industry

There are many studies on measuring the relative efficiencies of sectors that cover the automotive industry in literature. In other words, most studies compare the efficiencies of sectors. However, the number of studies which focus on specifically automotive industry or the relative efficiencies of automotive companies is very low. One of these studies was performed by Lieberman and Dhawan (2000) for US and Japan automotive companies.

Lieberman and Dhawan (2000) stated that the automotive industry has a dynamic environment for assessing the performance factors. The studies of Womack, Jones and Roos (1990) and Lieberman, Lau and Williams (1990) have demonstrated the differences in efficiency among auto producers in Japan and the US. For example, in the beginning, General Motors (GM) was the world’s most efficient automotive company but in 1990s Toyota took the leadership in automotive industry by the new production type called lean production. Toyota and other Japanese automotive firms surpassed the US firms in labor productivity level. Later, Ford and Chrysler started to activate the sector where Japanese firms were becoming stable. One can apply to Womack, Jones and Roos (1990) and Lieberman, Lau and Williams (1990) for more detailed information about the history of production in automotive industry. According to the developments mentioned above, Lieberman and Dhawan (2000) also concluded that the productivity differences stem from firm specific factors rather than national factors.

Lieberman and Dhawan incorporate the measures of resources and capabilities that may be important in the auto industry to explain the productivity differences of automotive companies. These measures determined as investment, company size, degree of vertical integration and skills in manufacturing and product design. Actually, the measures of Lieberman and Dhawan (2000) were used as references for determining the inputs and outputs of DEA model in this study.

Labor Productivity

The dependent variable in their study is labor productivity, defined as real value added per worker. Here, it should be noted that the term “dependent variable” shows that Lieberman and Dhawan used a regression-based method. The real value added was computed by dividing nominal value added by the domestic producer price index for motor vehicles. Dividing by employment gives the value added per worker which is a standard measure of labor productivity.

Investment

Normally, investment increases the worker productivity that is defined as the dependent variable. However, an automotive company can not gain a sustained competitive advantage by only increasing its rate of investment. Therefore, the capital stock per worker was added in the model as a control variable.

Company Size

Economies of scale are significant in the automotive industry because larger company size allows cost savings in production, as well as product design and marketing. One measure of company size is total employment. Lieberman and Dhawan also used vehicle output as an alternative measure of company size.

Moreover, they distinguished the economies of scale as firm-level and plant-level economies of scale. Lieberman and Dhawan stated that the studies of Pratten (1971) indicated that plant level economies are effectively achieved above a threshold volume of approximately 200,000 annual vehicles per assembly plant. It has also been stated that it is difficult for competitors to imitate such plants due to very high costs. Therefore, it was concluded that plant level scale economies provide competitive advantage.

Shop Floor Manufacturing Capabilities

Lieberman and Dhawan explain that the level of work-in-process (WIP) is an indicator of proficiency on the shop floor. Besides, Lieberman and Demeester (1999) show that WIP reductions cause productivity gains, and lower WIP levels causes higher labor productivity. They also show that the WIP/sales ratio reflects the "leanness" of the company's production system. One can also apply to Womack, Jones and Roos (1990) for more information about the importance of WIP in automotive industry and the lean production.

Vertical Integration

Another measure used by Lieberman and Dhawan is the companies' degree of vertical integration. The US automotive companies mostly produced parts via in-house manufacturing operations. On the other hand, the Japanese assemblers had subcontracting and close collaboration with their suppliers.

The measure of the degree of vertical integration is indicated by the company's annual value added as a proportion of sales.

Product Design

The studies of Clark and Fujimoto (1991), Nobeoka and Cusumano (1997) and Cusumano and Nobeoka (1998) state that the product development and design is an important area of production operations in automotive industry where companies differ in their capabilities. Design performance has multiple dimensions, including development time and cost, rate of new product introduction, and degree of product appeal to consumers. Because the data on these dimensions are not available, Lieberman and Dhawan (2000) collected information on design quality by the help of a car magazine.

Cumulative Output

Argote (1991) states that as organizations produces more of a product, the unit cost of production typically decreases at a decreasing rate and this pattern is named as "learning curve" or "experience curve". The logic behind this concept is "learning by doing". Montgomery (1983) can also be applied for more detailed information about this topic. Models of the learning curve or experience curve commonly use cumulative output to represent the level of organizational learning (Argote, 1999). Therefore, Lieberman and Dhawan (2000) used the cumulative historical production of vehicles for each company.

After determining the measures of resources and capabilities, Lieberman and Dhawan used Stochastic Frontier Analysis (SFA) in order to estimate the parameters of the related measures for each company.

Another study on benchmarking the efficiencies of automotive companies was performed by Yılmaz, Özdil and Akdoğan (2002). They used DEA for finding the relative efficiency scores of 9 automotive companies in Turkey. The data was received from the research of ISO (Istanbul Chamber of Industry) that is called "Top 500 Industry Firms of Turkey – 2001".

The outputs in the model are turnover (in trillion TL), profit before tax (in trillion TL) and export (in trillion TL). Besides, net assets (in trillion TL), capital stock (in trillion TL) and the number of employments are the inputs. At the end, the efficiency score of each automotive company was calculated and the ranks of the companies found from DEA and the ranks in "Top 500 Industry Firms of Turkey – 2001" were compared.

However, the results of the study mentioned above are suspicious because the rule regarding the number of DMUs (or variables) is violated. (Nunamaker 1985) states that the number of DMUs in the sample should be at least three times greater than the sum of the number of outputs and inputs. In this study, totally 6 variables (inputs plus outputs) were used and according to the rule there should be at least 3 x 6 = 18 DMUs to be observed.

Besides, the analysis of the results of study is too superficial. For example, nothing was performed for the reference sets (role models) of inefficient DMUs so there is no interpretation about the possible improvements of inefficiencies.

Moreover, the efficiency scores found are the overall (total) efficiency scores of DMUs because the model was established under the constant returns to scale. Since a BCC model (will be discussed in next section) that assumes variable returns to scale is not used technical and scale efficiencies of DMUs can not be known.

Lastly, the data of year 2001 is used for calculating the efficiency scores via DEA. If panel data had used instead of only year 2001, the efficiency changes of DMUs by time could have been analyzed.

Indeed, one of the objectives of this study is to extend the study of Yılmaz, Özdil and Akdoğan (2002) and complete the lacks mentioned above.

2.2 DATA ENVELOPMENT ANALYSIS

In many cases, the simple ratio analysis is used despite of multiple inputs and outputs. However, when there are multiple inputs and multiple outputs, the simple ratio approach is not adequate because most efficient unit according to a ratio can not be efficient according to another ratio. To prevent the deficiency of simple ratio approach in multiple inputs / outputs cases, the ratio of the quantity of all outputs (virtual output) to all inputs (virtual) input is used. Total Factor Productivity (TFP) is the index of that ratio. As mentioned in section 2.1.4, one of the most important advantages of DEA is that it allows considering multiple inputs and multiple outputs. Here, DEA performs it through the concept of total factor productivity.

The model developed by Charnes, Cooper and Rhodes (1978) and based on the concept of TFP is as follows:

$$\text{Max} \qquad h = \frac{\sum_{r=1}^{s} u_{rk} Y_{rk}}{\sum_{i=1}^{m} v_{ik} X_{ik}} \tag{2.1}$$

s.t.

$$\frac{\sum_{r=1}^{s} u_{rk} Y_{rj}}{\sum_{i=1}^{m} v_{ik} X_{ij}} \leq 1 \qquad \text{j = 1, …, N} \tag{2.2}$$

$$u_{rk} \geq 0, \quad v_{ik} \geq 0 \qquad \text{r = 1, …, s;} \quad \text{i = 1, …, m} \tag{2.3}$$

where the representations of indexes are as follow:

j : represents the DMUs and varies from 1 to n (there are n DMUs).

i : the input index and varies from 1 to m (there are m inputs).

r : the output index and varies from 1 to s (there are s outputs).

X_{ij} : represents the value of the i^{th} input for the j^{th} DMU (X_{ik} represents the value of i^{th} input for the DMU that is under evaluation).

Y_{rj} : represents the value of the r^{th} output for the j^{th} DMU (Y_{rk} represents the value of r^{th} ouput for the DMU that is under evaluation).

v_{ik} : the weight of the i^{th} input for the DMU that is under evaluation.

u_{rk} : the weight of the r^{th} output for the DMU that is under evaluation.

The objective function (2.1) measures the ratio of weighted sum of multiple outputs to weighted sum of multiple inputs. The constraint (2.2) states that if the weights of a DMU are used for another DMUs their efficiencies should not exceed 100%. The second constraint (2.3) provides the non-negativity of weights. However, it should be noted that the above model is the basis for the input-oriented CCR model that will be discussed in next section.

2.2.1 Basic CCR Model

There is not a methodology such as simplex algorithm in order to solve the fractional programming models; so the above model was transformed to linear programming model for easy solving.

Charnes and Cooper stated that if (u^*, v^*) is a possible solution that maximizes the objective function of the above model under the constraint of (2.2) then all (αu^*, αv^*) maximize the objective function where $\alpha > 0$. Therefore,

$$\sum_{i=1}^{m} v_{ik} X_{ik} = 1$$

performs the transformation from fractional programming to linear programming model as follows:

Model M_I

$$\text{Max} \quad \varphi_k = \sum_{r=1}^{s} u_{rk} Y_{rk} \tag{2.4}$$

s.t.

$$[\,\theta_k\,] \quad \sum_{r=1}^{s} u_{rk} Y_{rj} - \sum_{i=1}^{m} v_{ik} X_{ij} \leq 0 \qquad j = 1, \ldots, N \tag{2.5}$$

$$[\,\lambda_{jk}\,] \quad \sum_{i=1}^{m} v_{ik} X_{ik} = 1 \tag{2.6}$$

$$u_{rk} \geq 0, \quad v_{ik} \geq 0 \qquad r = 1, \ldots, s;\ i = 1, \ldots, m$$

The linear programming model developed according to TFP concept is called as the multiplier model or M_I where index I represents that the model is input oriented. The objective of the input-oriented CCR model is to minimize inputs while using at least given outputs. The important point for this model is that the model measures the total efficiency under constant returns to scale (CRS) assumption.

As mentioned before one of the advantages of DEA is to highlight the possible efficiency improvements for inefficient DMUs. In other words, DEA shows how the inefficient DMUs can be moved onto the efficient frontier by the help of the reference sets (peers) of the related inefficient DMUs. Envelopment model (E_I) is used for finding the reference sets. It is seen that a dual variable "λ_{jk}" is defined for each DMU in M_I model. The E_I model is established by all defined dual variables which are λ_{jk} and θ_k.

Model E_I

Min θ_k (2.7)

s.t.

$$\sum_{j=1}^{N} Y_{rj}\lambda_{jk} \geq Y_{rk} \qquad r = 1, \ldots, s \tag{2.8}$$

$$\theta_k X_{ik} - \sum_{j=1}^{N} X_{ij}\lambda_{jk} \geq 0 \qquad i = 1, \ldots, m \tag{2.9}$$

$$\lambda_{jk} \geq 0 \qquad j = 1, \ldots, N$$

θ_k urs (unrestricted in sign) $\equiv$ ($-\infty < \theta_k < \infty$)

The simple logical interpretations of the constraints are as follow:

- For the unit "k" find the minimum proportion θ_k
- for each input, the weighted combination of input does not exceed the proportion of θ_k
- for each output, the weighted combination of output is at least as great as that of unit "k"

It is a fact that the dual model should also be interpreted technically according to fundamentals of linear programming and duality theory for understanding the logic and benefits of DEA.

Because of the equality constraint in M_I model the dual variable θ_k is free of sign which means that θ_k can be either positive or negative values. The objective function of the M_I model gives the efficiency score that can not be a negative value. Because the optimal solutions of primal and dual models should be the same according to duality theory, θ_k can not be negative although it is free of sign. On the other hand if θ_k is zero then there is a contradiction. When θ_k is zero it is seen in the second constraint that

$$-\sum_{j=1}^{N} X_{ij}\lambda_{jk} \geq 0$$

Since all X_{ij} s are positive the equation is satisfied if and only if $\lambda_{jk} = 0$. However, the condition of $\lambda_{jk} = 0$ violates the first constraint so θ_k can never be zero. In sum, the domain set of θ_k is (0,1).

Besides, the interpretation of λ_{jk} is more complex than θ_k. Complementary slackness theorem states that $\lambda_{jk} > 0$ if and only if the equation in M_I that belongs to DMU k is satisfied. This condition shows the DMU j is efficient. For instance if $\lambda_{jk} > 0$ then

$$\sum_{r=1}^{s} u_{rk} Y_{rj} - \sum_{i=1}^{m} v_{ik} X_{ij} = 0 \qquad \text{or} \qquad \frac{\sum_{r=1}^{s} u_{rk} Y_{rj}}{\sum_{i=1}^{m} v_{ik} X_{ij}} = 1 \qquad \text{for DMU k.}$$

In other words, DMU j is efficient according to the weights of DMU k (u_{rk} and v_{ik}) when all DMUs are also taken into consideration. In conclusion, DMU j is relatively efficient even the model is established for DMU k. Actually, all DMUs of which dual variables are positive in the primal model of DMU k are efficient and the set of those efficient DMUs (peers) is called as the reference set of DMU k. If k is efficient then the only DMU in its reference set is its own and $\lambda_{kk} = 1$. The reference set of a DMU shows what can be done for improvement via the role model for that DMU.

$$X_{i\kappa} = \sum_{q \in R_\kappa} \lambda_{kq} X_{iq} \qquad \text{i = 1, …, m}$$

$$Y_{r\kappa} = \sum_{q \in R_\kappa} \lambda_{kq} Y_{rq} \qquad \text{r = 1, …, s}$$

Where R_κ is the reference set of DMUs. The equations shows that DMU k can decrease its inputs from X_{ik} to $X_{i\kappa}$ while producing outputs $Y_{r\kappa}$ which are at least Y_{rk}.

The other type of CCR models is the output-oriented CCR model and called as M_O where O represents that the model is output-oriented. The output-oriented CCR model maximizes the outputs without using more of given inputs. However, the constant returns to scale (CRS) assumption is still valid. The multiplier and envelope output-oriented CCR models are as follow:

Model M_O

$$\text{Min } g_k = \sum_{i=1}^{m} v_{ik} X_{ik} \tag{2.10}$$

s.t.

$$-\sum_{r=1}^{s} u_{rk} Y_{rj} + \sum_{i=1}^{m} v_{ik} X_{ij} \geq 0 \qquad j = 1, \ldots, N \tag{2.11}$$

$$\sum_{r=1}^{s} u_{rk} Y_{rk} = 1$$

$$u_{rk} \geq 0, \quad v_{ik} \geq 0 \qquad r = 1, \ldots, s; \quad i = 1, \ldots, m \tag{2.12}$$

The dual model of M_O is E_O which is an envelopment model:

Model E_O

$$\text{Max } z_k \tag{2.13}$$

s.t.

$$-\sum_{j=1}^{N} Y_{rj} \lambda_{jk} + Y_{rk} z_k \leq 0 \qquad r = 1, \ldots, s \tag{2.14}$$

$$\sum_{j=1}^{N} X_{ij} \lambda_{jk} \leq X_{ik} \qquad i = 1, \ldots, m \tag{2.15}$$

$$\lambda_{jk} \geq 0 \qquad j = 1, \ldots, N$$

z_k urs

The calculations, interpretations about the reference sets of input-oriented CCR models are valid for output-oriented CCR models too.

Assume that a DMU uses an input much more than or produces an output much less than the other DMUs. Normally, this DMU wants to give the minimum weight for that input or output in order to make its efficiency score greater. Because the primal models (multiplier models) mentioned above allow the DMUs to give "zero" weights to their inputs and outputs, the optimal weights may be zero. Charnes, Cooper and Rhodes (1979) stated to set the variables $u_{rk} \geq \varepsilon$, $v_{ik} \geq \varepsilon$ instead of $u_{rk} \geq 0$, $v_{ik} \geq 0$ in the primal models and called those models as "non-Archimedean" models. The non-Archimedean M_I (with its dual variables) and E_I models are given below:

Model M_I^{ε}

$$\text{Max} \quad \varphi_k = \sum_{r=1}^{s} u_{rk} Y_{rk} \tag{2.16}$$

s.t.

$$[\,\theta_k\,] \quad \sum_{r=1}^{s} u_{rk} Y_{rj} - \sum_{i=1}^{m} v_{ik} X_{ij} \leq 0 \qquad j = 1, \ldots, N \tag{2.17}$$

$$[\,\lambda_{jk}\,] \quad \sum_{i=1}^{m} v_{ik} X_{ik} = 1 \tag{2.18}$$

$$[\,s_{rk}^{+}\,] \quad u_{rk} \geq \varepsilon \qquad r = 1, \ldots, s \tag{2.19}$$

$$[\,s_{ik}^{-}\,] \quad v_{ik} \geq \varepsilon \qquad i = 1, \ldots, m \tag{2.20}$$

The dual model of M_I^{ε}, E_I^{ε} is established by all defined dual variables which are λ_{jk} , θ_k , s_{rk}^{+} and s_{ik}^{-} .

Model E_I^{ε}

$$\text{Min} \quad \theta_k - \varepsilon\left[\sum_{r=1}^{s} s_{rk}^{+} + \sum_{i=1}^{m} s_{ik}^{-}\right] \qquad (2.21)$$

s.t.

$$\sum_{j=1}^{n} Y_{rj}\lambda_{jk} - s_{rk}^{+} = Y_{rk} \qquad r = 1, \ldots, s \qquad (2.22)$$

$$\theta_k X_{ik} - \sum_{j=1}^{N} X_{ij}\lambda_{jk} - s_{ik}^{-} = 0 \qquad i = 1, \ldots, m \qquad (2.23)$$

$$\lambda_{jk},\ s_{rk}^{+},\ s_{ik}^{-} \geq 0$$

θ_k urs

The E_I^{ε} model is also known as "slack-adjusted model" in literature. The objective function of E_I^{ε} includes the term $-\varepsilon\left[\sum_{r=1}^{s} s_{rk}^{+} + \sum_{i=1}^{m} s_{ik}^{-}\right]$ that is different from the objective function of Archimedean model. This term states that if the sum of slack variables is greater than zero then the efficiency score gets under 1 even $\theta_k = 1$ because the sum of slack variables is multiplied by "– ε". Therefore, there are two conditions to be satisfied in order to say a DMU is efficient:

i. $\theta_k = 1$

ii. All slack variables are zero.

The conditions above are closely related to the definition of Pareto-Koopmans efficiency and one can apply to resource Charnes and Cooper (1961) for more detailed information about Pareto-Koopmans efficiency.

Charnes, Cooper and Rhodes (1979) stated a two-phase methodology to remove the inconveniences of setting ε *a priori*. Firstly, the E_I model is solved and θ_k is calculated. If $\theta_k = 1$ then in the second phase by taking θ_k as 1 a new model called "additive model" is established to maximize the sum of slack variables.

$$\text{Max} \quad \sum_{r=1}^{s} s_{rk}^{+} + \sum_{i=1}^{m} s_{ik}^{-} \tag{2.24}$$

s.t.

$$\sum_{j=1}^{n} Y_{rj}\lambda_{jk} - s_{rk}^{+} = Y_{rk} \qquad r = 1, \ldots, s \tag{2.25}$$

$$X_{ik} - \sum_{j=1}^{N} X_{ij}\lambda_{jk} - s_{ik}^{-} = 0 \qquad i = 1, \ldots, m \tag{2.26}$$

$$\lambda_{jk}\,,\ s_{rk}^{+},\ s_{ik}^{-} \geq 0$$

If the objective function is zero then the DMU k is efficient. However, if it is not zero which means that any slack variable is positive, the DMU k is not efficient even $\theta_k = 1$. For instance, assume that s_{ik}^{-} is positive, so the objective function is greater than zero. It means that X_{ik} can be decreased without any decrease in outputs. Therefore, the DMU k is not efficient although $\theta_k = 1$.

2.2.2 Technical Efficiency and Scale Efficiency

Technical efficiency is expressed as the non-existence of any waste. In other words, technical efficiency is the success of producing the maximum output through utilizing the inputs in a most efficient way. It is a fact that all technical efficient DMUs are located on the efficient frontier and the DMUs below the efficient frontier waste their resources relatively. This situation is illustrated in Figure 2.4.

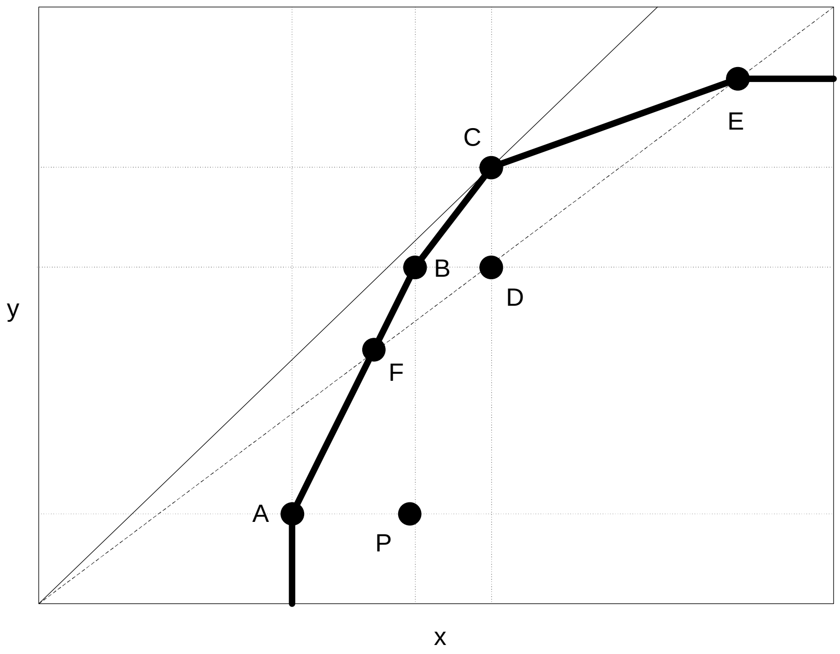

Figure 2.4 Technical Efficiency

When the output/input ratios of A, B and P are calculated it is seen that P is the least productive and B is the most productive unit among them. In Figure 2.4, it is also seen that the productivity of A is less than B although A is called as technical efficient.

Unit P can increase its technical efficiency and productivity by moving towards B because both it gets closer to efficient frontier and the output/input ratio gets larger. Besides, A can increase its productivity by moving towards B while keeping its technical efficiency constant because it is still on the efficient frontier and the output/input ratio is increased. Banker (1984) stated that C which is the relatively most productive unit possesses the “Most Productive Scale Size (MPSS)” and the closeness to MPSS is called as *scale efficiency*.

It is seen that F can increase its productivity (getting closer to MPSS) by increasing its scale while keeping its technical efficiency. This is called as “Increasing Returns to Scale (IRS)”. In other words, the relationship between the input and output of F is expressed by a curve which increases more steeply than a straight line that is for Constant Returns to Scale (CRS) (Banker, 1984).

Besides, E can increase its productivity (getting closer to MPSS) by decreasing its scale while keeping its technical efficiency. This is called as “Decreasing Returns to Scale (DRS)”. In other words, the relationship between the input and output of E is expressed by a curve which increases less steeply than a straight line.

Finally, if all IRS, DRS and CRS intervals exist on the efficient frontier together then it is called as “Variable Returns to Scale (VRS)”.

2.2.3 Basic BCC Model

The total efficiency scores calculated by CCR models under the CRS assumption includes technical and scale efficiencies together. However, technical and scale efficiencies can not be found separately from CCR models.

If the postulates that are explained in section 2.1.3 are remembered, it is seen that Postulate 2.6 and 2.7 are the ones which satisfy the Constant Returns to Scale (CRS). Banker, Charnes and Cooper (1984) stated that if the Postulates 2.6 and 2.7 (Constant Returns to Scale postulate) is cancelled then the DMUs with the efficiency score of 1 will be the ones on the efficient frontier. It means that the DMUs are evaluated only according to their technical efficiencies with the independence of the deviations from Most Productive Scale Size (MPSS). Therefore, the technical efficiencies of DMUs can be calculated separately. After the total efficiency score is calculated from CCR models and technical efficiency score from BCC models, the scale efficiency score of a DMU can also be calculated by the help of the formula created by Farrell (1957):

$$\text{Scale efficiency score} = \frac{\text{Total efficiency score (CCR)}}{\text{Technical efficiency score (BCC)}}$$

If the value of this ratio is one, then the DMU is apparently operating at optimal scale. If the ratio is less than one then the DMU appears to be either too small or too large relative to its optimum size.

The input oriented linear programming model that is also known as BCC model under the assumption of Variable Returns to Scale (VRS) is as follows:

Model e_I

Min θ_k (2.27)

s.t.

$$\sum_{j=1}^{N} Y_{rj}\lambda_{jk} \geq Y_{rk} \qquad r = 1, \ldots, s \tag{2.28}$$

$$\theta_k X_{ik} - \sum_{j=1}^{N} X_{ij}\lambda_{jk} \geq 0 \qquad i = 1, \ldots, m \tag{2.29}$$

$$\sum_{j=1}^{N} \lambda_{jk} = 1 \tag{2.30}$$

$$\lambda_{jk} \geq 0 \qquad j = 1, \ldots, N$$

θ_k urs

As it is seen in the model above the only difference from the E_I model is the last constraint (convexity constraint), $\sum_{j=1}^{N} \lambda_{jk} = 1$ which satisfies the VRS instead of CRS.

The dual of the e_I model is:

Model m_I

$$\text{Max} \quad \varphi_k = \sum_{r=1}^{s} u_{rk} Y_{rk} - \mu_0 \tag{2.31}$$

s.t.

$$\sum_{r=1}^{s} u_{rk} Y_{rj} - \sum_{i=1}^{m} v_{ik} X_{ij} - \mu_0 \leq 0 \qquad j = 1, \ldots, N \tag{2.32}$$

$$\sum_{i=1}^{m} v_{ik} X_{ik} = 1 \tag{2.33}$$

$$u_{rk} \geq 0, \quad v_{ik} \geq 0 \qquad r = 1, \ldots, s; \quad i = 1, \ldots, m$$

μ_0 urs

The possibility of being zero for the optimal weights is still valid for the BCC models as previous CCR models. Therefore, the non-Archimedean models for both m_I and e_I can be established similarly as performed for CCR models. Afterwards, the additive model that is similar to (2.24) – (2.26) can be established and used to control whether there are any positive slack variable.

Both the objective functions of e_I and m_I give the technical efficiency score of a DMU. Additionally, the variable μ_0 in m_I model gives the direction of returns to scale as the following:

- Increasing Returns to Scale $\Leftrightarrow$ $\mu_0^* < 0$
- Constant Returns to Scale $\Leftrightarrow$ $\mu_0^* = 0$
- Decreasing Returns to Scale $\Leftrightarrow$ $\mu_0^* > 0$

However, it should not be forgotten that the above interpretations about the direction of returns to scale via μ_0 are valid if and only if the optimal solution is unique. Otherwise, Banker-Thrall method can be used for alternative solutions case. One can apply to Banker and Thrall (1992) for more details about that method.

2.3 MALMQUIST TOTAL FACTOR PRODUCTIVITY

Generally, efficiency analysis is performed for a specific time period. However, the change of efficiency by time is an important topic to be considered. For example, if there has been a significant change in technology over the sample period, it is difficult to assess whether increases in efficiency scores each year are a result of improvements in technical efficiency or technological change. The change in total factor productivity by time can be analyzed if the panel data (a data set that contains observations on multiple variables observed over multiple time periods) is available.

Many indexes are used to measure the changes in total factor productivity. These indexes are the ratios of output indexes to input indexes. Here, it is necessary to explain what an index is. Indexes are the tools that are used to measure the changes in the levels of economical variables. An index number is defined as a real number which measures the changes in a set of related variables. They are used to compare the values of a variable that change by time, place or both of them. Price indexes can give the consumer prices, input/output prices, import/export prices but on the other hand quantity indexes can measure the changes in outputs produced or inputs used by time (Büyükkılıç and Yavuz, 2005).

Malmquist TFP index is an index that is used for measuring the changes in total factor productivity of DMUs by time. More technically, as Estache (2004) stated the Malmquist TFP index measures the TFP change between two data points by calculating the ratio of the distances of each data point relative to a common technology. The distance function is used for this measurement. Distance function defines the production technologies for multiple inputs and multiple outputs without any need for cost minimization of profit maximization objectives. Input distance function defines the production technology according to the most contracted input vector when the output vector is given. Similarly, output distance function defines the production technology according to the most expanded input vector when the input vector is given (Fare, 1994). Because the idea of calculating indexes by the help of distance functions belongs to Sten Malmquist, Caves et al (1982) called their index as Malmquist.

According to Fare (1994), the output oriented Malmquist TFP change index between time period s and t is:

$$m_0(\vec{x}_s, \vec{y}_s, \vec{x}_t, \vec{y}_t) = \sqrt{\frac{d_0^s(\vec{x}_t, \vec{y}_t)}{d_0^s(\vec{x}_s, \vec{y}_s)} * \frac{d_0^t(\vec{x}_t, \vec{y}_t)}{d_0^t(\vec{x}_s, \vec{y}_s)}}$$

where $d_0^s(\vec{x}_t, \vec{y}_t)$ indicates the distance of the observation of time s from the technology of time t. If the function m(.) > 1 then it means that TFP increases from time s to time t. In opposite, if the function m(.) < 1 then it means that TFP decreases from time s to time t. The above equation can also be written as:

$$m_0(\vec{x}_s,\vec{y}_s,\vec{x}_t,\vec{y}_t)=\underbrace{\frac{d_0^t(\vec{x}_t,\vec{y}_t)}{d_0^s(\vec{x}_s,\vec{y}_s)}}_{\text{Efficiency change}}\underbrace{\sqrt{\frac{d_0^s(\vec{x}_t,\vec{y}_t)}{d_0^t(\vec{x}_t,\vec{y}_t)}*\frac{d_0^s(\vec{x}_s,\vec{y}_s)}{d_0^t(\vec{x}_s,\vec{y}_s)}}}_{\text{Technical change}}$$

The first term on the right hand side of the equation is the measure of Farrell's output oriented efficiency change between time s and time t. Additionally, the term in square-root determines the technical change. These expressions are explained by the help of the figure below:

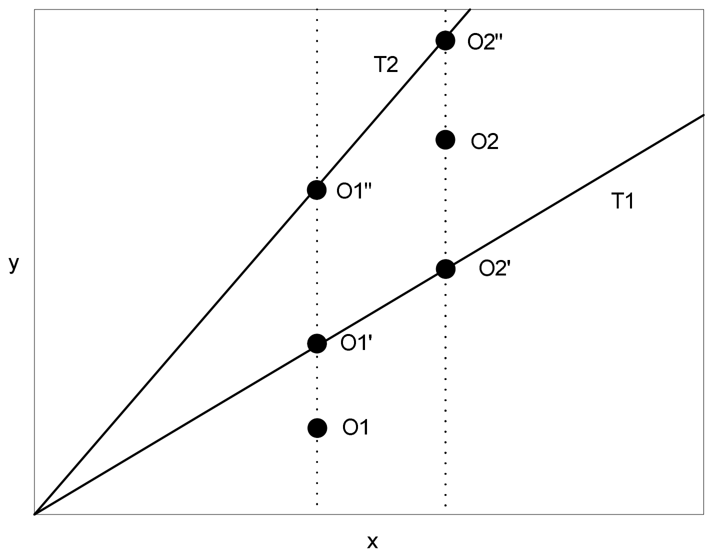

Figure 2.5 Efficiency Change and Technical Change

In Figure 2.5, only one DMU "O" is analyzed where there are single input and single output under constant returns to scale CRS assumption. O1 is the location of DMU O under technology T1 in period s. Similarly, O2 is the location of DMU O under technology T2 in period t. The formulations of efficiency change and technology change are as follow:

Efficiency change = $\dfrac{y_{O2}/y''_{O2}}{y_{O1}/y'_{O1}}$ and Technical change = $\left[\dfrac{y_{O2}/y'_{O2}}{y_{O2}/y''_{O2}} x \dfrac{y_{O1}/y'_{O1}}{y_{O1}/y''_{O1}}\right]^{1/2}$

Malmquist TFP index can be calculated by two different approaches which are parametric and non-parametric. In parametric approach, the distance functions are determined by parametric methods or in other words, the production frontier is a stochastic frontier. However, in non-parametric approach the distance functions are determined by non-parametric methods such as Data Envelopment Analysis (DEA). The most popular non-parametric approach used for calculating the distance functions is the linear programming models developed by Fare (1994). The output oriented models are as follow:

$$\begin{aligned}
&\left[d_0^t(\vec{x}_t,\vec{y}_t)\right]_k^{-1} = \max\theta_k \\
&s.t. \\
&-\theta_k Y_{rk}^t + \sum_{j=1}^{N}\lambda_{jk}Y_{rj}^t \geq 0 \\
&X_{ik}^t - \sum_{j=1}^{N}\lambda_{jk}X_{ij}^t \geq 0 \\
&\lambda_{jk} \geq 0
\end{aligned}
\qquad
\begin{aligned}
&\left[d_0^s(\vec{x}_s,\vec{y}_s)\right]_k^{-1} = \max\theta_k \\
&s.t. \\
&-\theta_k Y_{rk}^s + \sum_{j=1}^{N}\lambda_{jk}Y_{rj}^s \geq 0 \\
&X_{ik}^s - \sum_{j=1}^{N}\lambda_{jk}X_{ij}^s \geq 0 \\
&\lambda_{jk} \geq 0
\end{aligned}$$

$$\begin{aligned}
&\left[d_0^t(\vec{x}_s,\vec{y}_s)\right]_k^{-1} = \max\theta_k \\
&s.t. \\
&-\theta_k Y_{rk}^s + \sum_{j=1}^{N}\lambda_{jk}Y_{rj}^t \geq 0 \\
&X_{ik}^s - \sum_{j=1}^{N}\lambda_{jk}X_{ij}^t \geq 0 \\
&\lambda_{jk} \geq 0
\end{aligned}
\qquad
\begin{aligned}
&\left[d_0^s(\vec{x}_t,\vec{y}_t)\right]_k^{-1} = \max\theta_k \\
&s.t. \\
&-\theta_k Y_{rk}^t + \sum_{j=1}^{N}\lambda_{jk}Y_{rj}^s \geq 0 \\
&X_{ik}^t - \sum_{j=1}^{N}\lambda_{jk}X_{ij}^s \geq 0 \\
&\lambda_{jk} \geq 0
\end{aligned}$$

If N is the number of observations and t is the number of time periods, n(3t-2) linear programming models must be solved to calculate the values of all distance functions defined above.

Tatje and Lovell (1995) showed that Malmquist TFP index does not measure the TFP change correctly under the variable returns to scale (VRS) assumption. Therefore, distance functions should be calculated according to the constant returns to scale (CRS) assumption.

In sum, Malmquist TFP index can be used to measure the TFP changes of DMUs by time. Besides, it helps to understand that the TFP change is whether a result of efficiency change (getting closer of DMUs to efficient frontier) or technical change(change of efficient frontier). Moreover, Malmquist TFP index has the main advantage of avoiding having to work with input and output prices like Tornqvist and Fisher indexes. It relies on input and output weights estimated directly.

CHAPTER 3

THE MODEL AND ITS APPLICATION

3.1 INTRODUCTION

In this study, the process developed by Norman and Stoker (1991) for performance measuring system via DEA is used as a framework. The complete process of introducing DEA into a performance measuring system consists of 9 steps which are define the units, define the role, identify the objectives of units, choose output factors, choose input factors, collect data, model construction, run the model and analyze the results. The complete process can bee seen in Figure 3.1.

There is no problem about the steps of define the units, define the role and identify the objectives for this study because it is clear that the units are 17 automotive companies of which efficiency scores will be calculated. Besides, the role of an automotive company is manufacturing motor vehicles and selling them. The main objectives that are related the roles can be listed as increasing sales, reducing costs, improving performance, identifying the reasons of poor performance and etc.

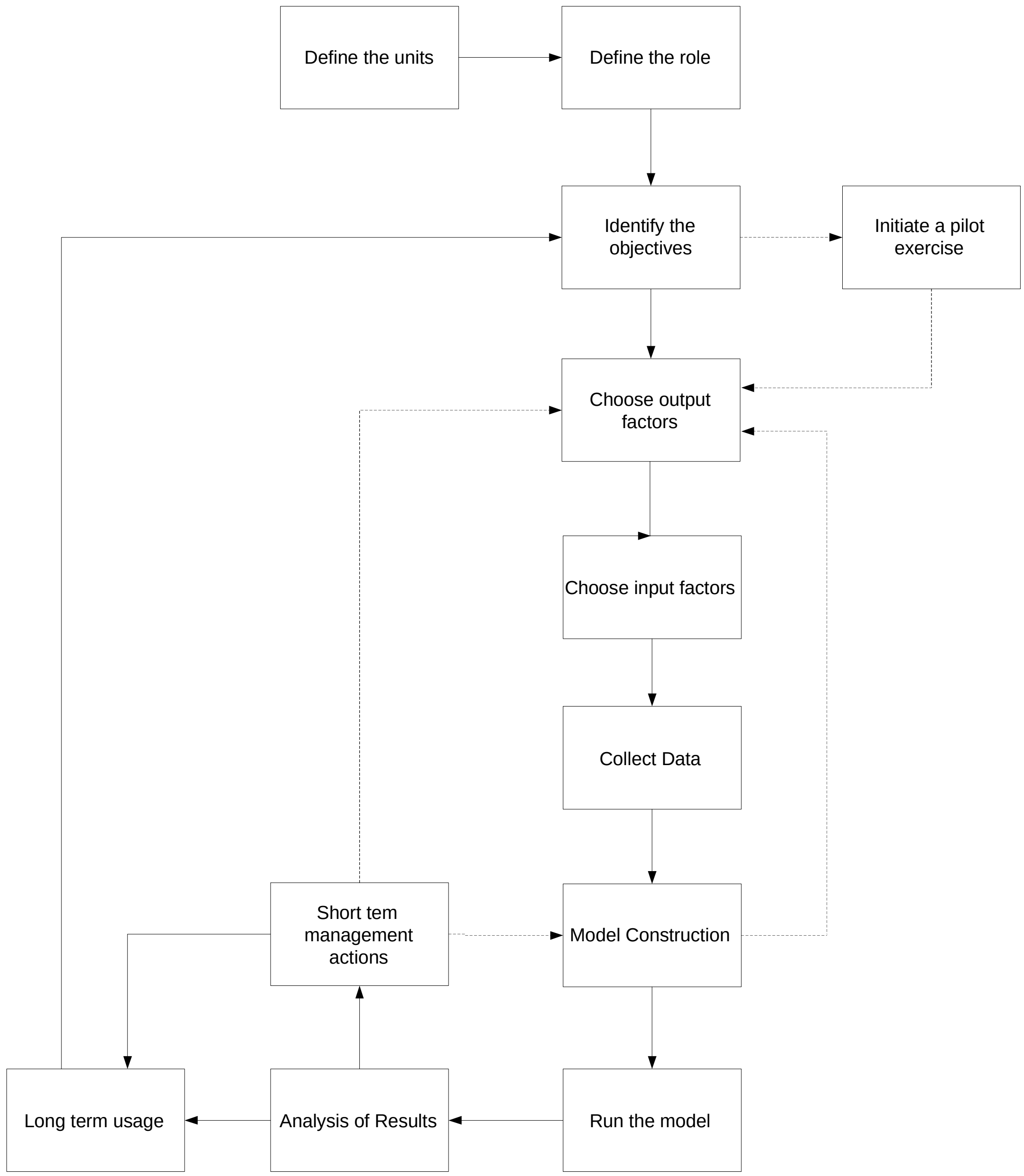

Figure 3.1 The Process of Introducing DEA into Performance Measuring System

On the other hand, choosing output factors, input factors and collecting data are problematic steps. These steps are also strongly interrelated because the input and output factors should be easy collectable, otherwise it is not possible to use the factors in the model even if they are meaningful. Therefore, in this study the possible data resources for automotive companies were researched before deciding the input and output factors. After determining the factors and collecting the appropriate data the model is constructed and run. Then, the results of the DEA models are analyzed and interpreted. Finally, another step is performed which does not exist in Figure 3.1. This step is calculation of Malmquist Total Factor Productivity (TFP) indexes by using the panel data that include the years 2001-2005 and interpretations about the change of efficiency by time for each company. In latter sections, all the steps mentioned above will be discussed in detail.

3.2 MODEL CONSTRUCTION

The most important and difficult part of this study is to determine the input and output factors for model construction because the inputs and outputs must relate to the objectives of the DMUs, be consistent across DMUs, and be quantifiable. In section 2.1.5, the studies on the performance measurement of automotive companies are briefly discussed.

Lieberman and Dhawan (2000) defines some measures that can be considered as important for comparing the productivities of automotive companies. These measures are investment, company size, degree of vertical integration and skills in manufacturing and product design. At first, they seem meaningful factors such that they can be introduced to the DEA model but the availability of the data regarding these measures is an important point and it will be discussed later.

Besides, ISO (Istanbul Chamber of Industry) does a research called "Top 500 Industry Firms of Turkey – 2001" annually. ISO lists the top 500 industry firms of each year according to the annual sales of companies. The other factors used for ranking the firms are the total turnover, gross value added, capital, equity capital, net assets, profit before tax or loss, export and the number of employees. It is seen that they are financial based factors rather than the production based factors in Lieberman and Dhawan (2000). Also, Yılmaz, Özdil and Akdoğan (2002) used turnover (in trillion TL), profit before tax (in trillion TL), export (in trillion TL) as outputs and net assets (in trillion TL), capital stock (in trillion TL) and the number of employments as the inputs in DEA model. In sum, these factors can also be appropriate for using in DEA model, but the availability of data is again a problem.

In addition to availability of data, the total number of inputs and outputs is another restriction for constructing the model. There are 17 DMUs in our study so the total number of inputs and outputs should not exceed 5 (or 6) according to the rule of Nunamaker (1985) which states that the number of DMUs should be at least three times greater than the sum of the number of outputs and inputs included. Details of factor determination for DEA model are given next section.

3.3 FACTOR DETERMINATION

As a result of research on data resources for automotive industry it is found that all data of automotive industry in Turkey are collected and classified only by OSD (Automotive Manufacturing Association). OSD presents the annual data of 17 member automotive companies as .pdf files called "*General and Statistical Information Bulletin Of Automotive Manufacturers"* on its webpage. This file includes the following data for each year. One can apply to the reports on the website of OSD for more information.

- Company name
- Starting year of production of company
- Capital of company
- Foreign capital of company
- Covered area of company
- Total area of company
- Turnover of company
- Payment of company for raw material
- Payment of company for components
- Taxes, Wages and Salaries Paid in company
- Vehicle based production capacities of companies (passenger car, truck, pick up, bus, mini-bus, midi-bus, tractor)
- Vehicle based production amounts of company (passenger car, truck, pick up, bus, mini-bus, midi-bus, tractor)
- Exports of company
- Employment of company
- The specifications of models produced by company

- Vehicle based total production in automotive sector (passenger car, truck, pick up, bus, mini-bus, midi-bus, tractor)
- Year and vehicle based total production amounts (from 1963 to current year)
- Vehicle based total capacity usage (passenger car, truck, pick up, bus, mini-bus, midi-bus, tractor)
- Total imports in automotive sector
- Realized sectorial investment (in $)

Moreover, the availability of the measures defined by Lieberman and Dhawan (2000) is checked. In other words, it is tried to answer the question “Can these measures be covered by the data obtained from OSD?”

One of the measures is investment which can be effective on the relative efficiency of an automotive industry. However, only the total investments are available in the reports of OSD rather than company based investment amounts. Although this data can be obtained from the financial reports of companies, only the companies quoted to IMKB announce their financial reports officially. Therefore, it is not possible to obtain this data for all companies. As a result, the investment factor is ignored.

Another important measure defined by Lieberman and Dhawan (2000) is the level of work-in-process (WIP) and WIP/sales ratio is used as an indicator of the “leanness” of a company’s production system. However, it was mentioned in previous section that the data in hand are mostly financial based rather than production based, so there is not any data about the WIP levels of companies. Hence, it is ignored as investment too.

Another measure is the degree of vertical integration. The degree of vertical integration shows whether the company produces parts via in-house manufacturing or it has subcontracting with the suppliers. The measure of the degree of vertical integration is indicated by the company’s annual value added as a proportion of sales. Since the data of value added is not available for each company it is ignored too.

Lieberman and Dhawan (2000) used the design quality of a company as another measure because product development and design is important in automotive industry.

They used a car magazine to get information about the design quality of companies. Similarly, a research on the awards such as “Best Car of the Year”, “Best Truck of the Europe” was performed in this study. The aim of that research was to find the number of awards received by a company and use it as the indicator of the design quality of that company. However, the research proved that there are many different publications and awards in this topic. Currently, there are many awards based on various criteria such as vehicle type, country, region, magazine, world and etc. In sum, it is too difficult to define a common indicator for the design quality of automotive industries. Also, there is not any data in OSD. Therefore, it is ignored.

Cumulative historical production of vehicles for each company is also used by Lieberman and Dhawan (2000) as an indicator of the experience of a company. However, it is difficult to apply this method to this study because as mentioned before the production amounts excessively vary from one vehicle type to another. It means that the cumulative historical production amount of a car manufacturer and a truck or a bus manufacturer is too different. In other words, large production volumes and high cumulative historical production of a passenger car manufacturer does not imply that it is more experienced than a truck manufacturer. Hence, the cumulative output is not used in this study. However, as discussed in next sections the data about the ages of companies are available and evaluated as potential input factor.

The economies of scale are significant in the automotive industry because larger company size allows cost savings. Lieberman and Dhawan (2000) define total employment as one measure of company size. Lieberman and Dhawan also used vehicle output as an alternative measure of company size. Vehicle output is not considered as a measure of company size in this study because 17 automotive companies in this study produce many types of vehicles such as passenger cars, trucks, buses and etc. The annual production amounts excessively differ from type to type. For instance, a passenger car manufacturer in Turkey can produce hundreds of thousand while a truck manufacturer can not produce more than 20-30 thousands. Therefore, total employment is selected as a possible input factor in this study. It is defined as “possible” because the factors used in model are selected by stepwise approach among the possible ones.

In sum, the measures mentioned above are important and effective factors on the efficiency of automotive companies. However, there should be more input and output factors which are available to be used in DEA model. Therefore, the data obtained from OSD are analyzed to determine those factors.

3.3.1 Stepwise Approach

Sengupta (1988) introduced a useful method for selecting and using appropriate inputs/outputs in DEA. The method is based on stepwise regression and called as the stepwise approach to DEA. The stepwise approach is an iterative procedure in which productivity is measured in terms of the important factors as seen in Figure 3.2 (Sigala et al, 2005).

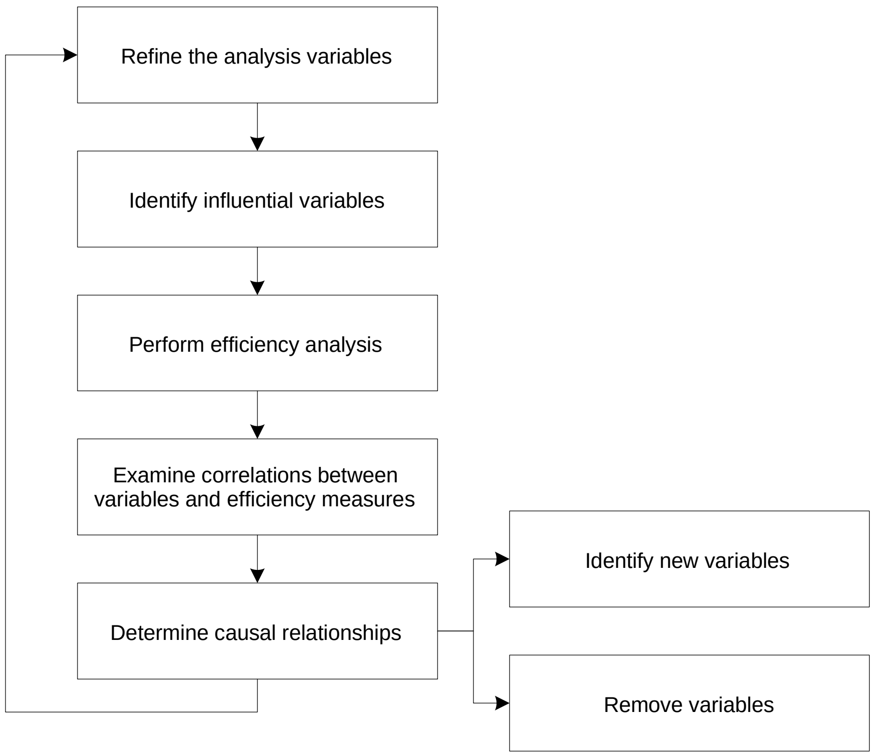

Figure 3.2 The Stepwise Approach

Other important factors are determined by examining the factors that correlate with the measure of efficiency and their causal relationships. The reason of examining the correlations of factors with the efficiency measure is that if a factor which influences performance is excluded from the efficiency measure, then the efficiency measure must be biased in relation to that factor. Hence, a high statistical correlation between that factor and the efficiency measure is expected. However, it can not be concluded that a factor influences performance from the observation of a high statistical correlation alone. There must be also a logical causal relationship to explain why or how the factor influences performance. In other words, any change in the value of an input should be reflected in either no change in each output or if there is a change, one in the ‘right’ direction. Hence it would be an unhelpful model such as a model that allows an “increase in investment” to be reflected in a “decrease in performance”. If this case is in reality, the causal relationships between factors would need to be re-examined and a new model constructed (Norman and Stoker, 1991). On the other hand, the existence of a causal relationship can be rejected only if it is based on a logical explanation of the statistical relationship.

In stepwise DEA approach, a factor should be broken down into as few constituent parts as possible if the components have a significant effect on efficiency (Norman and Stoker, 1991) because an aggregate productivity metric and model may obscure and hide trade-offs among productivity variables (Sigala, 2003). In literature, the significant effect of constituents on efficiency measure is defined as the significant Pearson correlations between DEA scores and partial metrics (Sigala, 2003, Norman and Stoker, 1991).

As mentioned in section 3.1 the role of an automotive company is manufacturing motor vehicles and selling them, so the main objective of an automotive company is making as high profit as possible. This can be performed by increasing sales or reducing costs. Therefore, the profit based stepwise approach that was developed by Norman and Stoker (1991) is used in this study. However, it is a fact that measuring the profit alone does not indicate i) how well a DMU is being managed where external factors influence its profitability ii) the potential for improvement that may exist iii) realistic targets iv) which DMUs would benefit most from additional resources.

Since it is a profit-based approach, it implies as high revenue and low cost as possible. Hence, first “Revenue/Cost” can be considered as the efficiency measure. According to the stepwise approach concept mentioned above, it is a fact that the factors correlated with revenue or cost may exhibit a correlation between efficiency. Therefore, another important factor is identified by examining factors which are correlated with that measure of efficiency and applying judgment in terms of cause and effect. Then, the new factor is incorporated into the efficiency measure and the process is repeated until no further important factors emerge. Finally, a measure will be constructed which accounts for all identifiable factors which influence performance.

Sigala et al. (2005) state that the stepwise approach helps to interpret why particular units are efficient by examining the result of each step. The units found to become efficient from one step to another are efficient because of the incorporation of the respective inputs/outputs in the step they were found to be efficient.

However, as Cinca et al. (2002) stated this approach has the disadvantage that correlations may not be affected by changes in efficiencies. For example, if the incorporation of a variable results in a proportional increase of the efficiencies of all DMUs, the correlation coefficient does not change.

Kittelsen (1993) explained that the stepwise approach used by Norman and Stoker (1991) have also disadvantages. Since variables may be collinear and the excluded variable can contain essentially the same information as an included variable, the Pearson correlation coefficient is not partial enough. There is no reason to presuppose that an excluded variable is not correlated with efficiency. Lastly, there is no significance test to decide when to stop disaggregating.

3.3.2 Data Set and Model Application

In this section, the input and output factors to be used in DEA model are determined via stepwise approach mentioned above. The data of year 2005 is used in stepwise approach. The data of year 2005 in Table 3.1 is obtained from the reports of *General and Statistical Information Bulletin Of Automotive Manufacturers 2005 – I* and *General and Statistical Information Bulletin Of Automotive Manufacturers 2006 – I* in the website of OSD.

The first column in Table 3.1 includes the names of 17 automotive companies. The values in the other columns are the *Payment for Raw Materials and Components*, *Payment for Wages and Insurances of Employees*, *Total Cost*, *Domestic Sales*, *Exports*, *Turnover*, *Production*, *Capacity Usage*, *Age* respectively. “1MYTL” represents that the amounts are in million New Turkish Liras and “1000” represents that the production amount is in thousand units.

Payment for Raw Materials and Components is the amount that the company has paid for buying raw materials and components. *Payment for Wages and Insurances of Employees* is the amount that the company has paid for the employees’ salaries and social security insurances. In other words, it is a kind of labor cost. *Total Cost* is the sum of *Payment for Raw Materials and Components* and *Payment for Wages and Insurances of Employees*. Although, there are other cost types such as many direct and indirect costs but only these two are available. *Domestic Sales* is the revenue come from the sales in Turkey. *Export* is the revenue come from the sales to other countries. Besides, *Total Revenue* is assumed to be as *Turnover* that is equal to the sum of *Domestic Sales* and *Exports*. *Production* is the number of vehicles produced in current year. *Capacity Usage* is the ratio of *Production* to *Capacity.* It can be an important factor because it is seen from Table 3.1 that the capacity usages are very low for most of the companies. It must not be forgotten that low capacity usage means high costs. Therefore, it can be concluded that the low capacity usage is a problem in automotive industry in Turkey. Lastly, *Age* is the time passed from the starting date of production of a company to current year. For example, if the company has started production in 1970 then its *Age* is 2005 – 1970 = 35 (current year is assumed as 2005).

Table 3.1 The Data of Year 2005

COMPANY	RAW (1MYTL)	WAGE (1MYTL)	TOTCOST (1MYTL)	DOMSALES (1MYTL)	EXPORT (1MYTL)	TURNOVER (1MYTL)	PRD (1000)	PRD/CAP (%)	AGE (Years)
A.I.O.S.	220.068	8.966	229.035	254.671	58.018	312.689	6.762	0.51	39
ASKAM	77.580	4.604	82.184	170.009	1.181	171.191	2.439	0.27	41
B.M.C.	526.412	25.405	551.816	637.845	105.415	743.261	12.5	0.57	39
FORD OTOSAN	3812.820	69.227	3882.047	2581.965	2781.015	5362.980	243.423	1.00	46
HONDA	177.028	7.978	185.007	162.673	53.603	216.276	11.236	0.37	8
HYUNDAI ASSAN	627.389	10.411	637.800	489.308	281.903	771.212	60.02	0.48	8
KARSAN	254.609	10.727	265.337	218.316	9.097	227.413	13.146	0.53	39
M.A.N.	276.144	28.040	304.184	121.044	268.590	389.634	2.03	0.62	39
M.BENZ TÜRK	115.557	49.352	164.909	1524.941	612.118	2137.059	13.916	1.00	37
OTOKAR	128.297	11.234	139.530	158.162	104.580	262.742	2.59	0.33	42
OTOYOL	132.082	20.156	152.237	140.891	29.963	170.854	3.634	0.29	39
OYAK RENAULT	2523.678	67.345	2591.023	1005.299	1906.286	2911.585	179.669	0.76	34
TEMSA	526.680	15.256	541.937	299.254	174.212	473.466	8.161	0.78	18
TOFAŞ	1828.138	70.653	1898.791	1439.011	1148.820	2587.832	161.36	0.65	34
TOYOTA	1142.347	27.597	1169.943	221.069	3104.675	3325.744	158.566	1.00	11
TÜRK TRAKTÖR	288.736	10.340	299.077	335.105	150.755	485.860	17.87	0.51	51
UZEL	123.610	19.518	143.128	339.704	60.454	400.158	17.037	0.68	43

Because the approach used is a profit-based approach, high revenue with low cost is the objective. Hence, “Revenue/Cost” can be considered as the efficiency measure. The “Revenue/Cost” ratio is calculated by dividing “Turnover” by “Total Cost” for each company. The scores and the ranks are shown in Table 3.2.

Table 3.2 Step 1 Efficiency Scores

Company Name	Rank	Total Revenue/ Total Cost	Step1 Efficiency	Efficiency from DEA
A.I.O.S.	8	1,37	0,11	0,11
ASKAM	4	2,08	0,16	0,16
B.M.C.	10	1,35	0,10	0,10
FORD OTOSAN	7	1,38	0,11	0,11
HONDA	13	1,17	0,09	0,09
HYUNDAI ASSAN	12	1,21	0,09	0,09
KARSAN	17	0,86	0,07	0,07
M.A.N.	11	1,28	0,10	0,10
M.BENZ TÜRK	1	12,96	1,00	1,00
OTOKAR	5	1,88	0,15	0,15
OTOYOL	15	1,12	0,09	0,09
OYAK RENAULT	14	1,12	0,09	0,09
TEMSA	16	0,87	0,07	0,07
TOFAŞ	9	1,36	0,11	0,11
TOYOTA	2	2,84	0,22	0,22
TÜRK TRAKTÖR	6	1,62	0,13	0,13
UZEL	3	2,80	0,22	0,22

It is seen from the table that M.BENZ TÜRK has the maximum Total Revenue/Total Cost ratio with 12.96. Therefore, the efficiency score of it is set to 1 and the others’ efficiency scores are calculated by dividing their Total Revenue/Total Cost ratios by 12.96. As seen in the table, the last column includes the efficiency scores obtained by solving the basic CCR model with single input (total cost) and single output (total revenue). Normally, both the efficiency scores in last two columns are the same and called as *Step1* efficiency scores.

Norman and Stoker (1991) stated that if a factor which influences performance from the efficiency score then the efficiency measure must be biased in relation to that factor. Therefore, a high statistical correlation is expected between that factor and the efficiency measure. However, only statistical correlation is not enough. There must also be a logical causal relationship to explain how the factor affects performance. On the other hand, there must be a logical explanation of the statistical explanation in order to reject the causal relationship. Because of these reasons, the correlation between each factor in Table 3.1 and the current efficiency measure that is "Efficiency" in Table 3.2. The correlation of each factor with the current efficiency measure is shown in Table 3.3. Actually, the first column of Table 3.3 which includes the correlations between each factor and the efficiency score of Step1 is important to decide the new factor to be incorporated to the model. It is seen that the factor which has the maximum correlation with the Step1 efficiency score is *PRD/CAP*. It means that the *Capacity Usage* can be the new factor to be incorporated to model. Here, one can ask "Why are *Production* or *Capacity* not used as factors separately?" The answer is the very high correlation of *Production* with most of the other factors because using highly correlated factors together in DEA is a non-desirable situation. For example, as seen in Table 3.4 the correlation of *Production* with *Domestic Sales* is 0.723, with *Export* is 0.913 and with *Turnover* 0.935. It can be concluded that using *Production* as an output is not a good idea but it should be added somehow because it is one of the most important indicators for the performance of an automotive company. *Capacity Usage* reflects both the effects of production and capacity in the model. Therefore, incorporating it to the model is a statistically and logically good idea.

If *Capacity Usage* is added then the new model is a single input (*Total Cost*) and two outputs (*Total Revenue* and *Capacity Usage*). The Step2 efficiency scores and the ranks of companies are shown in Table 3.3

Table 3.3 Step 2 Efficiency Scores

Company Name	Rank	Step2 Efficiency	Company Name	Rank	Step2 Efficiency
A.I.O.S.	12	0,12	OTOKAR	6	0,20
ASKAM	5	0,22	OTOYOL	14	0,10
B.M.C.	11	0,13	OYAK RENAULT	7	0,20
FORD OTOSAN	8	0,19	TEMSA	17	0,09
HONDA	15	0,10	TOFAŞ	9	0,16
HYUNDAI ASSAN	13	0,12	TOYOTA	2	0,71
KARSAN	16	0,09	TÜRK TRAKTÖR	10	0,14
M.A.N.	4	0,24	UZEL	3	0,26
M.BENZ TÜRK	1	1,00			

Table 3.4 Correlations of Factors with Each Other and Step 1 Efficiency Scores

	Step1	RAW	WAGE	TOTCOST	DOMSALES	EXPORT	TURNOVER	PRD	PRD/CAP
RAW	-0,176 0,499								
WAGE	0,228 0,378	0,814 0							
TOTCOST	-0,168 0,519	1 0	0,821 0						
DOMSALE	0,320 0,211	0,802 0	0,847 0	0,806 0					
EXPORT	0,051 0,847	0,81 0	0,679 0,003	0,81 0	0,585 0,014				
TURNOVE	0,178 0,494	0,902 0	0,835 0	0,904 0	0,841 0	0,931 0			
PRD	-0,110 0,674	0,948 0	0,800 0	0,948 0	0,723 0,001	0,913 0	0,935 0		
PRD/CAP	0,474 0,055	0,551 0,022	0,639 0,006	0,555 0,021	0,63 0,007	0,742 0,001	0,779 0	0,604 0,01	
AGE	0,080 0,760	0,057 0,829	0,169 0,516	0,059 0,821	0,225 0,385	-0,163 0,533	-0,007 0,979	-0,086 0,744	-0,094 0,719

Cell Contents: Pearson correlation
P-Value

If Step1 and Step2 efficiency scores and ranks are compared, it can be seen that the top three companies are not changed. M. BENZ TÜRK, TOYOTA and UZEL are the top three in both cases because their Total Revenue/Total Cost ratios are excessively high with respect to others.

The correlation matrix that shows the relationships between each factor and the Step2 efficiency scores is shown in Table 3.6. The most highly correlated factor with the Step2 efficiency scores is *EXP* with the correlation 0.394 so *Export* is a candidate for being the new factor to be added to model. As mentioned before *Turnover* is the sum of *Export* and *Domestic Sales.* Therefore, if *Export* is added to model it means that *Turnover* is subdivided into its constituent parts. By the way, if *Export* is added then *Domestic Sales* should be added to model. However, the causal relationship should also be discussed to ensure the incorporation of the new factor. Actually, the simple logic is that if the *Export* and *Domestic Sales* of a company increase then the revenue and the profit of company increase respectively. In sum, adding the factors *Export* and *Domestic Sales* as outputs is a good idea from the view of statistics and causal relationship.

When *Export* and *Domestic Sales* are added as outputs instead of *Total* Revenue then the new model is a single input (*Total Cost*) and three outputs (*Domestic Sales, Export* and *Capacity Usage*). The Step3 efficiency scores and the ranks of companies are shown in Table 3.5

Table 3.5 Step 3 Efficiency Scores

Company Name	Rank	Step3 Efficiency
A.I.O.S.	6	0,35
ASKAM	4	0,52
B.M.C.	16	0,16
FORD OTOSAN	14	0,19
HONDA	8	0,32
HYUNDAI ASSAN	17	0,12
KARSAN	9	0,31
M.A.N.	7	0,32
M.BENZ TÜRK	1	1,00
OTOKAR	5	0,37
OTOYOL	10	0,30
OYAK RENAULT	13	0,20
TEMSA	12	0,22
TOFAŞ	15	0,16
TOYOTA	3	0,71
TÜRK TRAKTÖR	11	0,27
UZEL	2	0,74

Table 3.6 Correlations of Factors with Each Other and Step 2 Efficiency Scores

	Step2	RAW	WAGE	TOTCOST	DOMSALES	EXPORT	TURNOVER	PRD	PRD/CAP
RAW	-0,035								
	0,895								
WAGE	0,282	0,814							
	0,273	0							
TOTCOST	-0,028	1	0,821						
	0,915	0	0						
DOMSALES	0,257	0,802	0,847	0,806					
	0,320	0	0	0					
EXPORT	0,394	0,81	0,679	0,81	0,585				
	0,118	0	0,003	0	0,014				
TURNOVER	0,379	0,902	0,835	0,904	0,841	0,931			
	0,134	0	0	0	0	0			
PRD	0,127	0,948	0,8	0,948	0,723	0,913	0,935		
	0,627	0	0	0	0,001	0	0		
PRD/CAP	0,650	0,551	0,639	0,555	0,63	0,742	0,779	0,604	
	0,005	0,022	0,006	0,021	0,007	0,001	0	0,01	
AGE	-0,086	0,057	0,169	0,059	0,225	-0,163	-0,007	-0,086	-0,094
	0,742	0,829	0,516	0,821	0,385	0,533	0,979	0,744	0,719

Cell Contents: Pearson correlation
P-Value

According to Step3 efficiency scores the only efficient company is still M.BENZ TÜRK because it has very high *Domestic Sales* and *Export* despite of its very low *Total Cost*. It should also be noted that its capacity usage is 100 %. Actually, the *Capacity Usages* of M.BENZ TÜRK, FORD OTOSAN and TOYOTA were greater than 100 % in the data obtained from OSD. However, the capacity usage can not exceed 100 % theoretically. Therefore, the capacity usages of those three companies are set to 100 % to prevent the abnormalities that will be discussed next chapter.

Table 3.8 shows the correlations between each factor and the Step3 efficiency scores. *RAW* is the factor that has the highest correlation with the Step3 efficiency scores. Hence, it means that *Payment for Raw Materials and Components* is the candidate for the new factor to be added to model. *Payment for Raw Materials and Components* is a constituent part of *Total Cost* because *Total Cost* is the sum of *Payment for Raw Materials and Components* and *Payment for Wages and Insurances of Employees.* Therefore, if *Payment for Raw Materials and Components* is added as an input then *Payment for Wages and Insurances of Employees* should also be added as another input. It is a fact that increasing of *Payment for Raw Materials and Components* and *Payment for Wages and Insurances of Employees* results in increasing of costs and so decreasing of profit. Therefore, it can be concluded that there is a causal relationship between those two factors and the efficiency score.

As *Payment for Raw Materials and Components* and *Payment for Wages and Insurances of Employees* are incorporated to model as inputs instead of *Total Cost* the new model becomes a model with two inputs (*Payment for Raw Materials and Components* and *Payment for Wages and Insurances of Employees*) and three outputs (*Domestic Sales, Export* and *Capacity Usage*). The Step4 efficiency scores and the related ranks of companies are shown in Table 3.7.

Table 3.7 Step 4 Efficiency Scores

Company Name	Rank	Step4 Efficiency	Company Name	Rank	Step4 Efficiency
A.I.O.S.	6	0,99	OTOKAR	12	0,74
ASKAM	1	1,00	OTOYOL	17	0,41
B.M.C.	13	0,67	OYAK RENAULT	16	0,52
FORD OTOSAN	7	0,95	TEMSA	9	0,90
HONDA	11	0,82	TOFAŞ	15	0,60
HYUNDAI ASSAN	2	1,00	TOYOTA	4	1,00
KARSAN	10	0,83	TÜRK TRAKTÖR	8	0,90
M.A.N.	14	0,63	UZEL	5	1,00
M.BENZ TÜRK	3	1,00			

Table 3.8 Correlations of Factors with Each Other and Step 3 Efficiency Scores

	Step3	RAW	WAGE	TOTCOST	DOMSALES	EXPORT	TURNOVER	PRD	PRD/CAP
RAW	-0,342								
	0,179								
WAGE	-0,052	0,814							
	0,843	0							
TOTCOST	-0,337	1	0,821						
	0,185	0	0						
DOMSALES	-0,04	0,802	0,847	0,806					
	0,88	0	0	0					
EXPORT	0,072	0,81	0,679	0,81	0,585				
	0,782	0	0,003	0	0,014				
TURNOVER	0,03	0,902	0,835	0,904	0,841	0,931			
	0,908	0	0	0	0	0			
PRD	-0,194	0,948	0,8	0,948	0,723	0,913	0,935		
	0,456	0	0	0	0,001	0	0		
PRD/CAP	0,376	0,551	0,639	0,555	0,63	0,742	0,779	0,604	
	0,137	0,022	0,006	0,021	0,007	0,001	0	0,01	
AGE	0,052	0,057	0,169	0,059	0,225	-0,163	-0,007	-0,086	-0,094
	0,843	0,829	0,516	0,821	0,385	0,533	0,979	0,744	0,719

Cell Contents: Pearson correlation
P-Value

It is seen that there is an important difference between the Step4 efficiencies and the previous ones. In Step1, Step2, Step3 there is always one efficient company that is M.BENZ TÜRK. However, according to the Step4 efficiency scores there are four companies of which efficiency score is equal to one. In other words, M.BENZ TÜRK, TOYOTA, UZEL, HYUNDAI ASSAN and ASKAM are found as the efficient companies according to the model with 2 inputs and 3 outputs. Actually, the number of efficient companies proves that the number of total variables is high with respect to the number of DMUs in the model.

The correlations between each factor and the Step4 efficiency scores are shown in Table 3.9. It is seen that the only variable that may be incorporated to model is *AGE* . However, the correlation between *AGE* and the Step4 efficiency score is 0.171 that is a very small value. Therefore, it can be concluded that there is not any other factors which can be added to model. Indeed, if one more factor is added then the number of total variables becomes 6 and the rule of (Nunamaker 1985) which states that three times of the number of total variables should not exceed the number of DMUs in the model. In sum, the model with 2 inputs (*Payment for Raw Materials and Components* and *Payment for Wages and Insurances of Employees*) and three outputs (*Domestic Sales, Export* and *Capacity Usage*) was constructed via the stepwise approach.

Table 3.9 Correlations of Factors with Each Other and Step 4 Efficiency Scores

	Step4	RAW	WAGE	TOTCOST	DOMSALES	EXPORT	TURNOVER	PRD	PRD/CAP
RAW	-0,127								
	0,628								
WAGE	-0,315	0,814							
	0,218	0							
TOTCOST	-0,131	1	0,821						
	0,616	0	0						
DOMSALES	0,046	0,802	0,847	0,806					
	0,86	0	0	0					
EXPORT	0,063	0,81	0,679	0,81	0,585				
	0,81	0	0,003	0	0,014				
TURNOVER	0,063	0,902	0,835	0,904	0,841	0,931			
	0,81	0	0	0	0	0			
PRD	-0,062	0,948	0,8	0,948	0,723	0,913	0,935		
	0,812	0	0	0	0,001	0	0		
PRD/CAP	0,299	0,551	0,639	0,555	0,63	0,742	0,779	0,604	
	0,244	0,022	0,006	0,021	0,007	0,001	0	0,01	
AGE	-0,171	0,057	0,169	0,059	0,225	-0,163	-0,007	-0,086	-0,094
	0,513	0,829	0,516	0,821	0,385	0,533	0,979	0,744	0,719

Cell Contents: Pearson correlation
P-Value

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 CCR Models

First, the envelopment model E_I is solved by using the necessary data in Table 3.1 to find the dual variables (λ s) in addition to total efficiency scores of the companies. The model E_I is as follows:

Min θ_k

s.t.

$$\sum_{j=1}^{N} Y_{rj}\lambda_{jk} \geq Y_{rk} \qquad r = 1, \ldots, s$$

$$\theta_k X_{ik} - \sum_{j=1}^{N} X_{ij}\lambda_{jk} \geq 0 \qquad i = 1, \ldots, m$$

$$\lambda_{jk} \geq 0 \qquad j = 1, \ldots, N$$

θ_k urs

The θ_k s and λ s are shown in Table 4.1. The “Theta” column includes the values of θ_k s and the each row includes the dual variables of each constraint in the model solved for DMU k. The last column named “REF” shows the reference sets of inefficient units. For example, DMU 2 and DMU 15 are the members of DMU 1’s reference set. Besides, it is seen that DMUs 2, 6, 9, 15 and 17 are found as efficient. Normally, only the dual variable λ_{kk} is equal to one for the efficient DMUs.

Table 4.1 Efficiency Scores and Dual Variables for CCR Model E_I without Capacity

EI	Theta	Lamda(1)	Lamda(2)	Lamda(3)	Lamda(4)	Lamda(5)	Lamda(6)	Lamda(7)	Lamda(8)	Lamda(9)	Lamda(10)	Lamda(11)	Lamda(12)	Lamda(13)	Lamda(14)	Lamda(15)	Lamda(16)	Lamda(17)	REF
1	0,995	0,000	1,830	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,018	0,000	0,000	2, 15
2	1	0,000	1,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	
3	0,672	0,000	2,549	0,000	0,000	0,000	0,238	0,000	0,000	0,058	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	2, 6, 9
4	1	0,000	0,000	0,000	1,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	
5	0,820	0,000	1,320	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,017	0,000	0,000	2, 15
6	1	0,000	0,000	0,000	0,000	0,000	1,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	
7	0,835	0,000	1,932	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,002	0,000	0,000	2, 15
8	0,645	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,013	0,000	0,000	0,000	0,000	0,000	0,068	0,000	0,797	9, 15, 17
9	1	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	
10	0,750	0,000	0,336	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,027	0,000	0,313	2, 15, 17
11	0,412	0,000	0,009	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,001	0,000	0,421	2, 15, 17
12	0,533	0,000	0,000	0,000	0,135	0,000	0,552	0,000	0,000	0,195	0,000	0,000	0,000	0,000	0,000	0,405	0,000	0,000	4, 6, 9, 15
13	0,904	0,000	2,665	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,055	0,000	0,000	2, 15
14	0,607	0,000	0,000	0,000	0,155	0,000	0,584	0,000	0,000	0,481	0,000	0,000	0,000	0,000	0,000	0,083	0,000	0,000	4, 6, 9, 15
15	1	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1,000	0,000	0,000	
16	0,907	0,000	1,488	0,000	0,000	0,000	0,152	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,034	0,000	0,000	2, 6, 15
17	1	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1,000	

After finding the dual variables by the help of E_I model, the projections are calculated by the following formulas

$$X_{i\kappa} = \sum_{q \in R_\kappa} \lambda_{kq} X_{iq} \qquad i = 1, \ldots, m$$

$$Y_{r\kappa} = \sum_{q \in R_\kappa} \lambda_{kq} Y_{rq} \qquad r = 1, \ldots, s$$

Where R_κ is the reference set of DMUs. The projections can be seen in Table 4.2. For example, the projection of *Payment for Raw Materials and Components* for A.I.O.S is calculated as follow:

$$X_{1,17} = \lambda_{2,17} X_{1,2} + \lambda_{2,15} X_{1,15} \quad = 1.830*77.580 + 0.018*1142.347 = 162.533$$

In the formula, lambdas of DMU 2 ($\lambda_{2,17}$) and DMU 15 ($\lambda_{2,15}$) are multiplied with the values of *Payment for Raw Materials and Components* for DMU 2 ($X_{1,2}$) and DMU 15 ($X_{1,15}$) respectively because they are the only DMUs in the reference set of A.I.O.S. It is seen that, the result, 162.533 is a bit different from 162.546 in Table 4.2 because of the number of decimals in Excel. The results come from LINGO are stored in Excel tables and the number of decimals in results are mostly high such as 6-7 decimals. However, they are seen in Tables as if they are 3-decimal numbers for easy reading. Then, as the real numbers are multiplied in Excel the results may be a bit different from the results found by multiplied the 3-decimal numbers manually. However, these differences are negligible in the analysis of results.

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In the column that includes the projection values of *Capacity Usage*, it is seen that FORD OTOSAN, OYAK RENAULT and TOFAŞ have values greater than 1. Actually, a company is not able to produce more than its capacity but DEA model states that these three companies can increase their *Capacity Usages* to greater than 1. This situation is caused by the lack of a restriction on the *Capacity Usage* variable.

Table 4.2 Projections of Inputs and Outputs without Capacity Usage Constraint

		RAW(1MYTL)	Projections	WAGE(1MYTL)	Projections	DOMSALES(1MYTL)	Projections	EXPORT(1MYTL)	Projections	PRD/CAP(%)	Projections	REFERENCE SET
1	A.I.O.S.	220,068	162,546	8,966	8,923	254,670	315,145	58,018	58,018	0,514	0,514	2, 15
2	ASKAM	77,580		4,604		170,010		1,181		0,271		
3	B.M.C.	526,412	353,580	25,405	17,064	637,850	637,848	105,415	105,415	0,573	0,863	2, 6, 9
4	FORD OTO	3812,820	3614,516	69,227	65,627	2581,960	2581,975	2781,015	2781,015	1,000	2,857	6, 9, 15
5	HONDA	177,028	121,702	7,978	6,549	162,670	228,444	53,603	53,603	0,375	0,375	2, 15
6	HYUNDAI	627,389		10,411		489,310		281,903		0,480		
7	KARSAN	254,609	152,459	10,727	8,959	218,320	329,091	9,097	9,097	0,526	0,526	2, 15
8	M.A.N.	276,144	178,330	28,040	18,108	121,040	306,033	268,590	268,590	0,625	0,625	9, 15, 17
9	M.BENZ T	115,557		49,352		1524,940		612,118		1,000		
10	OTOKAR	128,297	96,188	11,234	8,422	158,160	169,696	104,580	104,580	0,332	0,332	2, 15, 17
11	OTOYOL	132,082	54,457	20,156	8,310	140,890	145,072	29,963	29,963	0,291	0,291	2, 15, 17
12	OYAK REI	2523,678	1324,078	67,345	35,333	1005,300	1005,302	1906,286	1906,286	0,765	1,251	6, 9, 15
13	TEMSA	526,680	269,603	15,256	13,785	299,250	465,060	174,212	174,212	0,777	0,777	2, 15
14	TOFAŞ	1828,138	1091,247	70,653	42,174	1439,010	1439,013	1148,820	1148,820	0,645	1,292	6, 9, 15
15	TOYOTA	1142,347		27,597		221,070		3104,675		1,000		
16	TÜRK TRA	288,736	249,701	10,340	9,386	335,100	335,107	150,755	150,755	0,511	0,511	2, 6, 15
17	UZEL	123,610		19,518		339,700		60,454		0,681		

Therefore, the constraint $\sum_{j=1}^{N} Y_{3j}\lambda_{jk} \leq 1$ is added to model to ensure that the capacity usage ratio can not exceed 1. Since, the value of $\sum_{j=1}^{N} Y_{3j}\lambda_{jk}$ gives the projection of third output of DMU k, $\sum_{j=1}^{N} Y_{3j}\lambda_{jk} \leq 1$ means that the projection of capacity usage for DMU k can not exceed 1. In other words, the capacity usage of an inefficient DMU can increase in terms of improvement but it can not exceed 1.

All the following models in this study are established by considering the capacity usage restriction. The new E_I model after adding the capacity usage constraint is as follows:

Min θ_k

s.t.

$$\sum_{j=1}^{N} Y_{rj}\lambda_{jk} \geq Y_{rk} \qquad r = 1, \ldots, s$$

$$\theta_k X_{ik} - \sum_{j=1}^{N} X_{ij}\lambda_{jk} \geq 0 \qquad i = 1, \ldots, m$$

$$\sum_{j=1}^{N} Y_{3j}\lambda_{jk} \leq 1$$

$$\lambda_{jk} \geq 0 \qquad j = 1, \ldots, N$$

θ_k urs

The efficiency scores, dual variables and the reference sets are shown in Table 4.3. In addition, the projections can be seen in Table 4.4. There is an important difference between the results of the non-restricted and restricted CCR models. FORD OTOSAN becomes an efficient company when the capacity usage constraint is added to model because when there is not any capacity usage constraint FORD OTOSAN tries to increase its capacity usage ratio to be efficient. However, its capacity usage is actually 100 % and it is impossible to make capacity usage greater than 1 theoretically. When the constraint is added, it normally becomes one of the efficient companies.

Table 4.3 Efficiency Scores and Dual Variables for CCR Model E_I with Capacity Usage Constraint

EI	Theta	Lamda(1)	Lamda(2)	Lamda(3)	Lamda(4)	Lamda(5)	Lamda(6)	Lamda(7)	Lamda(8)	Lamda(9)	Lamda(10)	Lamda(11)	Lamda(12)	Lamda(13)	Lamda(14)	Lamda(15)	Lamda(16)	Lamda(17)	REF
1	0,995	0,000	1,830	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,018	0,000	0,000	2, 15
2	1	0,000	1,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	
3	0,672	0,000	2,549	0,000	0,000	0,000	0,238	0,000	0,000	0,058	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	2, 6, 9
4	1	0,000	0,000	0,000	1,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	
5	0,820	0,000	1,320	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,017	0,000	0,000	2, 15
6	1	0,000	0,000	0,000	0,000	0,000	1,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	
7	0,835	0,000	1,932	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,002	0,000	0,000	2, 15
8	0,645	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,013	0,000	0,000	0,000	0,000	0,000	0,068	0,000	0,797	9, 15, 17
9	1	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	
10	0,750	0,000	0,336	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,027	0,000	0,313	2, 15, 17
11	0,412	0,000	0,009	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,001	0,000	0,421	2, 15, 17
12	0,533	0,000	0,000	0,000	0,135	0,000	0,552	0,000	0,000	0,195	0,000	0,000	0,000	0,000	0,000	0,405	0,000	0,000	4, 6, 9, 15
13	0,904	0,000	2,665	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,055	0,000	0,000	2, 15
14	0,607	0,000	0,000	0,000	0,155	0,000	0,584	0,000	0,000	0,481	0,000	0,000	0,000	0,000	0,000	0,083	0,000	0,000	4, 6, 9, 15
15	1	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1,000	0,000	0,000	
16	0,907	0,000	1,488	0,000	0,000	0,000	0,152	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,034	0,000	0,000	2, 6, 15
17	1	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1,000	

Table 4.4 Projections of Inputs and Outputs with Capacity Usage Constraint

		RAW (1MYTL)	Projections	WAGE (1MYTL)	Projections	DOMSALES (1MYTL)	Projections	EXPORT (1MYTL)	Projections	PRD/CAP (%)	Projections	REFERENCE SET
1	A.I.O.S.	220,068	162,553	8,966	8,924	254,670	315,161	58,018		0,514		2, 15
2	ASKAM	77,580		4,604		170,010		1,181		0,271		
3	B.M.C.	526,412	353,584	25,405	17,064	637,850	637,847	105,415	105,415	0,573	0,863	2, 6, 9
4	FORD OTOSAN	3812,820		69,227		2581,960		2781,015		1,000		
5	HONDA	177,028	121,569	7,978	6,541	162,670	228,151	53,603		0,375		2, 15
6	HYUNDAI ASSAN	627,389		10,411		489,310		281,903		0,480		
7	KARSAN	254,609	152,413	10,727	8,957	218,320	328,990	9,097		0,526	0,526	2, 15
8	M.A.N.	276,144	178,160	28,040	18,091	121,040	305,886	268,590		0,625		9, 15, 17
9	M.BENZ TÜRK	115,557		49,352		1524,940		612,118		1,000		
10	OTOKAR	128,297	96,166	11,234	8,420	158,160	169,640	104,580	104,579	0,332		2, 15, 17
11	OTOYOL	132,082	54,373	20,156	8,297	140,890	144,818	29,963		0,291		2, 15, 17
12	OYAK RENAULT	2523,678	1344,676	67,345	35,883	1005,300		1906,286	1906,285	0,765	1,000	4, 6, 9, 15
13	TEMSA	526,680	269,671	15,256	13,789	299,250	465,210	174,212		0,777		2, 15
14	TOFAŞ	1828,138	1109,273	70,653	42,871	1439,010	1439,011	1148,820		0,645	1,000	4, 6, 9, 15
15	TOYOTA	1142,347		27,597		221,070		3104,675		1,000		
16	TÜRK TRAKTÖR	288,736	250,092	10,340	9,380	335,100	335,106	150,755		0,511		2, 6, 15
17	UZEL	123,610		19,518		339,700		60,454		0,681		

To ensure that the DMUs with efficiency score of 1 are really efficient the “additive model” should be solved for the DMUs of which efficiency scores are 1. If all the slacks are found as zero then it can be concluded that those DMUs are efficient. The additive model solved is as the following:

$$\text{Max} \quad \sum_{r=1}^{s} s_{rk}^{+} + \sum_{i=1}^{m} s_{ik}^{-}$$

s.t.

$$\sum_{j=1}^{n} Y_{rj}\lambda_{jk} - s_{rk}^{+} = Y_{rk} \qquad r = 1, \ldots, s$$

$$X_{ik} - \sum_{j=1}^{N} X_{ij}\lambda_{jk} - s_{ik}^{-} = 0 \qquad i = 1, \ldots, m$$

$$\sum_{j=1}^{n} Y_{3j}\lambda_{jk} \leq 1$$

$$\lambda_{jk}\,,\ s_{rk}^{+}\,,\ s_{ik}^{-} \geq 0$$

The optimal values of slack variables and the objective function for each DMU is shown in Table 4.5.

Table 4.5 The Solution of Additive Model

DMU	SLACK VARIABLES					OBJECTIVE
	s1(1,j)	s1(2,j)	s2(1,j)	s2(2,j)	s2(3,j)	
1	54,066	0,000	58,852	12,489	0,000	125,407
2	0,000	0,000	0,000	0,000	0,000	0,000
3	215,867	0,000	0,000	853,188	0,044	1069,099
4	0,000	0,000	0,000	0,000	0,000	0,000
5	0,000	0,000	56,927	227,527	0,000	284,454
6	0,000	0,000	0,000	0,000	0,000	0,000
7	0,000	0,000	74,113	388,035	0,000	462,149
8	0,000	0,000	622,006	618,709	0,030	1240,744
9	0,000	0,000	0,000	0,000	0,000	0,000
10	0,000	0,000	157,066	201,458	0,000	358,524
11	0,000	0,000	432,163	437,611	0,152	869,927
12	1673,700	26,503	0,000	0,000	0,235	1700,438
13	138,589	0,000	109,754	428,865	0,000	677,208
14	1242,245	22,536	0,000	0,000	0,355	1265,135
15	0,000	0,000	0,000	0,000	0,000	0,000
16	0,000	0,000	0,000	138,613	0,000	138,613
17	0,000	0,000	0,000	0,000	0,000	0,000

In Table 4.5, it is seen that the optimal values of all slack variables and objective function of each efficient unit are zero, so it can be concluded that the DMUs found as efficient via E_I models are really efficient and there are totally 6 efficient companies among 17. The high number of efficient companies may be caused by the high number of inputs and outputs with respect to the number of DMUs because as mentioned before the greater the number of variables, the higher the proportion of DMUs that achieve a relative efficiency score of 1.

Lastly, the following multiplier model M_I, the dual of E_I, is solved to find the optimal weights of inputs and outputs.

$$\text{Max} \quad \varphi_k = \sum_{r=1}^{s} u_{rk} Y_{rk} + c_k$$

s.t.

$$\sum_{r=1}^{s} u_{rk} Y_{rj} - \sum_{i=1}^{m} v_{ik} X_{ij} + c_k Y_{3j} \leq 0 \qquad j = 1, \ldots, N$$

$$\sum_{i=1}^{m} v_{ik} X_{ik} = 1$$

$$u_{rk} \geq 0, \quad v_{ik} \geq 0, \quad c_k \leq 0 \qquad r = 1, \ldots, s;\ i = 1, \ldots, m$$

The variable c_k is the dual variable of the capacity usage restriction constraint in E_I model. The optimal weights and objective function are given in Table 4.6.

Table 4.6 Efficiency Scores and Optimal Weights for CCR Model M_I

		OUTPUT			INPUT		
MI	**Phi**	**u(1,j)**	**u(2,j)**	**u(3,j)**	**v(1,j)**	**v(2,j)**	**c(j)**
1	0,995	0,000000	0,000382	1,893090	0,000000	0,111528	0
2	1,000	0,000842	0,000000	3,161988	0,008762	0,069564	0
3	0,672	0,001032	0,000130	0,000000	0,000320	0,032739	0
4	1,000	0,000284	0,000106	0,000000	0,000093	0,009307	-0,02801
5	0,820	0,000000	0,000429	2,127554	0,000000	0,125341	0
6	1,000	0,002044	0,000000	0,000000	0,000000	0,096052	0
7	0,835	0,000000	0,000319	1,582341	0,000000	0,093221	0
8	0,645	0,000000	0,000535	0,802836	0,001700	0,018924	0
9	1,000	0,000000	0,001634	0,000000	0,008654	0,000000	0
10	0,750	0,000000	0,001234	1,868691	0,003921	0,044234	0
11	0,412	0,000000	0,000876	1,325764	0,002782	0,031383	0
12	0,533	0,000330	0,000123	0,000000	0,000108	0,010794	-0,03248
13	0,904	0,000000	0,000224	1,112597	0,000000	0,065547	0
14	0,607	0,000343	0,000128	0,000000	0,000113	0,011239	-0,03382
15	1,000	0,000000	0,000322	0,000000	0,000826	0,002062	0
16	0,907	0,000558	0,000404	1,291373	0,000000	0,096711	0
17	1,000	0,000000	0,000000	1,467394	0,005387	0,017121	0

If the efficiency scores in Table 4.3 that are calculated from E_I model and the efficiency scores in Table 4.6 that are calculated from M_I model, they are expected to be the same because of the duality theorem. Table 4.7 controls whether the values of objective functions and optimal weights obtained from E_I and M_I models are same or not.

Table 4.7 Comparison of Optimal Solutions of CCR Models

			OUTPUT						INPUT			
EI	Technical Efficiency		u(1,j)		u(2,j)		u(3,j)		v(1,j)		v(2,j)	
1	0,995	✓	0,000000	✓	0,000382	✓	1,893090	✓	0,000000	✓	0,111528	✓
2	1,000	✓	0,000842	✓	0,000000	✓	3,161988	✓	0,008762	✓	0,069564	✓
3	0,672	✓	0,001032	✓	0,000130	✓	0,000000	✓	0,000320	✓	0,032739	✓
4	1,000	✓	0,000283	✓	0,000101	✓	0,000000	✓	0,000089	✓	0,009548	✓
5	0,820	✓	0,000000	✓	0,000429	✓	2,127554	✓	0,000000	✓	0,125341	✓
6	1,000	✓	0,001618	✓	0,000739	✓	0,000000	✓	0,000000	✓	0,096052	✓
7	0,835	✓	0,000000	✓	0,000319	✓	1,582341	✓	0,000000	✓	0,093221	✓
8	0,645	✓	0,000000	✓	0,000535	✓	0,802836	✓	0,001700	✓	0,018924	✓
9	1,000	✓	0,000656	✓	0,000000	⊠	0,000000	✓	0,008654	✓	0,000000	✓
10	0,750	✓	0,000000	✓	0,001234	✓	1,868691	✓	0,003921	✓	0,044234	✓
11	0,412	✓	0,000000	✓	0,000876	✓	1,325764	✓	0,002782	✓	0,031383	✓
12	0,533	✓	0,000326	✓	0,000117	✓	0,000000	✓	0,000102	✓	0,011008	✓
13	0,904	✓	0,000000	✓	0,000162	✓	1,112597	✓	0,000000	✓	0,065547	✓
14	0,607	✓	0,000338	✓	0,000121	✓	0,000000	✓	0,000106	✓	0,011406	✓
15	1,000	✓	0,000000	✓	0,000322	✓	0,000000	✓	0,000826	✓	0,002062	✓
16	0,907	✓	0,000558	✓	0,000404	✓	1,291373	✓	0,000000	✓	0,096711	✓
17	1,000	✓	0,000000	✓	0,000000	✓	1,467394	✓	0,005387	✓	0,017121	✓

The technical efficiency scores in Table 4.7 are the optimal values of the objection functions in model E_I. The optimal weights of inputs and outputs in Table 4.7 are actually the dual variables of the constraints in E_I. In other words, it is checked whether the optimal solutions of *dual of dual* are the same or not. The sign of "check" indicates that the values obtained from models E_I and M_I are same; the sign of "cross" indicates that the optimal values of variables in models E_I and M_I are different. It is seen that all efficiency scores are same for each company. However, there is a difference between the weights of second output for DMU 9. The situation is an indicator of an alternative solution.

4.2 BCC Models

The total efficiency scores in Table 4.3 are calculated by solving the E_I model which is a CCR model. The total efficiency scores found via CCR models under the CRS assumption include technical and scale efficiencies together. Besides, it is impossible to calculate the technical and scale efficiencies separately from CCR models. Therefore, the following model e_I is solved to calculate the technical efficiency score of each DMU.

Min θ_k

s.t.

$$\sum_{j=1}^{N} Y_{rj}\lambda_{jk} \geq Y_{rk} \qquad r = 1, \dots, s$$

$$\theta_k X_{ik} - \sum_{j=1}^{N} X_{ij}\lambda_{jk} \geq 0 \qquad i = 1, \dots, m$$

$$\sum_{j=1}^{N} \lambda_{jk} = 1$$

$$\sum_{j=1}^{N} Y_{3j}\lambda_{jk} \leq 1$$

$$\lambda_{jk} \geq 0 \qquad j = 1, \dots, N$$

θ_k urs

The technical efficiency scores and the dual variables (λ s) are given in Table 4.8. The DMUs with the technical efficiency score of 1 are DMUs 1, 2, 4, 6, 9, 13, 15, 16, 17. In other words, A.I.O.S., ASKAM, FORD OTOSAN, HYUNDAI ASSAN, M.BENZ TÜRK, TEMSA, TOYOTA, TÜRK TRAKTÖR and UZEL are technically efficient companies.

Table 4.8 Efficiency Scores and Dual Variables for BCC Model e_I

el	Technical Efficiency	Lamda(1)	Lamda(2)	Lamda(3)	Lamda(4)	Lamda(5)	Lamda(6)	Lamda(7)	Lamda(8)	Lamda(9)	Lamda(10)	Lamda(11)	Lamda(12)	Lamda(13)	Lamda(14)	Lamda(15)	Lamda(16)	Lamda(17)	REF	Total Lamdas
1	1,000	1,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000		1,000
2	1,000	0,000	1,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000		1,000
3	0,710	0,166	0,132	0,000	0,000	0,000	0,480	0,000	0,000	0,222	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1, 2, 6, 9	1,000
4	1,000	0,000	0,000	0,000	1,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000		1,000
5	0,822	0,397	0,593	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,010	0,000	0,000	1, 2	1,000
6	1,000	0,000	0,000	0,000	0,000	0,000	1,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000		1,000
7	0,882	0,943	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,025	0,000	0,000	0,000	0,032	1, 13, 17	1,000
8	0,645	0,000	0,225	0,000	0,000	0,000	0,000	0,000	0,000	0,048	0,000	0,000	0,000	0,000	0,000	0,064	0,000	0,663	2, 9, 15, 17	1,000
9	1,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000		1,000
10	0,772	0,000	0,901	0,000	0,000	0,000	0,000	0,000	0,000	0,082	0,000	0,000	0,000	0,000	0,000	0,017	0,000	0,000	2, 9, 15	1,000
11	0,601	0,000	0,953	0,000	0,000	0,000	0,000	0,000	0,000	0,047	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	2, 9	1,000
12	0,537	0,000	0,000	0,000	0,199	0,000	0,230	0,000	0,000	0,195	0,000	0,000	0,000	0,000	0,000	0,377	0,000	0,000	4, 6, 9, 15	1,000
13	1,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1,000	0,000	0,000	0,000	0,000		1,000
14	0,611	0,000	0,000	0,000	0,222	0,000	0,242	0,000	0,000	0,482	0,000	0,000	0,000	0,000	0,000	0,054	0,000	0,000	4, 6, 9, 15	1,000
15	1,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1,000	0,000	0,000		1,000
16	1,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1,000	0,000		1,000
17	1,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	1,000		1,000

After finding the technical efficiency scores, the scale efficiency score of each company can be calculated by the following formula:

$$\text{Scale efficiency score} = \frac{\text{Total efficiency score (CCR)}}{\text{Technical efficiency score (BCC)}}$$

The scale efficiencies of each company can be seen in Table 4.9. According to the scale efficiency scores, it can be concluded that ASKAM (2), FORD OTOSAN (4), HYUNDAI ASSAN (6), MAN (8), M.BENZ TÜRK (9), TOYOTA (15) and UZEL (17) are the scale efficient companies. However, MAN is not technical efficient although it is scale efficient. On the other hand, A.I.O.S., TEMSA and TÜRK TRAKTOR are not scale efficient even they are technically efficient. It means that they do not waste any resource but they have inefficiency due to their scale size.

Table 4.9 Scale Efficiencies

DMU	Total Efficiency (from EI)	Technical Efficiency (from el)	Scale Efficiency
1	0,995	1,000	0,995
2	1,000	1,000	1,000
3	0,672	0,710	0,946
4	1,000	1,000	1,000
5	0,820	0,822	0,997
6	1,000	1,000	1,000
7	0,835	0,882	0,947
8	0,645	0,645	1,000
9	1,000	1,000	1,000
10	0,750	0,772	0,972
11	0,412	0,601	0,685
12	0,533	0,537	0,993
13	0,904	1,000	0,904
14	0,607	0,611	0,993
15	1,000	1,000	1,000
16	0,907	1,000	0,907
17	1,000	1,000	1,000

In addition to e_I model, the multiplier BCC model m_I (the dual of e_I) is solved to check whether there are any alternative optimal solutions or not. The model m_I can be seen below and the results are in Table 4.10.

Max $\quad \varphi_k = \sum_{r=1}^{s} u_{rk} Y_{rk} + c_k - \mu_0$

s.t.

$$\sum_{r=1}^{s} u_{rk} Y_{rj} - \sum_{i=1}^{m} v_{ik} X_{ij} + c_k Y_{3j} - \mu_0 \leq 0 \qquad j = 1, \ldots, N$$

$$\sum_{i=1}^{m} v_{ik} X_{ik} = 1$$

$$u_{rk} \geq 0, \quad v_{ik} \geq 0 \qquad r = 1, \ldots, s; \quad i = 1, \ldots, m$$

$$c_k \leq 0$$

$$\mu_0 \text{ urs}$$

Table 4.10 Efficiency Scores and Optimal Weights for BCC Model m_I

			OUTPUT			INPUT	
mI	Technical Efficiency	mu	u(1,j)	u(2,j)	u(3,j)	v(1,j)	v(2,j)
1	1,000	0,006	0,000	0,000	1,914	0,000	0,112
2	1,000	-1,000	0,000	0,000	0,000	0,013	0,000
3	0,710	0,097	0,001	0,000	0,487	0,000	0,033
4	1,000	0,012	0,000	0,000	0,000	0,000	0,010
5	0,822	0,006	0,000	0,000	2,151	0,000	0,125
6	1,000	-0,248	0,001	0,001	0,000	0,000	0,096
7	0,882	0,719	0,000	0,000	3,044	0,001	0,061
8	0,645	-0,001	0,000	0,001	0,800	0,002	0,019
9	1,000	0,000	0,000	0,002	0,000	0,009	0,000
10	0,772	-0,549	0,000	0,002	0,000	0,006	0,024
11	0,601	-0,587	0,000	0,000	0,000	0,008	0,000
12	0,537	0,014	0,000	0,000	0,000	0,000	0,011
13	1,000	0,190	0,000	0,000	1,495	0,000	0,066
14	0,611	0,014	0,000	0,000	0,000	0,000	0,011
15	1,000	0,000	0,000	0,000	0,000	0,001	0,002
16	1,000	0,172	0,001	0,001	1,189	0,001	0,070
17	1,000	0,000	0,000	0,000	1,467	0,005	0,017

Table 4.10 includes the values of optimal weights and the variable “mu” which indicates the direction of returns to scale according to its sign when there is not an alternative solution. Therefore, the results of e_I and m_I are compared in Table 4.11.

Table 4.11 Comparison of Optimal Solutions of BCC Models

			OUTPUT						INPUT			
eI	Technical Efficiency		u(1,j)		u(2,j)		u(3,j)		v(1,j)		v(2,j)	
1	1,000	✓	0,001	✓	0,000	✓	1,992	☒	0,002	☒	0,059	☒
2	1,000	✓	0,000	✓	0,000	✓	0,000	✓	0,013	✓	0,000	✓
3	0,710	✓	0,001	✓	0,000	✓	0,487	✓	0,000	✓	0,033	✓
4	1,000	✓	0,000	✓	0,000	✓	0,000	✓	0,000	✓	0,010	✓
5	0,822	✓	0,000	✓	0,000	✓	2,151	✓	0,000	✓	0,125	✓
6	1,000	✓	0,002	✓	0,001	✓	0,000	✓	0,000	✓	0,096	✓
7	0,882	✓	0,000	✓	0,000	✓	3,044	✓	0,001	✓	0,061	✓
8	0,645	✓	0,000	✓	0,001	✓	0,800	✓	0,002	✓	0,019	✓
9	1,000	✓	0,001	✓	0,000	✓	0,000	✓	0,009	✓	0,000	✓
10	0,772	✓	0,000	✓	0,002	✓	0,000	✓	0,006	✓	0,024	✓
11	0,601	✓	0,000	✓	0,000	✓	0,000	✓	0,008	✓	0,000	✓
12	0,537	✓	0,000	✓	0,000	✓	0,000	✓	0,000	✓	0,011	✓
13	1,000	✓	0,000	✓	0,000	✓	1,686	☒	0,001	✓	0,037	☒
14	0,611	✓	0,000	✓	0,000	✓	0,000	✓	0,000	✓	0,011	✓
15	1,000	✓	0,000	✓	0,000	✓	0,000	✓	0,001	✓	0,002	✓
16	1,000	✓	0,002	✓	0,001	✓	1,189	✓	0,001	✓	0,070	✓
17	1,000	✓	0,000	✓	0,000	✓	1,467	✓	0,005	✓	0,017	✓

The technical efficiency scores in Table 4.11 are the optimal values of the objection functions in model e_I and they are taken from Table 4.8. The optimal weights of inputs and outputs in Table 4.11 are actually the dual variables of the constraints in e_I. In other words, it is checked whether the optimal solutions of *dual of dual* are the same or not. The sign of “check” indicates that the values obtained from models e_I and m_I are same; the sign of “cross” indicates that the optimal values of variables in models e_I and m_I are different. It is seen that all the technical efficiency scores are the same. However, there are different optimal weights of third output, first and second inputs. Hence, it can be concluded that there are alternative solutions for this problem. If there are alternative solutions, the variable “mu” in model m_I does not give any information about the direction of returns to scale. In such cases, Banker-Thrall method can be used to determine the direction of returns to scale for DMUs. One can apply to Banker and Thrall (1992) for more information about that method.

4.4 Malmquist Total Factor Productivity (TFP) Index

All previous efficiency analysis in this study was performed for a specific time period which is year 2005. However, the change of efficiency by time is an important topic to be considered because it is difficult to assess whether increases/decreases in efficiency scores of each year are a result of increases/decreases in technical efficiency or technological change. Deliktaş (2002) states that Mahadevan (2002) defines the efficiency change as catching-up effect (reaching the production frontier) and the technical (technological) change as technological change frontier effect (shifting of the production frontier).

Therefore, the panel data that includes the five years from 2001-2005. The data of 2004 and 2005 are available on the webpage of OSD but it is thought that more number of years can present more realistic results. Hence, the data of years 2001, 2002 and 2003 were requested and obtained from Hakan Yontar who is responsible of editing the reports published by OSD. In sum, the panel data that includes 5 years is used to analyze the efficiency changes of companies.

Malmquist TFP index is used for measuring the changes in total factor productivity of companies by time. As mentioned in Section 2.3, the distance function is used for this measurement. The output oriented Malmquist TFP change index between time period s and t is calculated by the following formula developed by Fare et. al (1994):

$$m_0(\vec{x}_s, \vec{y}_s, \vec{x}_t, \vec{y}_t) = \underbrace{\frac{d_0^t(\vec{x}_t, \vec{y}_t)}{d_0^s(\vec{x}_s, \vec{y}_s)}}_{\text{Efficiency change}} \underbrace{\sqrt{\frac{d_0^s(\vec{x}_t, \vec{y}_t)}{d_0^t(\vec{x}_t, \vec{y}_t)} * \frac{d_0^s(\vec{x}_s, \vec{y}_s)}{d_0^t(\vec{x}_s, \vec{y}_s)}}}_{\text{Technical change}}$$

where $d_0^s(\vec{x}_t, \vec{y}_t)$ indicates the distance of the observation of time s from the technology of time t. If the function m (.) > 1 then it means that TFP increases from time s to time t. In opposite, if the function m (.) < 1 then it means that TFP decreases from time s to time t.

In this study, the Data Envelopment Analysis that is one of the non-parametric approaches is used for determining the distance functions. The linear programming models developed by Fare et. al (1994) were mentioned in Section 2.3. After adding the capacity usage constraints the new output-oriented models are as follow (the last constraints are the capacity usage constraints):

$$
\begin{aligned}
&\left[d_0^t(\vec{x}_t,\vec{y}_t)\right]_k^{-1} = \max\theta_k \\
&s.t. \\
&-\theta_k Y_{rk}^t + \sum_{j=1}^{N}\lambda_{jk}Y_{rj}^t \geq 0 \\
&X_{ik}^t - \sum_{j=1}^{N}\lambda_{jk}X_{ij}^t \geq 0 \\
&\sum_{j=1}^{N}\lambda_{jk}Y_{3j}^t \leq 1 \\
&\lambda_{jk} \geq 0
\end{aligned}
\qquad
\begin{aligned}
&\left[d_0^s(\vec{x}_s,\vec{y}_s)\right]_k^{-1} = \max\theta_k \\
&s.t. \\
&-\theta_k Y_{rk}^s + \sum_{j=1}^{N}\lambda_{jk}Y_{rj}^s \geq 0 \\
&X_{ik}^s - \sum_{j=1}^{N}\lambda_{jk}X_{ij}^s \geq 0 \\
&\sum_{j=1}^{N}\lambda_{jk}Y_{3j}^s \leq 1 \\
&\lambda_{jk} \geq 0
\end{aligned}
$$

$$
\begin{aligned}
&\left[d_0^t(\vec{x}_s,\vec{y}_s)\right]_k^{-1} = \max\theta_k \\
&s.t. \\
&-\theta_k Y_{rk}^s + \sum_{j=1}^{N}\lambda_{jk}Y_{rj}^t \geq 0 \\
&X_{ik}^s - \sum_{j=1}^{N}\lambda_{jk}X_{ij}^t \geq 0 \\
&\sum_{j=1}^{N}\lambda_{jk}Y_{3j}^t \leq 1 \\
&\lambda_{jk} \geq 0
\end{aligned}
\qquad
\begin{aligned}
&\left[d_0^s(\vec{x}_t,\vec{y}_t)\right]_k^{-1} = \max\theta_k \\
&s.t. \\
&-\theta_k Y_{rk}^t + \sum_{j=1}^{N}\lambda_{jk}Y_{rj}^s \geq 0 \\
&X_{ik}^t - \sum_{j=1}^{N}\lambda_{jk}X_{ij}^s \geq 0 \\
&\sum_{j=1}^{N}\lambda_{jk}Y_{3j}^s \leq 1 \\
&\lambda_{jk} \geq 0
\end{aligned}
$$

It is seen that $\sum_{j=1}^{N}\lambda_{jk} = 1$, that satisfies the variable returns to scale (VRS) does not exist in the models above because Tatje and Lovell (1995) showed that Malmquist TFP index does not measure the TFP change correctly under the variable returns to scale (VRS) assumption. Therefore, distance functions should be calculated according to the constant returns to scale (CRS) assumption.

If N is the number of observations and t is the number of time periods, n(3t-2) linear programming models must be solved to calculate the values of all distance functions defined above. Hence, 17x((3x5)-2) = ***221*** models are solved in this study. It should be emphasized that the financial data of all five years are deflated by 2001 based Producer Price Index (PPI) in order to stabilize the variance of random or seasonal fluctuations and/or highlight cyclical patterns in the data. The deflated data and more information about the process of deflation are in Appendix A.

Then, the distance functions are calculated by using the deflated data of five years and shown in Tables 4.12 – 4.15.

Table 4.12 Distance Functions for Period 2001-2002

s=2001 t=2002	$\left[d_0^t(\vec{x}_t,\vec{y}_t)\right]_k^{-1}$	$\left[d_0^s(\vec{x}_s,\vec{y}_s)\right]_k^{-1}$	$\left[d_0^t(\vec{x}_s,\vec{y}_s)\right]_k^{-1}$	$\left[d_0^s(\vec{x}_t,\vec{y}_t)\right]_k^{-1}$
A.I.O.S.	1,000000	3,532484	0,693784	1,322815
ASKAM	1,000000	1,126446	0,073208	1,327636
B.M.C.	1,238915	2,345832	0,192268	1,974056
FORD OTOSAN	1,470301	1,000000	0,213922	1,660646
HONDA	1,052737	4,043249	0,433450	1,529215
HYUNDAI ASSAN	1,432522	2,256453	0,408197	1,753713
KARSAN	1,000000	1,486235	0,421715	0,823920
M.A.N.	1,410600	1,132476	0,460392	1,692872
M.BENZ TÜRK	1,000000	1,253166	0,843939	0,940813
OTOKAR	1,000000	1,000000	0,056526	1,120965
OTOYOL	1,468790	1,047449	0,187632	1,902116
OYAK RENAULT	1,000000	1,000000	0,479498	0,988910
TEMSA	1,268287	2,560637	1,007732	1,304901
TOFAŞ	1,064049	1,127952	0,543790	1,171307
TOYOTA	1,000000	6,743198	0,552683	0,961853
TÜRK TRAKTÖR	1,204220	2,121163	0,311640	1,447008
UZEL	1,515174	1,823759	0,328650	1,621200

Table 4.13 Distance Functions for Period 2002-2003

s=2002 t=2003	$\left[d_0^t(\vec{x}_t,\vec{y}_t)\right]_k^{-1}$	$\left[d_0^s(\vec{x}_s,\vec{y}_s)\right]_k^{-1}$	$\left[d_0^t(\vec{x}_s,\vec{y}_s)\right]_k^{-1}$	$\left[d_0^s(\vec{x}_t,\vec{y}_t)\right]_k^{-1}$
A.I.O.S.	1,109050	1,000000	1,278723	0,826418
ASKAM	1,000000	1,000000	4,339255	0,590392
B.M.C.	1,077894	1,238915	1,569219	0,944153
FORD OTOSAN	1,000636	1,470301	1,795872	0,759454
HONDA	1,000000	1,052737	1,322365	0,265414
HYUNDAI ASSAN	1,084469	1,432522	1,694776	0,743344
KARSAN	1,000000	1,000000	0,911669	0,735048
M.A.N.	1,666667	1,410600	1,780276	1,387661
M.BENZ TÜRK	1,000000	1,000000	0,937737	1,029201
OTOKAR	1,031709	1,000000	1,204617	0,749114
OTOYOL	1,495104	1,468790	2,022507	1,031364
OYAK RENAULT	1,053697	1,000000	1,015913	0,856297
TEMSA	1,850063	1,268287	1,879553	1,396711
TOFAŞ	1,333976	1,064049	1,197449	1,179460
TOYOTA	1,000000	1,000000	1,090754	0,734761
TÜRK TRAKTÖR	1,000000	1,204220	1,406227	0,617510
UZEL	1,000000	1,515174	2,339913	0,046861

Table 4.14 Distance Functions for Period 2003-2004

s=2003 t=2004	$\left[d_0^t(\vec{x}_t,\vec{y}_t)\right]_k^{-1}$	$\left[d_0^s(\vec{x}_s,\vec{y}_s)\right]_k^{-1}$	$\left[d_0^t(\vec{x}_s,\vec{y}_s)\right]_k^{-1}$	$\left[d_0^s(\vec{x}_t,\vec{y}_t)\right]_k^{-1}$
A.I.O.S.	1,383033	1,109050	1,338192	1,150446
ASKAM	1,000000	1,000000	0,801666	0,017475
B.M.C.	1,340161	1,077894	1,464308	1,033717
FORD OTOSAN	1,006527	1,000636	1,282228	0,647548
HONDA	1,000000	1,000000	0,860368	0,725477
HYUNDAI ASSAN	1,145492	1,084469	1,465832	0,697381
KARSAN	1,000000	1,000000	1,239499	0,531432
M.A.N.	1,639344	1,666667	2,158793	1,484230
M.BENZ TÜRK	1,123596	1,000000	1,301729	0,887646
OTOKAR	1,389752	1,031709	1,137220	1,073048
OTOYOL	1,844086	1,495104	1,405587	1,574534
OYAK RENAULT	1,000000	1,053697	1,739519	0,126195
TEMSA	1,978098	1,850063	3,083240	1,399725
TOFAŞ	1,646498	1,333976	2,242939	1,258808
TOYOTA	1,000000	1,000000	1,268003	0,425132
TÜRK TRAKTÖR	1,000000	1,000000	1,142277	0,570744
UZEL	1,154776	1,000000	0,724397	0,822591

Table 4.15 Distance Functions for Period 2004-2005

s=2004 t=2005	$\left[d_0^t(\vec{x}_t,\vec{y}_t)\right]_k^{-1}$	$\left[d_0^s(\vec{x}_s,\vec{y}_s)\right]_k^{-1}$	$\left[d_0^t(\vec{x}_s,\vec{y}_s)\right]_k^{-1}$	$\left[d_0^s(\vec{x}_t,\vec{y}_t)\right]_k^{-1}$
A.I.O.S.	1,004788	1,383033	1,728915	0,788380
ASKAM	1,000000	1,000000	0,002911	0,553482
B.M.C.	1,461103	1,340161	2,416003	0,883020
FORD OTOSAN	1,000000	1,006527	1,161697	0,413166
HONDA	1,219769	1,000000	1,184103	0,942894
HYUNDAI ASSAN	1,000000	1,145492	2,020827	0,463133
KARSAN	1,197663	1,000000	1,233133	0,970345
M.A.N.	1,549981	1,639344	2,217309	1,278807
M.BENZ TÜRK	1,000000	1,123596	1,625371	0,372301
OTOKAR	1,334109	1,389752	1,917461	1,021274
OTOYOL	2,429186	1,844086	2,297898	1,842734
OYAK RENAULT	1,307961	1,000000	0,333448	0,877625
TEMSA	1,106413	1,978098	2,952423	0,841759
TOFAŞ	1,399959	1,646498	1,961958	0,802790
TOYOTA	1,000000	1,000000	1,276149	0,457607
TÜRK TRAKTÖR	1,102362	1,000000	1,466562	0,694127
UZEL	1,000000	1,154776	2,020456	0,747345

Finally, after determining the distance functions Efficiency Change and Technical Change of each company for each time interval are calculated in addition to Malmquist TFP Change Indexes (m_0) by using the following formula:

$$m_0(\vec{x}_s,\vec{y}_s,\vec{x}_t,\vec{y}_t)=\underbrace{\frac{d_0^t(\vec{x}_t,\vec{y}_t)}{d_0^s(\vec{x}_s,\vec{y}_s)}}_{\text{Efficiency change}}\underbrace{\sqrt{\frac{d_0^s(\vec{x}_t,\vec{y}_t)}{d_0^t(\vec{x}_t,\vec{y}_t)}*\frac{d_0^s(\vec{x}_s,\vec{y}_s)}{d_0^t(\vec{x}_s,\vec{y}_s)}}}_{\text{Technical change}}$$

The values of Efficiency change, Technical Change and Malmquist TFP Index of each company for each time interval are shown in Table 4.16. The first three column includes the changes from year 2001 to 2002. Similarly, the second, third and the fourth three columns show the changes in time intervals 2002-2003, 2003-2004 and 2004-2005 respectively. In addition, the last row indicated by μ (total) shows the average changes in total automotive industry for each time interval. As Tarım (2001) stated “geometric mean” is used for calculation the averages.

Table 4.16 Efficiency Change, Technical Change and Malmquist TFP Index

	2001-2002			2002-2003			2003-2004			2004-2005		
	Efficiency Change	Technical Change	Malmquist TFP Index	Efficiency Change	Technical Change	Malmquist TFP Index	Efficiency Change	Technical Change	Malmquist TFP Index	Efficiency Change	Technical Change	Malmquist TFP Index
A.I.O.S.	0,283	2,595	0,735	1,109	0,763	0,847	1,247	0,830	1,035	0,727	0,792	0,576
ASKAM	0,888	4,520	4,012	1,000	0,369	0,369	1,000	0,148	0,148	1,000	13,789	13,789
B.M.C.	0,528	4,409	2,329	0,870	0,832	0,724	1,243	0,754	0,937	1,090	0,579	0,631
FORD OTOSAN	1,470	2,298	3,378	0,681	0,788	0,536	1,006	0,709	0,713	0,994	0,598	0,594
HONDA	0,260	3,681	0,958	0,950	0,460	0,437	1,000	0,918	0,918	1,220	0,808	0,986
HYUNDAI ASSAN	0,635	2,601	1,652	0,757	0,761	0,576	1,056	0,671	0,709	0,873	0,512	0,447
KARSAN	0,673	1,704	1,147	1,000	0,898	0,898	1,000	0,655	0,655	1,198	0,811	0,971
M.A.N.	1,246	1,718	2,140	1,182	0,812	0,960	0,984	0,836	0,822	0,945	0,781	0,738
M.BENZ TÜRK	0,798	1,182	0,943	1,000	1,048	1,048	1,124	0,779	0,875	0,890	0,507	0,452
OTOKAR	1,000	4,453	4,453	1,032	0,776	0,801	1,347	0,837	1,127	0,960	0,745	0,715
OTOYOL	1,402	2,689	3,770	1,018	0,708	0,720	1,233	0,953	1,175	1,317	0,780	1,028
OYAK RENAULT	1,000	1,436	1,436	1,054	0,894	0,942	0,949	0,276	0,262	1,308	1,419	1,855
TEMSA	0,495	1,617	0,801	1,459	0,714	1,041	1,069	0,652	0,697	0,559	0,714	0,399
TOFAŞ	0,943	1,511	1,425	1,254	0,886	1,111	1,234	0,674	0,832	0,850	0,694	0,590
TOYOTA	0,148	3,426	0,508	1,000	0,821	0,821	1,000	0,579	0,579	1,000	0,599	0,599
TÜRK TRAKTÖR	0,568	2,860	1,624	0,830	0,727	0,604	1,000	0,707	0,707	1,102	0,655	0,722
UZEL	0,831	2,437	2,024	0,660	0,174	0,115	1,155	0,992	1,145	0,866	0,654	0,566
μ (total)	0,666	2,444	1,627	0,972	0,685	0,666	1,091	0,651	0,710	0,974	0,841	0,819

The results in Table 4.16 are illustrated by Figures 4.1–4.6. Both graphs are started with year 2001 of which values is set to 1. Then the graphs are drawn according to cumulative changes. For example, Figure 4.1 is the graph that shows the efficiency changes (cumulative) of A.I.O.S. The starting point of the graph is year 2001 with the efficiency score 1. Then, the first cell of Table 4.16 shows that efficiency change of A.I.O.S. between 2001 and 2002 is 0.283, so the indicator point goes to 1 * 0.283 = 0.283. The efficiency change score of A.I.O.S. for 2002-3003 is 1.109 in Table 4.16, so the indicator point goes from 0.283 to 0.283 * 1.109 = 0.314. The values of years 2004 and 2005 for A.I.O.S. in the graph are calculated similarly.

Figure 4.2 and 4.3 show the technical change and Malmquist TFP Index of A.I.O.S. The calculations are performed as mentioned above for Figure 4.1. The graphs that show the efficiency change, technical change and Malmquist TFP Index of all companies used in this study can be seen in Appendix B.

Figure 4.3 and 4.6 are the graphs that show the efficiency change, technical change and Malmquist TFP Index of total automotive industry. The method of graphing the values which are in the last row of Table 4.16 is the same as the method used for calculations of companies.

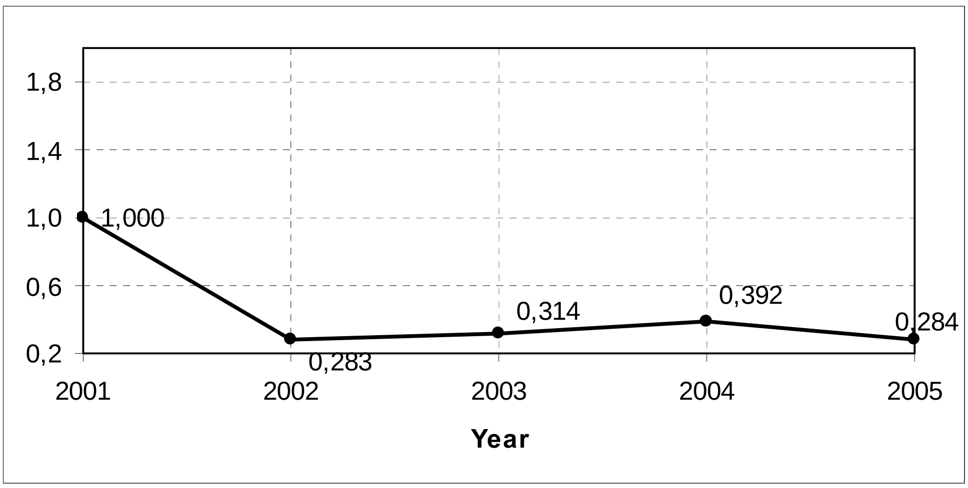

Figure 4.1 Efficiency Change of A.I.O.S.

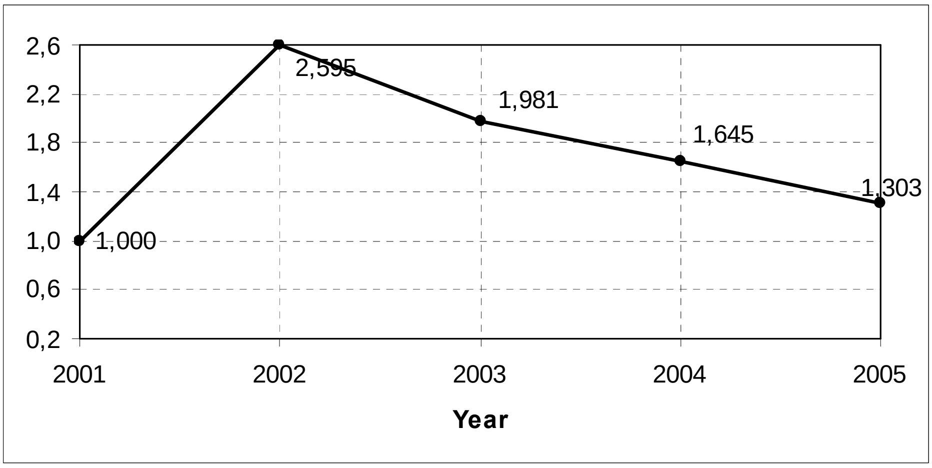

Figure 4.2 Technical Change of A.I.O.S.

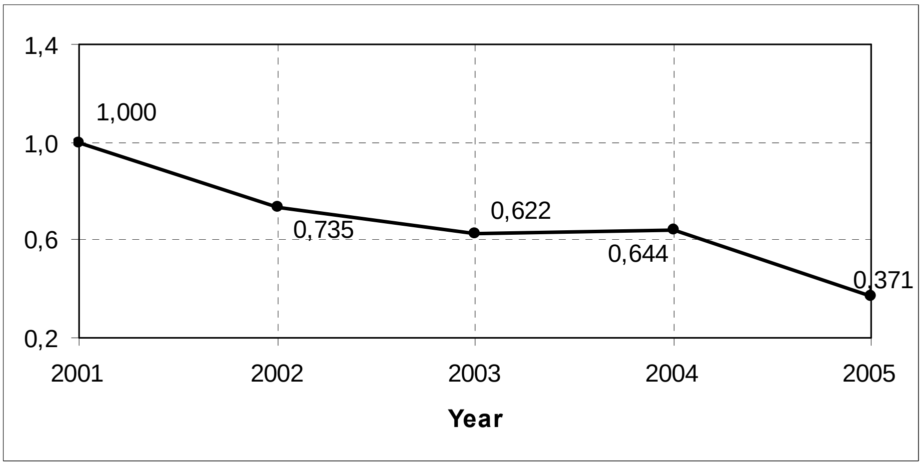

Figure 4.3 Malmquist TFP Index of A.I.O.S.

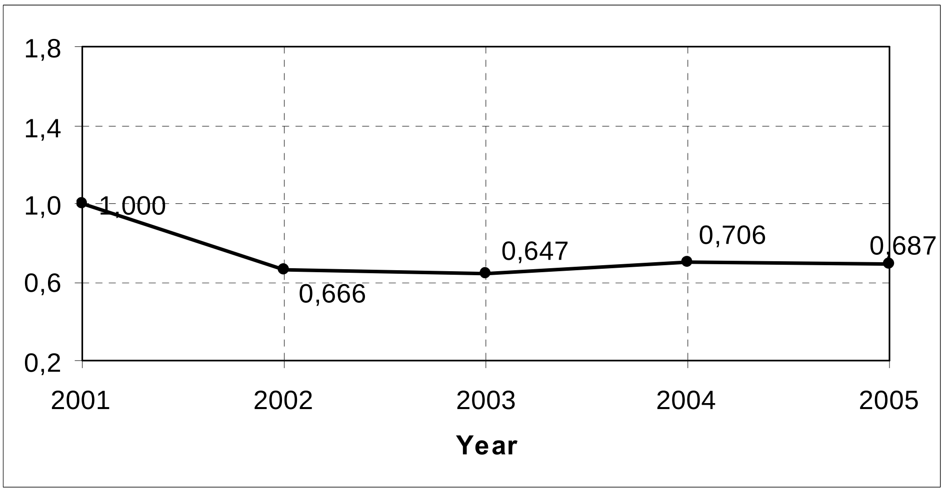

Figure 4.4 Average Efficiency Change of Automotive Industry

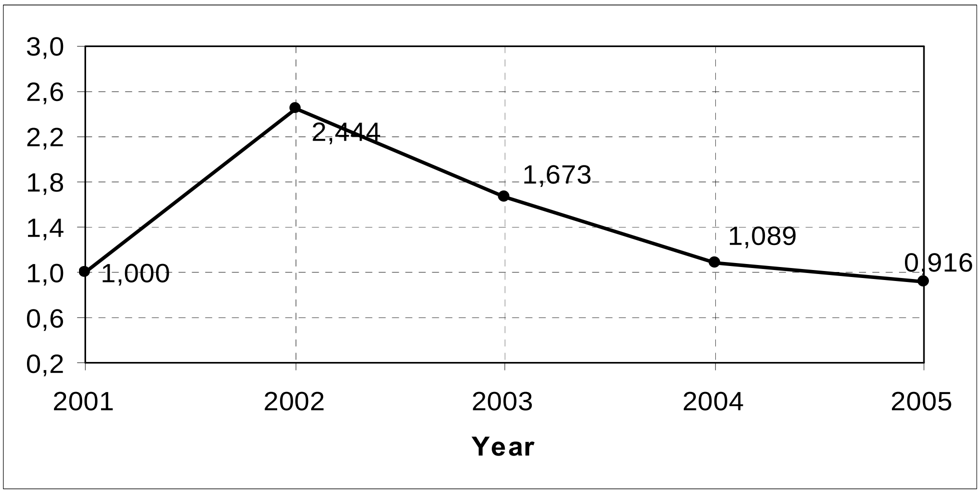

Figure 4.5 Average Technical Change of Automotive Industry

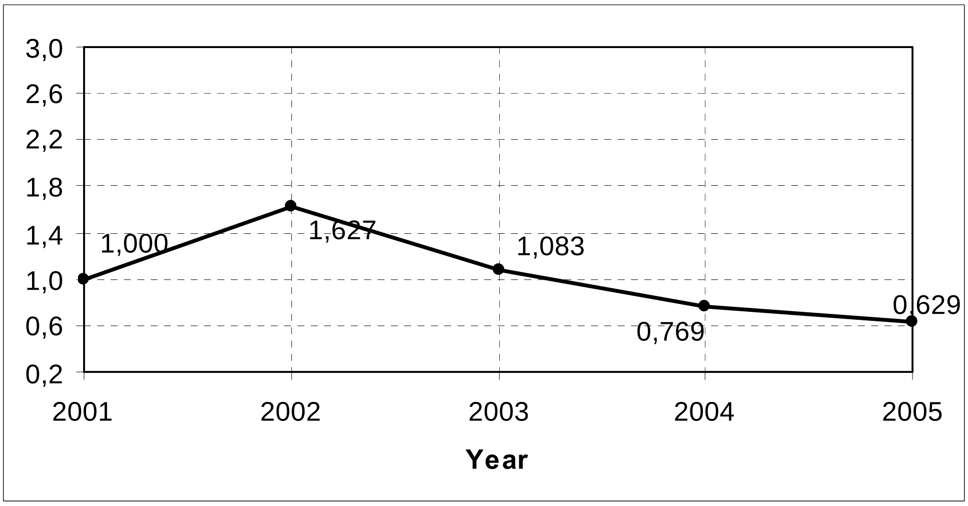

Figure 4.6 Average Malmquist TFP Index of Automotive Industry

In addition to Efficiency Change, Technical Change and Malmquist TFP Index, the changes in DEA scores by time can be another meaningful measure. Hence, DEA scores obtained from basic CCR and BCC models by using the deflated data are shown in Table 4.17 and 4.18.

Table 4.17 CCR Model Results

	2001	2002	2003	2004	2005
A.I.O.S.	0,283	1	0,902	0,723	0,995
ASKAM	0,888	1	1	1	1
B.M.C.	0,426	0,807	0,925	0,680	0,672
FORD OTOSAN	1	0,680	0,999	0,992	1
HONDA	0,189	0,950	1	1	0,820
HYUNDAI ASSAN	0,443	0,698	0,922	0,837	1
KARSAN	0,673	1	1	1	0,835
M.A.N.	0,883	0,709	0,575	0,450	0,645
M.BENZ TÜRK	0,798	1	1	0,788	1
OTOKAR	1	1	0,969	0,720	0,750
OTOYOL	0,955	0,681	0,669	0,542	0,412
OYAK RENAULT	1	1	0,942	1	0,533
TEMSA	0,391	0,788	0,541	0,506	0,904
TOFAŞ	0,887	0,940	0,720	0,540	0,607
TOYOTA	0,148	1	1	1	1
TÜRK TRAKTÖR	0,471	0,830	1	1	0,907
UZEL	0,548	0,660	1	0,866	1

Table 4.18 BCC Model Results

	2001	2002	2003	2004	2005
A.I.O.S.	0,484	1	0,914	0,744	1
ASKAM	1	1	1	1	1
B.M.C.	1	0,889	1	0,826	0,710
FORD OTOSAN	1	0,705	1	1	1
HONDA	0,190	1	1	1	0,822
HYUNDAI ASSAN	0,523	0,946	0,935	1	1
KARSAN	0,711	1	1	1	0,882
M.A.N.	0,885	0,935	1	0,516	0,645
M.BENZ TÜRK	0,991	1	1	1	1
OTOKAR	1	1	1	0,824	0,772
OTOYOL	0,970	1	0,760	0,619	0,601
OYAK RENAULT	1	1	1	1	0,537
TEMSA	0,475	0,793	0,573	0,521	1
TOFAŞ	1	1	0,774	0,597	0,611
TOYOTA	0,344	1	1	1	1
TÜRK TRAKTÖR	0,603	0,925	1	1	1
UZEL	0,552	0,660	1	0,933	1

From Tables 4.17 and 4.18 the scale efficiencies of each company for each year are calculated to observe the changes in scale efficiencies by time. The scale efficiencies are shown in Table 4.19.

Table 4.19 Scale Efficiencies

	2001	2002	2003	2004	2005
A.I.O.S.	0,585	1	0,986	0,972	0,995
ASKAM	0,888	1	1	1	1
B.M.C.	0,426	0,908	0,925	0,823	0,946
FORD OTOSAN	1	0,965	0,999	0,992	1
HONDA	0,996	0,950	1	1	0,997
HYUNDAI ASSAN	0,847	0,738	0,987	0,837	1
KARSAN	0,946	1	1	1	0,947
M.A.N.	0,998	0,758	0,575	0,873	1
M.BENZ TÜRK	0,806	1	1	0,788	1
OTOKAR	1	1	0,969	0,873	0,972
OTOYOL	0,984	0,681	0,880	0,877	0,685
OYAK RENAULT	1	1	0,942	1	0,993
TEMSA	0,823	0,995	0,944	0,971	0,904
TOFAŞ	0,887	0,940	0,930	0,904	0,993
TOYOTA	0,431	1	1	1	1
TÜRK TRAKTÖR	0,782	0,898	1	1	0,907
UZEL	0,993	0,999	1	0,928	1

CHAPTER 5

CONCLUSIONS

5.1 CONCLUSIONS

If the results in the tables are analyzed the following conclusions can be drawn:

- According to the results in Table 4.3 (the results of model solved by 2005 data), TOYOTA exists in 9 reference sets of inefficient units. Similarly, ASKAM exists in 8, HYUNDAI ASSAN and M.BENZ TÜRK exist in 4, UZEL exists in 3 and FORD OTOSAN exists in 2 reference sets (except their own) as peers. This type of DMUs which exist in many reference sets are called as "robustly efficient" units. They are likely to remain efficient unless there were major shifts in their fortunes (Norman and Stoker, 1991).

  On the hand, there is another type of efficient DMUs which are called as "marginally efficient" units. They will appear on only one or two reference sets (including their own). They are likely to drop below 1 if there was even a small drop in the value of an output variable (or a small increase in the value of an input variable). However, according to efficiency scores in Table 4.3 there is not a marginally efficient company.

  It is seen from Table 4.3 that the overall efficiency scores of A.I.O.S, TEMSA and TÜRK TRAKTÖR are greater than 0.9 but less than 1. They are called "marginally" inefficient units.

Lastly, according to data of year 2005, BMC, MAN, OTOYOL, OYAK RENAULT and TOFAŞ have overall efficiency scores less than 0.75. This type of DMUs are named as "distinctly inefficient" units. Norman and Stoker states that it is difficult to make those DMUs efficient in the short term and they remain inefficient until there was a major change in circumstances.

- Most of the companies are inefficient in 2001. It is seen from Table 4.17 that A.I.O.S., BMC, HONDA, HYUNDAI ASSAN, TEMSA, TOYOTA, TÜRK TRAKTÖR and UZEL have total efficiency scores smaller than 0.6. The reason of common inefficiency in automotive industry may be the "2001 Crisis" in Turkish economy. The situation can also be observed in Table 4.16 and Figure 4.4. In Table 4.16 and Figure 4.4, the value of μ (total) change that represents the average efficiency change of automotive industry is 0.666 for period 2001-2002 and it is the smallest among all periods.

- ASKAM and TOYOTA are two companies which are 100 % efficient in years 2002, 2003, 2004, 2005. However, the overall efficiency of TOYOTA in 2001 is just 0.148 in Table 4.17. The reason of very small efficiency score is actually the very low capacity usage because TOYOTA was able to produce only 2,862 vehicles in 2001 despite of its capacity of 100,000. Actually, it proves that TOYOTA is one of the companies which were deeply affected from the economic crisis in 2001. However, TOYOTA increased its capacity usage to 39 % by producing 38,899 vehicles in 2002 and its efficiency score has been 1 since 2002.

  The other most efficient company is ASKAM and actually its efficiency score is 1 in all five years under variable returns to scale (VRS) assumption. However, the scale efficiency of 0.888 in Table 4.19 explains that ASKAM could not be 100 % efficient in 2001 due to a small scale inefficiency.

- M.BENZ TÜRK, FORD OTOSAN, HONDA and OYAK RENAULT are the other companies of which total efficiency scores are relatively high. However, there are some points to be focused on about these companies. For example, OYAK RENAULT is one of the most efficient companies until 2005 but its overall efficiency score (from CCR model) is 0.533 in 2005. The reason of this decrease may be the high increase in *Payment for Raw Materials and Components* of OYAK RENAULTS. From Appendix A, it can be seen that in 2004, OYAK RENAULT paid 65.874 million YTL for *Payment for Raw Materials and Components.* However, the value increases to 1241.305 in 2005. Therefore, the high increase in one of the inputs results in inefficiency.

The situation of HONDA is interesting. According to Table 4.17 and Table 4.18 the overall and technical efficiency scores of HONDA are high. However, in Figure B-10 and B-12 it is seen that its efficiency change and Malmquist TFP Index scores are continues at low level with respect to the level in 2001. It may be interpreted that HONDA was deeply affected from 2001 Economic Crisis like TOYOTA.

- B.M.C. is another company to be focused on because all Table 4.18, Figure B-5 and Figure B-6 (in Appendix B) shows a continuous decrease in efficiency of B.M.C. The overall efficiency score of B.M.C in 2003 is 0.925 from Table 4.18. However, it decreases to 0.680 in 2004 and 0.672 in 2005. Besides, it is seen from Figure B-5 that there is a continuous decrease in technical change of B.M.C. Lastly, according to Figure B-6 it can be concluded that the total productivity of B.M.C. decreases too. It should also be noted that when the Malmquist TFP Index graphs of all companies are reviewed it is observed that the decreasing of total factor productivity is mostly a common trend. Especially, the truck and bus manufacturers such as B.M.C., M.A.N., M.BENZ TÜRK and TEMSA shows similar trends.

- From the conclusions above, it can be stated that automotive manufacturers should keep their capacity usage rates as high as possible because idle capacity means cost. Otherwise, they may be faced with the bad result that TOYOTA was faced in 2001. As remembered, TOYOTA was able to produce only 2,862 vehicles in 2001 although its capacity was 100,000.

In addition to capacity usage automotive manufacturers should also pay attention to their payments (costs). The situation of OYAK RENAULT in 2005 can be an example for this case because the continuous high efficiency of OYAK RENAULT ended due to the increase of its *Payment for Raw Materials and Components* from 65.877 million YTL to 1241.305.

However, it should always be beard in mind that all conclusions and interpretations above are performed according to the results of the DEA model in this study. In other words, there are improvement points, discussed in further research section, for better and more realistic solutions.

5.2 FURTHER RESEARCH

One of the common problems of Data Envelopment Analysis applications is determining the input and output factors. In this study, a method called stepwise approach has been used to decide the inputs and outputs. The starting point in this method was “profit” and the factor set consists of the factors that directly affect the profit of the company. However, it is a fact that there are non-profit based factors which are important for the company such as customer satisfaction, environmental sensitivity, etc. Therefore, new factors can be considered to extend the perspective of efficiency. For example, the number of technical services of the automotive company can be used as an output factor in terms of measuring the after-sales quality or customer satisfaction. The more number of technical services, the easier the customers reach the company for support. Another indicator of both design quality and customer satisfaction may be the number of times that a brand of the company has been selected as the vehicle of the year. Hence, it can be a meaningful output factor in the model.

The performance measures proposed by Lieberman and Dhawan (2000) for the automotive companies can be used if the necessary data is available. For example, investment is one of the most important measures for all sectors, not only the automotive industry. It is also used as an indicator in financial analysis of companies. Hence, the amount of investment for an automotive company can be an input factor.

The level of WIP is another important measure for an automotive industry because it has a direct effect on cost and so on profit. It also reflects the leanness of the company’s production system. Therefore, if the data is available it can be very useful to consider the level of WIP as an input factor.

In literature, most of the studies on DEA the effect of the inputs/outputs which are not incorporated to the model is observed. It is generally performed by adding the new variable of which effect is controlled and observing the new efficiency scores of DMUs. However, it is too difficult to apply this method in this study to understand the effect of other variables which do not exist in the model because the data about those variables such as investment, level of WIP, etc. of companies are not available. Moreover, there are variables which can not be directly incorporated into the DEA model because they can not be controlled by the management. This type of variables are known as non-discretionary variables in literature. In this study, there is not any non-discretionary in the DEA model. For example, 11 automotive companies among the 17 in Turkish automotive industry are multi-national companies which means "direct foreign investment". It is a fact that direct foreign investment causes technology transfer from the investor's country. Since technology brings productivity and competitive advantage in terms of cost and quality, there may be differences between the performances of domestic and multi-national companies. Therefore, the existence (or the ratio) of foreign capital in an automotive industry can be incorporated to the DEA model as an external variable.

The 17 automotive companies which are the members of OSD are used as DMUs in this study. These companies produce 7 main types of vehicles which are passenger car, truck, pick-up, bus, mini-bus, midi-bus and tractor. The types of vehicles produced by these companies vary from company to company. For example, TEMSA produces truck and bus, TOYOTA produces only passenger car, FORD OTOSAN produces passenger car, pick-up and minibus. The analysis in this study does not consider this diversity in terms of vehicle types. Actually, it is not too logical to compare two companies that produce truck and passenger car because there are important differences between those two companies such as production technology, demand, market and etc. Therefore, categorical variables can be used for each vehicle type. By the way, passenger car manufacturers can be compared with the companies that produce passenger car.

All the model improvements mentioned above require adding new factors to the DEA model. However, it should be noted that it might be difficult to add new factors due to low number of companies in Turkish automotive industry. According to Nunamaker (1985) three times of the total number of inputs and outputs should not exceed the number of DMUs. Otherwise, the discriminating power of DEA is reduced and many DMUs may be found as efficient. Therefore, the number of automotive companies should be increased for adding new factors to the model. Incorporating the companies that produce component parts might be a method for increasing the number of DMUs.

From Tables 4.7 and 4.11 it can be seen that there are many optimal weights which are equal to zero. Actually, zero weight means that the related input/output factor does not affect the efficiency of the DMU but it is nonsense because all the variables used in DEA have important effect on the efficiencies of DMUs. Therefore, adding weight restrictions to model might be useful. This can be performed by different approaches. Dyson and Thanassoulis (1988) set numerical limits on each weight. The other methods that can be used for weight restriction are Cone Ratio Method developed by Charnes, Cooper, Wei and Huang (1989) and the concept of Assurance Region developed by Thompson, Langemeier, Lee, Lee and Thrall (1990). All these methods provide weight restrictions to avoid zero weights but experts' or specialist' opinions are needed to understand the importance relationship between the input/output factors. Therefore, before adding weight restrictions to the model the opinion of anyone experienced in automotive industry should be taken.

Finally, Malmquist TFP Index has been used to observe the efficiency change and technical change of each company for time period 2001-2005. As discussed in conclusions part, the effect of 2001 crisis in Turkish economy is noted from the Malmquist TFP Indexes. If the panel data of a longer time period is available, the situation before and after crisis can be compared and more realistic interpretations can be performed.

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APPENDIX A

“Inflation adjustment” or "deflation", is accomplished by dividing a monetary time series by a price index, such as the Consumer Price Index (CPI) or Producer Price Index (PPI). The deflated series is then said to be measured in “constant” YTLs, dollars, etc. whereas the original series was measured in "nominal YTLs or dollars" or "current YTLs or dollars". Inflation is often a significant component of apparent growth in any series measured. If there is any growth, it is uncovered by adjusting for inflation. Moreover, the variance of random or seasonal fluctuations may be stabilized and/or cyclical patterns in the data may be highlighted.

Therefore the data of automotive companies are deflated by the PPI for Motor vehicles, trailers and half trailers which was obtained from the website of Turkish Statistical Institute (TURKSTAT).

Table A-1 The Producer Price Index (PPI) for Motor vehicles, trailers and half trailers

1994 Based Wholesale Price Indexes (WPI) for Motor vehicles, trailers and half trailers				
2001	**2002**	**2003**	**2004**	**2005**
34,24	53,35	66,59	71,05	69,62
2001	**2002**	**2003**	**2004**	**2005**
1,00	1,56	1,94	2,07	2,03

The first row is the original data which are the 1994 based Wholesale Price Indexes (WPI). Actually, WPI and PPI are the same indexes because the name of WPI was changed to PPI in recent years. Because, the data used in this study cover the period of 2001-2005, year 2001 is set as the base year for easy calculation and the new PPIs are in the second row of Table A-1. Then, the data of each year is divided by the related PPI and the deflated data in Table A-2, Table A-3, Table A-4, Table A-5 and Table A-6 are found.

Table A-2 The Deflated Data for Year 2001

	RAW (1MYTL)	WAGE (1MYTL)	DOMSALES (1MYTL)	EXPORT (1MYTL)	PRD/CAP (%)
A.I.O.S.	75,694	9,746	38,788	10,986	0,15
ASKAM	3,727	4,318	15,168	2,393	0,07
B.M.C.	38,285	18,856	74,812	9,553	0,16
FORD OTOSAN	226,085	8,013	167,564	85,098	0,19
HONDA	64,017	40,215	55,489	3,511	0,17
HYUNDAI ASSAN	54,840	10,201	50,475	23,995	0,03
KARSAN	99,962	7,729	48,861	27,703	0,30
M.A.N.	103,808	17,914	44,891	105,767	0,31
M.BENZ TÜRK	262,232	30,538	98,885	242,077	0,25
OTOKAR	13,156	4,879	60,308	13,784	0,32
OTOYOL	30,024	11,676	34,026	32,451	0,22
OYAK RENAULT	738,314	44,535	70,071	861,513	0,60
TEMSA	46,916	10,922	17,491	20,961	0,04
TOFAŞ	935,944	52,528	84,062	896,003	0,47
TOYOTA	28,900	12,700	19,646	2,518	0,03
TÜRK TRAKTÖR	40,782	7,910	49,166	11,620	0,17
UZEL	64,542	13,949	35,993	40,072	0,27

Table A-3 The Deflated Data for Year 2002

	RAW (1MYTL)	WAGE (1MYTL)	DOMSALES (1MYTL)	EXPORT (1MYTL)	PRD/CAP (%)
A.I.O.S.	45,788	5,756	42,769	23,506	0,25
ASKAM	2,539	2,955	0,561	2,088	0,03
B.M.C.	85,276	16,308	109,124	10,915	0,22
FORD OTOSAN	754,084	44,438	222,843	352,194	0,30
HONDA	35,287	5,121	35,794	21,202	0,18
HYUNDAI ASSAN	95,907	6,683	45,394	37,528	0,09
KARSAN	116,716	6,886	49,961	45,215	0,48
M.A.N.	179,709	17,999	75,473	98,936	0,48
M.BENZ TÜRK	301,357	31,680	368,707	196,818	0,34
OTOKAR	22,741	7,211	48,082	22,447	0,23
OTOYOL	45,645	12,938	50,919	26,630	0,29
OYAK RENAULT	615,203	43,230	71,280	725,330	0,62
TEMSA	45,758	9,793	24,565	40,353	0,14
TOFAŞ	775,739	45,353	56,014	749,031	0,43
TOYOTA	291,660	17,715	48,385	311,305	0,39
TÜRK TRAKTÖR	27,454	6,637	38,733	21,158	0,11
UZEL	50,417	12,529	23,091	35,301	0,22

Table A-4 The Deflated Data for Year 2003

	RAW (1MYTL)	WAGE (1MYTL)	DOMSALES (1MYTL)	EXPORT (1MYTL)	PRD/CAP (%)
A.I.O.S.	54,087	6,823	67,621	16,272	0,30
ASKAM	13,642	3,470	35,553	1,199	0,20
B.M.C.	160,782	20,279	210,752	17,592	0,46
FORD OTOSAN	943,893	52,326	578,612	683,644	0,70
HONDA	11,695	9,653	43,994	45,089	0,37
HYUNDAI ASSAN	209,480	10,166	115,629	131,870	0,29
KARSAN	63,880	6,355	75,095	5,165	0,33
M.A.N.	228,996	22,565	55,839	133,101	0,60
M.BENZ TÜRK	384,444	41,585	457,409	227,114	0,51
OTOKAR	48,512	8,114	81,328	19,860	0,38
OTOYOL	57,367	9,012	61,392	15,520	0,35
OYAK RENAULT	867,768	48,943	276,610	791,538	0,59
TEMSA	59,098	12,981	45,547	45,983	0,16
TOFAŞ	845,071	54,299	252,961	598,216	0,51
TOYOTA	471,437	22,406	57,467	526,938	0,71
TÜRK TRAKTÖR	156,464	7,501	95,832	103,973	0,49
UZEL	1,646	8,592	57,743	24,236	0,37

Table A-5 The Deflated Data for Year 2004

	RAW (1MYTL)	WAGE (1MYTL)	DOMSALES (1MYTL)	EXPORT (1MYTL)	PRD/CAP (%)
A.I.O.S.	100,825	9,188	92,234	33,047	0,46
ASKAM	0,035	6,426	69,748	0,865	0,21
B.M.C.	255,149	27,233	292,565	36,439	0,59
FORD OTOSAN	1648,073	72,455	864,733	1226,310	0,96
HONDA	94,168	5,989	86,952	46,614	0,52
HYUNDAI ASSAN	344,005	16,671	292,076	153,315	0,46
KARSAN	162,824	7,023	168,844	5,000	0,68
M.A.N.	209,324	25,389	91,364	122,954	0,61
M.BENZ TÜRK	509,767	39,289	472,212	193,994	0,89
OTOKAR	67,863	12,619	123,450	16,206	0,42
OTOYOL	73,211	13,799	91,035	15,567	0,38
OYAK RENAULT	65,874	55,129	479,087	1029,141	0,87
TEMSA	129,945	15,676	114,313	61,667	0,36
TOFAŞ	917,089	54,285	400,060	562,791	0,58
TOYOTA	1051,618	23,327	161,103	1271,122	0,90
TÜRK TRAKTÖR	179,677	7,769	173,902	83,890	0,60
UZEL	138,401	13,930	194,813	32,385	0,58

Table A-6 The Deflated Data for Year 2005

	RAW (1MYTL)	WAGE (1MYTL)	DOMSALES (1MYTL)	EXPORT (1MYTL)	PRD/CAP (%)
A.I.O.S.	108,244	4,410	112,654	125,264	0,51
ASKAM	38,159	2,265	40,423	83,621	0,27
B.M.C.	258,923	12,496	271,418	313,733	0,57
FORD OTOSAN	1875,387	34,050	1909,438	1269,975	1,00
HONDA	87,074	3,924	90,998	80,013	0,37
HYUNDAI ASSAN	308,590	5,121	313,710	240,673	0,48
KARSAN	125,233	5,276	130,509	107,382	0,53
M.A.N.	135,825	13,792	149,617	59,537	0,62
M.BENZ TÜRK	56,838	24,274	81,113	750,063	1,00
OTOKAR	63,104	5,525	68,630	77,794	0,33
OTOYOL	64,966	9,914	74,880	69,299	0,29
OYAK RENAULT	1241,305	33,125	1274,430	494,470	0,76
TEMSA	259,055	7,504	266,559	147,192	0,78
TOFAŞ	899,195	34,752	933,946	707,797	0,65
TOYOTA	561,879	13,574	575,452	108,736	1,00
TÜRK TRAKTÖR	142,019	5,086	147,105	164,826	0,51
UZEL	60,799	9,600	70,400	167,088	0,68

APPENDIX B

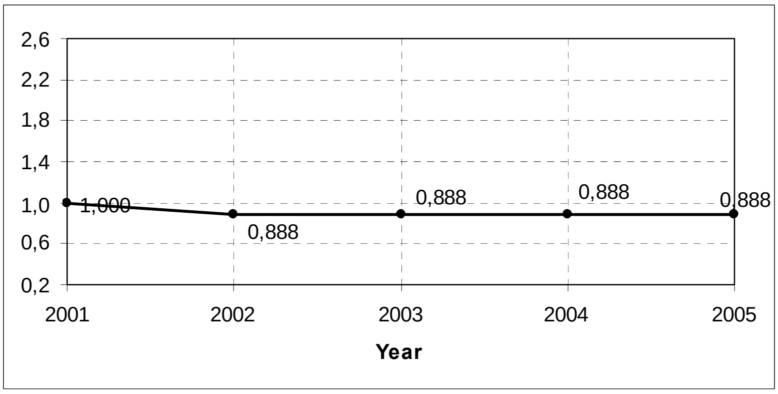

Figure B-1 Efficiency Change of ASKAM

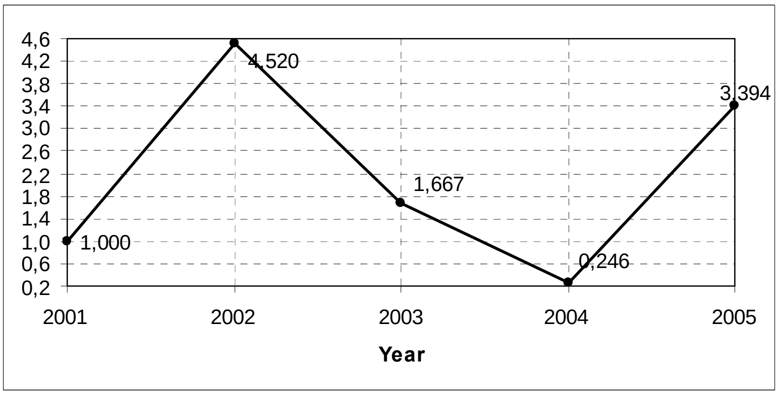

Figure B-2 Technical Change of ASKAM

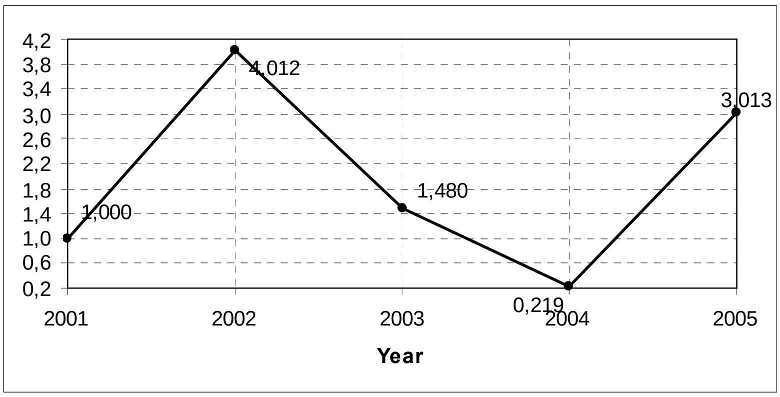

Figure B-3 Malmquist TFP Index of ASKAM

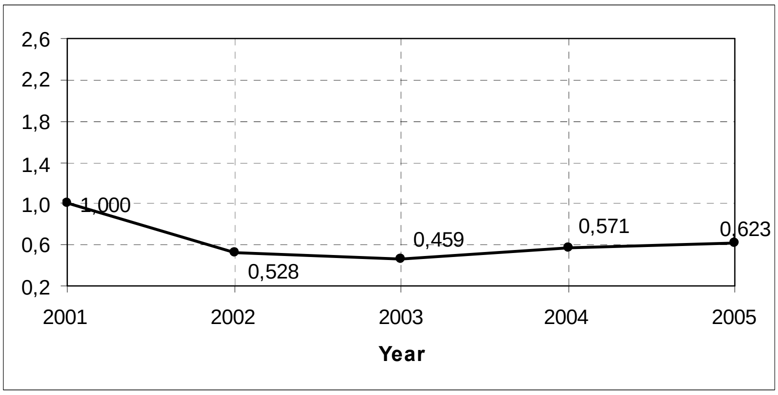

Figure B-4 Efficiency Change of B.M.C.

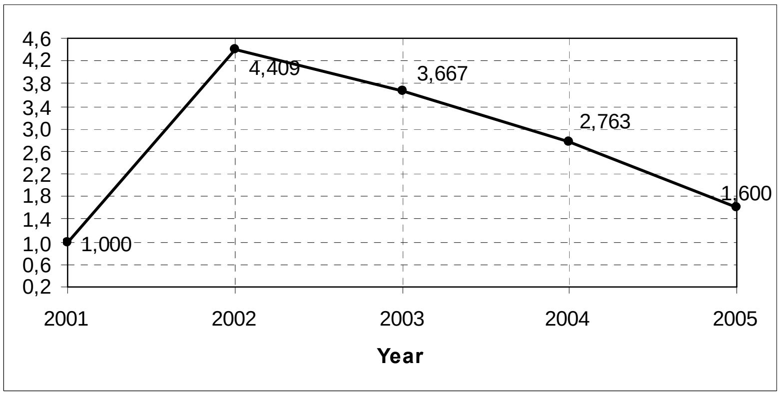

Figure B-5 Technical Change of B.M.C.

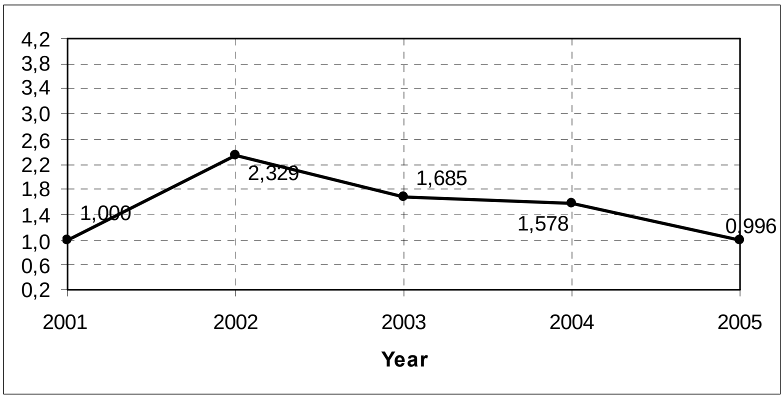

Figure B-6 Malmquist TFP of B.M.C.

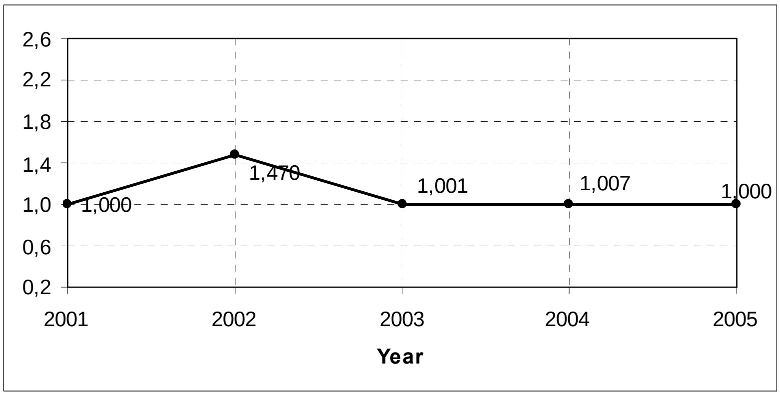

Figure B-7 Efficiency Change of FORD OTOSAN

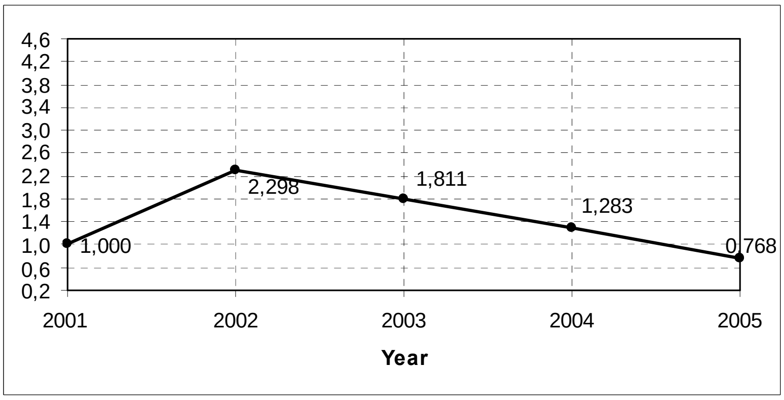

Figure B-8 Technical Change of FORD OTOSAN

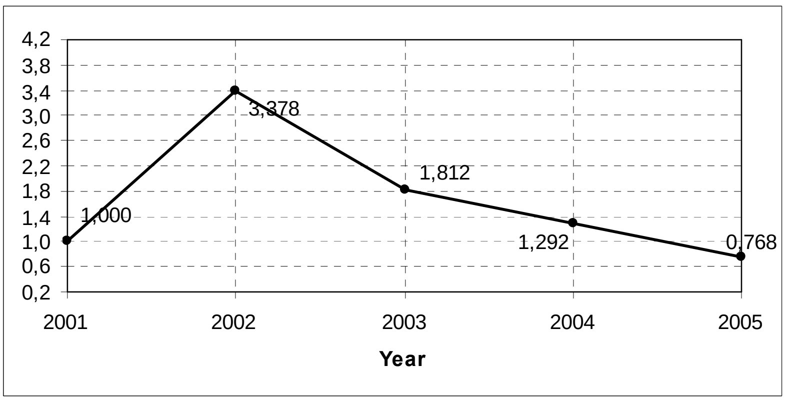

Figure B-9 Malmquist TFP Index of FORD OTOSAN

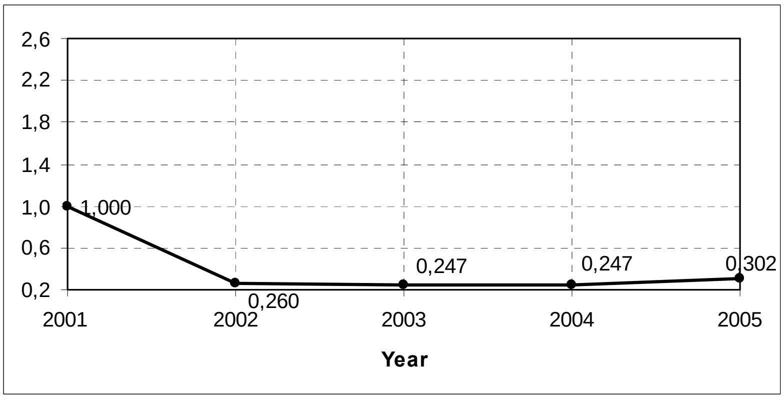

Figure B-10 Efficiency Change of HONDA

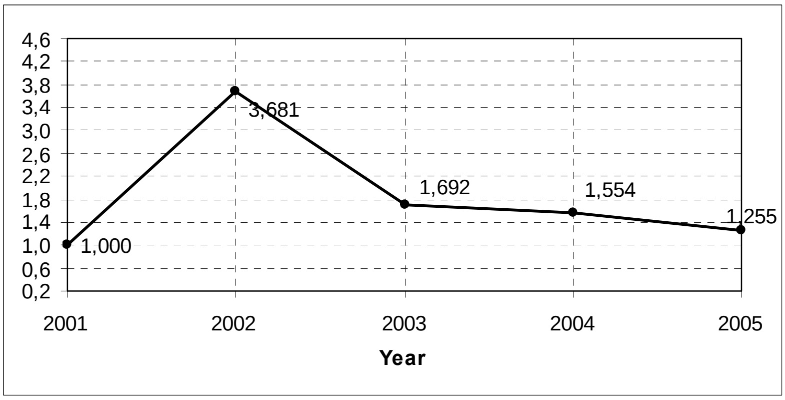

Figure B-11 Technical Change of HONDA

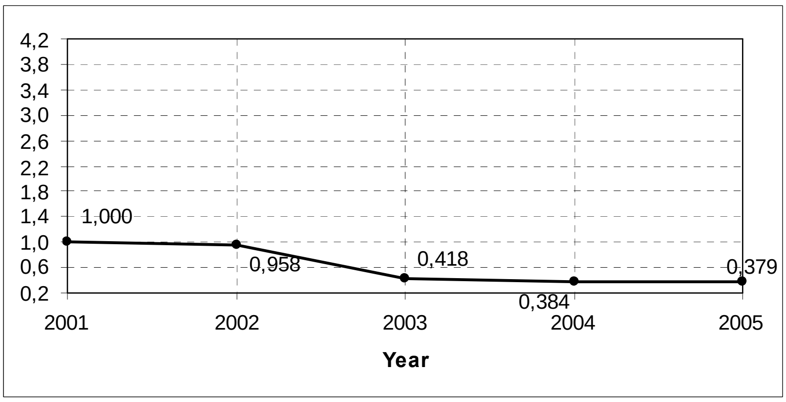

Figure B-12 Malmquist TFP Index of HONDA

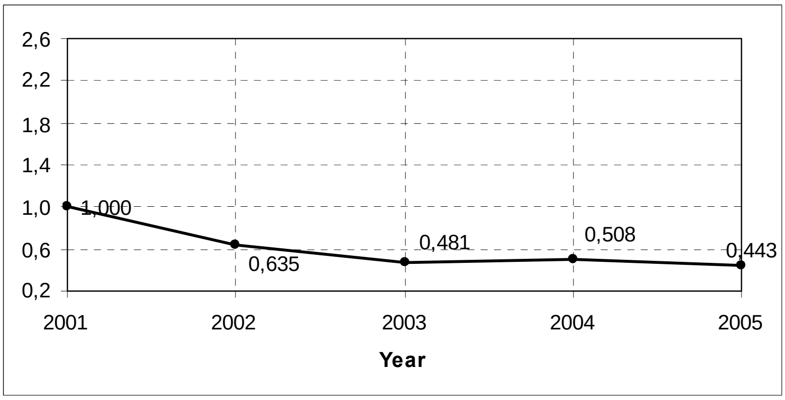

Figure B-13 Efficiency Change of HYUNDAI ASSAN

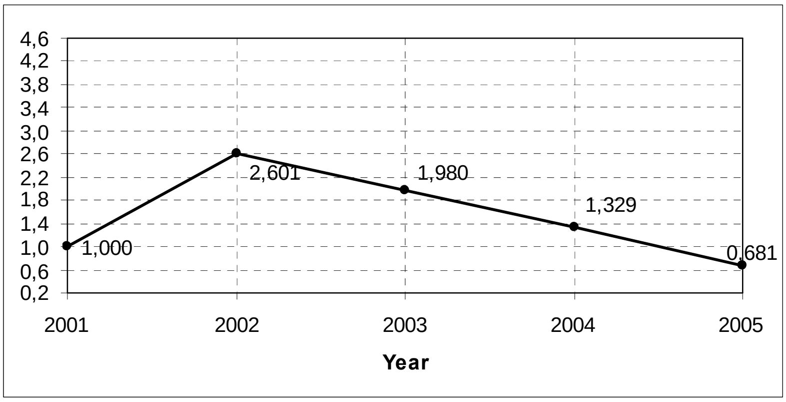

Figure B-14 Technical Change of HYUNDAI ASSAN

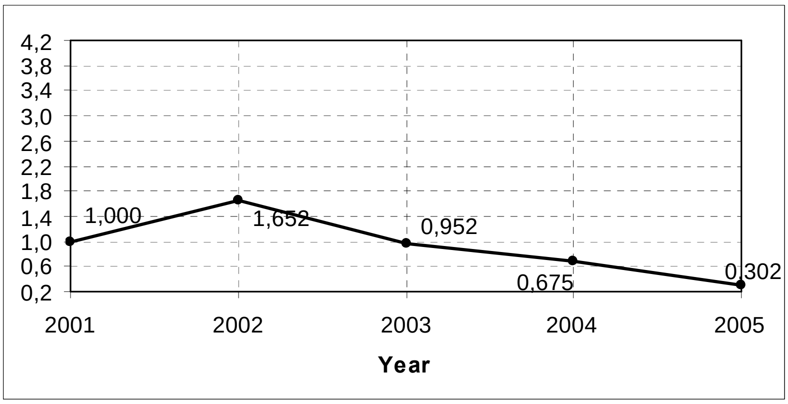

Figure B-15 Malmquist TFP Index of HYUNDAI ASSAN

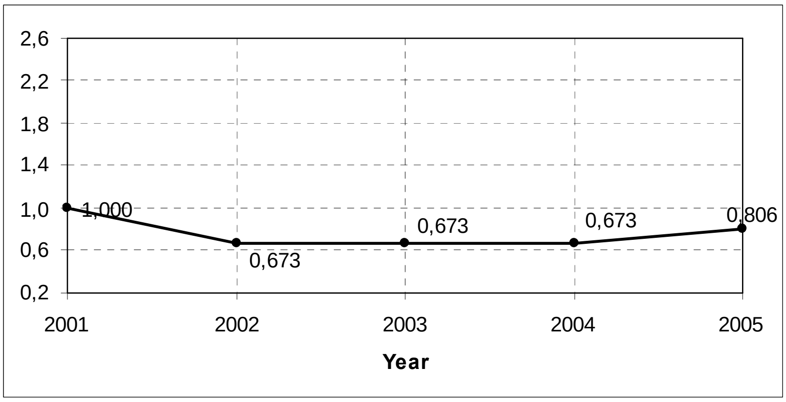

Figure B-16 Efficiency Change of KARSAN

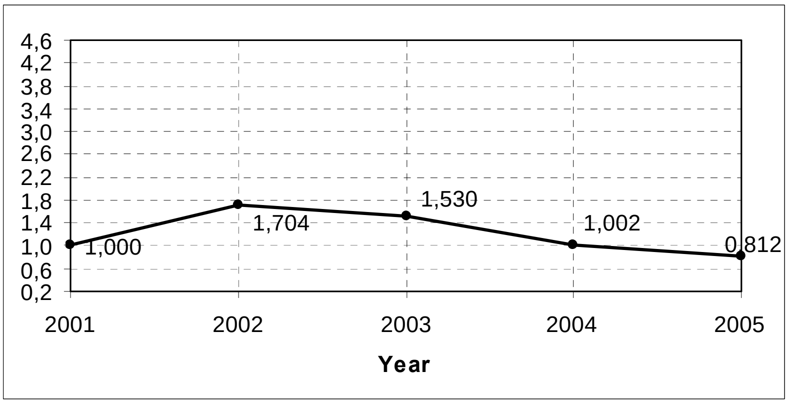

Figure B-17 Technical Change of KARSAN

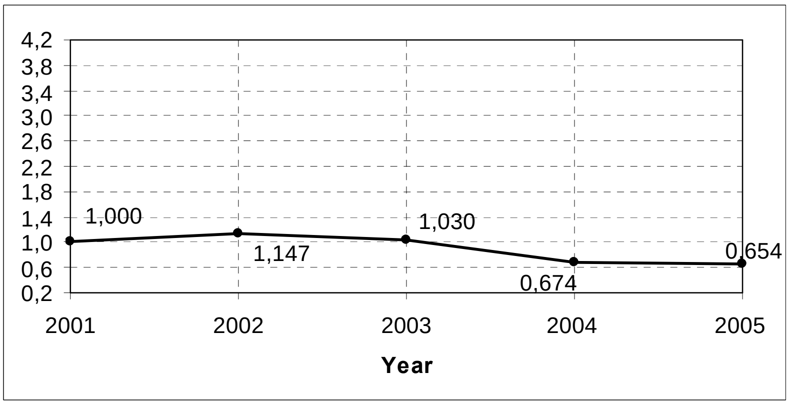

Figure B-18 Malmquist TFP Index of KARSAN

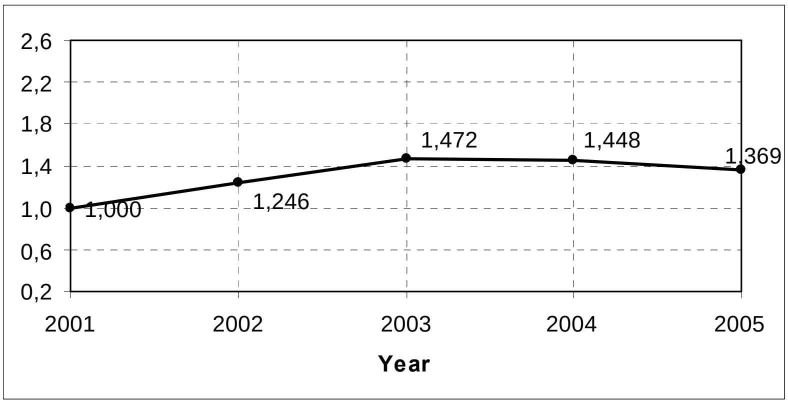

Figure B-19 Efficiency Change of M.A.N.

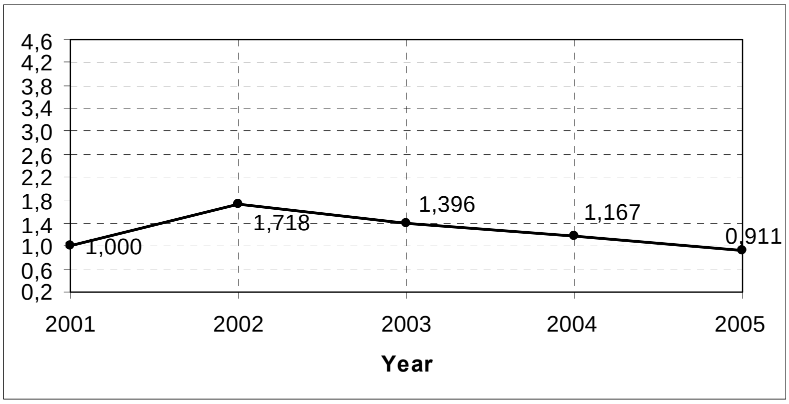

Figure B-20 Technical Change of M.A.N.

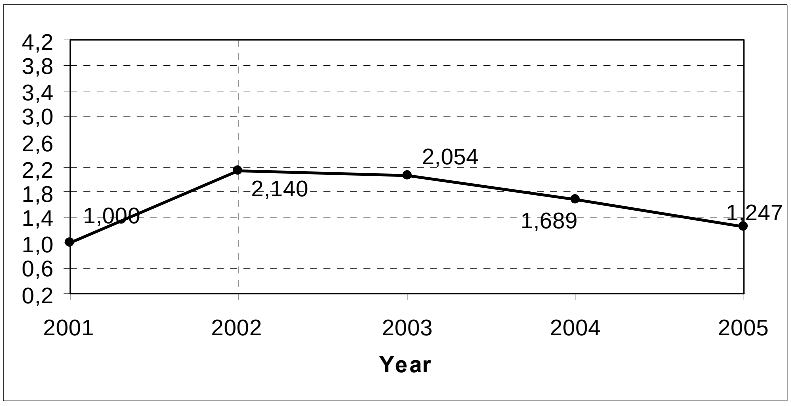

Figure B-21 Malmquist TFP Change of M.A.N.

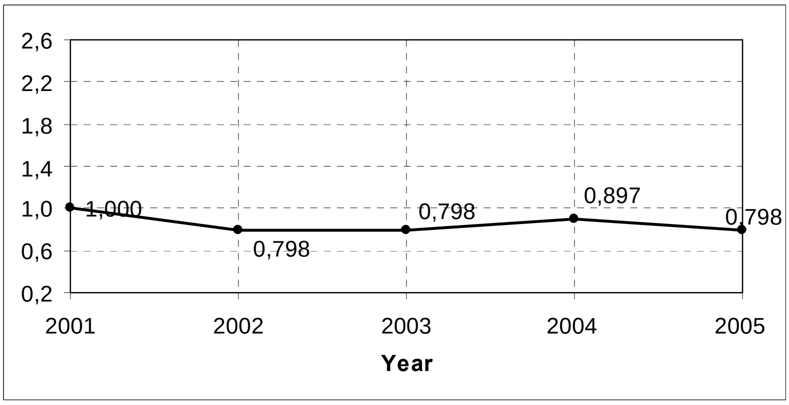

Figure B-22 Efficiency Change of M.BENZ TÜRK

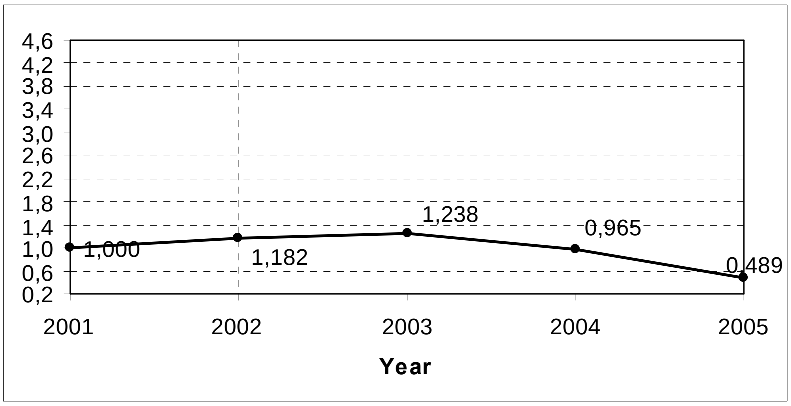

Figure B-23 Technical Change of M. BENZ. TÜRK

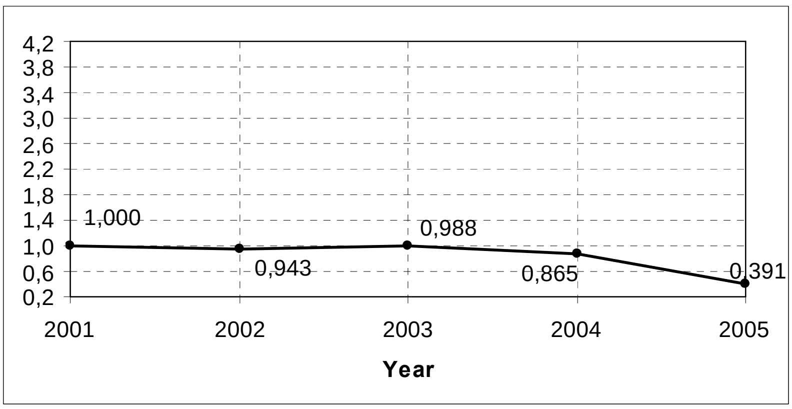

Figure B-24 Malmquist TFP Index of M.BENZ TÜRK

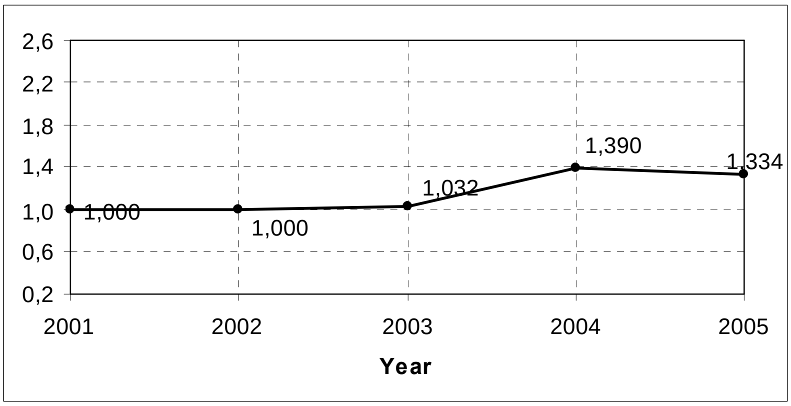

Figure B-25 Efficiency Change of OTOKAR

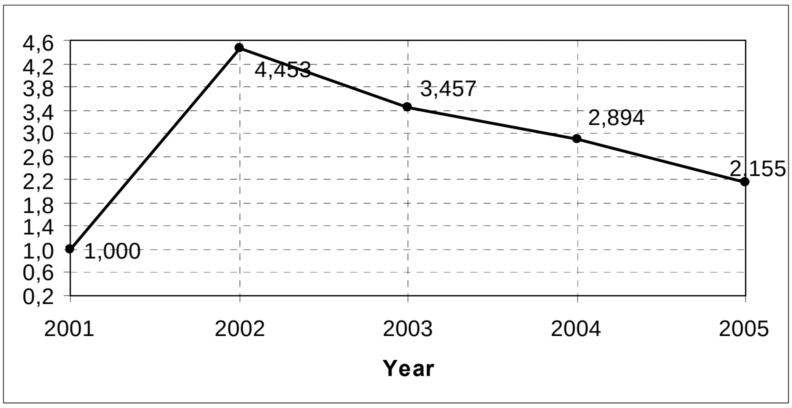

Figure B-26 Technical Change of OTOKAR

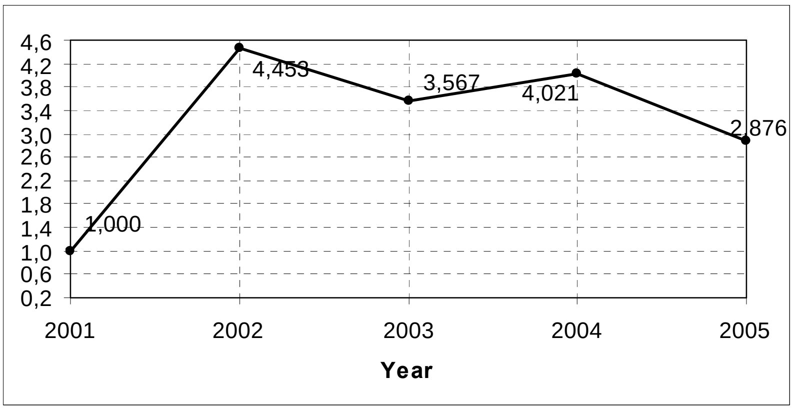

Figure B-27 Malmquist TFP Index of OTOKAR

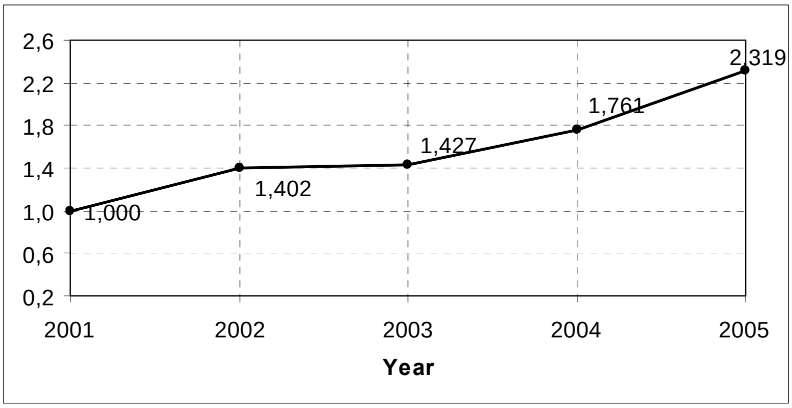

Figure B-28 Efficiency Change of OTOYOL

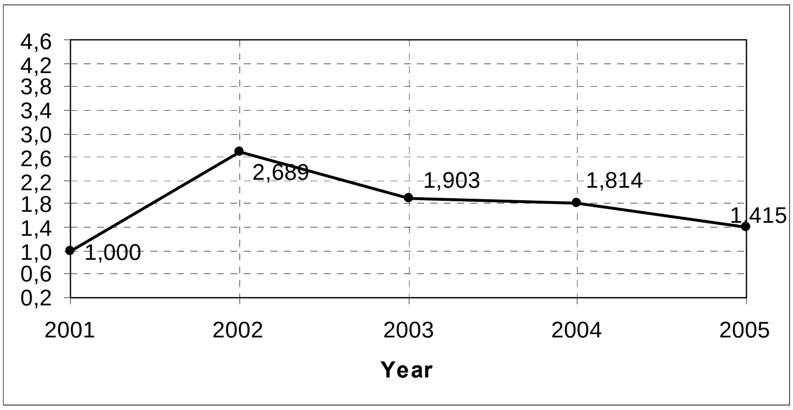

Figure B-29 Technical Change of OTOYOL

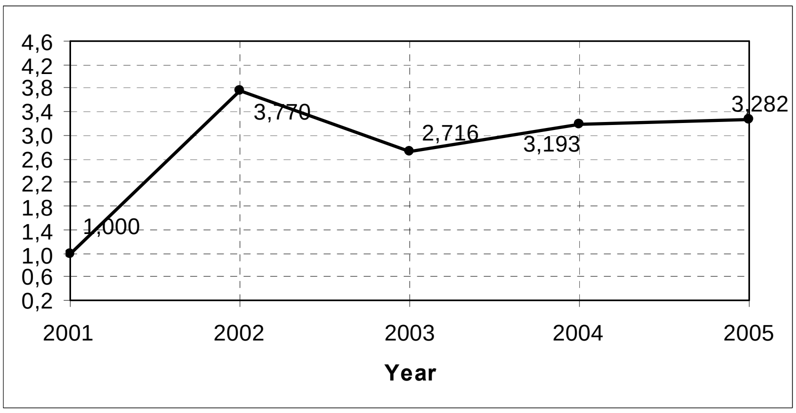

Figure B-30 Malmquist TFP Index of OTOYOL

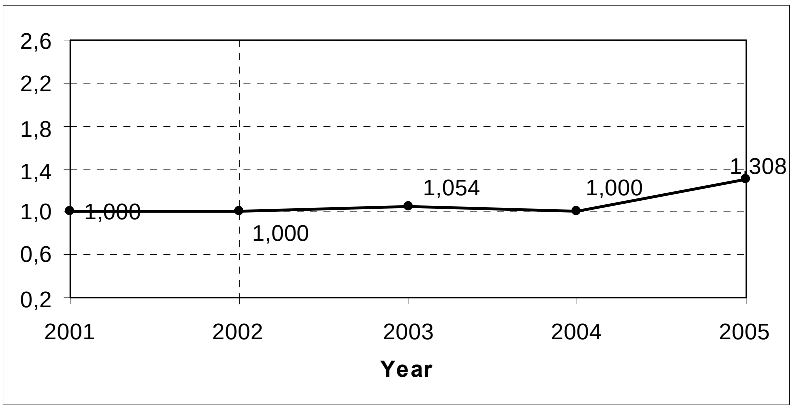

Figure B-31 Efficiency Change of OYAK RENAULT

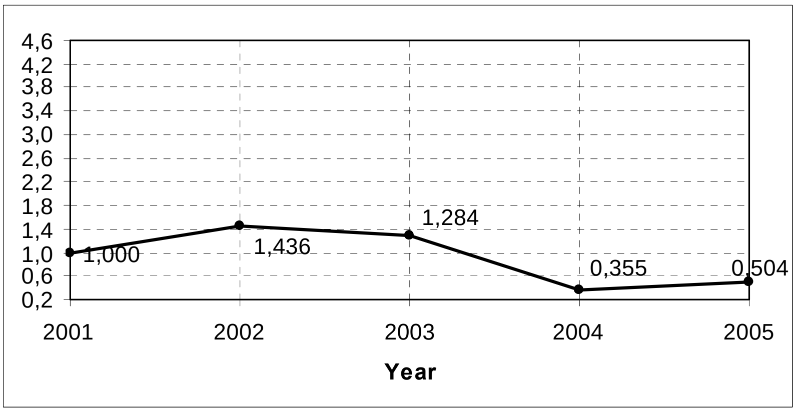

Figure B-32 Technical Change of OYAK RENAULT

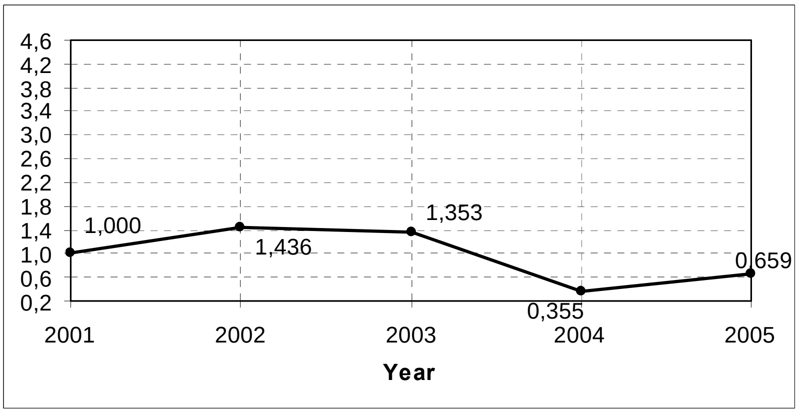

Figure B-33 Malmquist TFP Index OYAK RENAULT

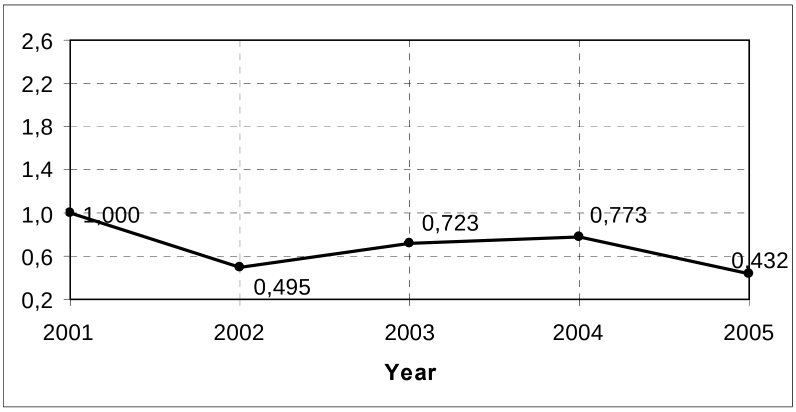

Figure B-34 Efficiency Change of TEMSA

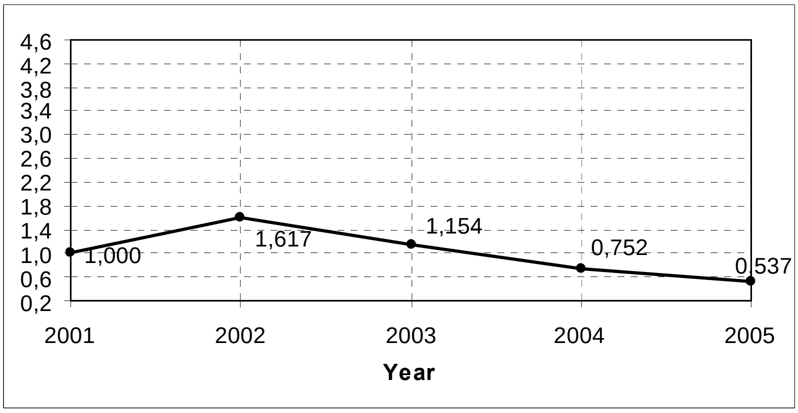

Figure B-35 Technical Change of TEMSA

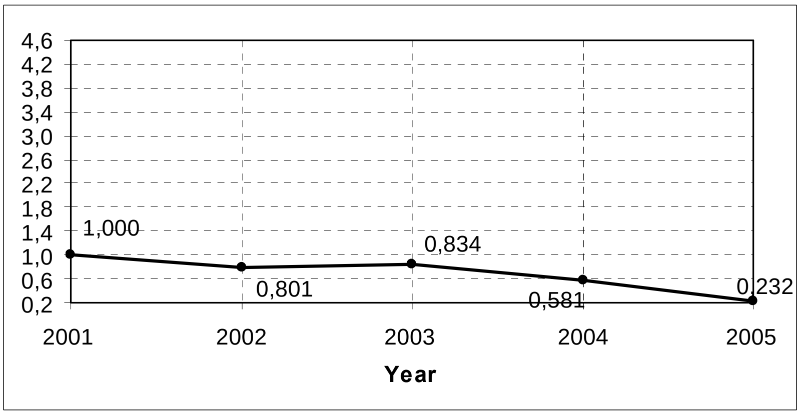

Figure B-36 Malmquist TFP Index of TEMSA

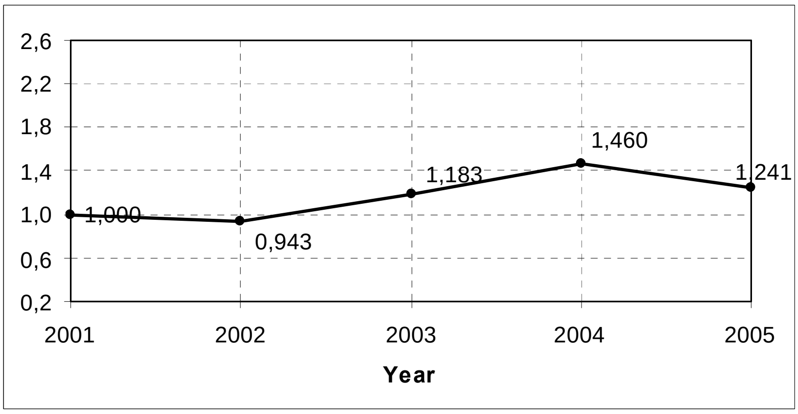

Figure B-37 Efficiency Change of TOFAŞ

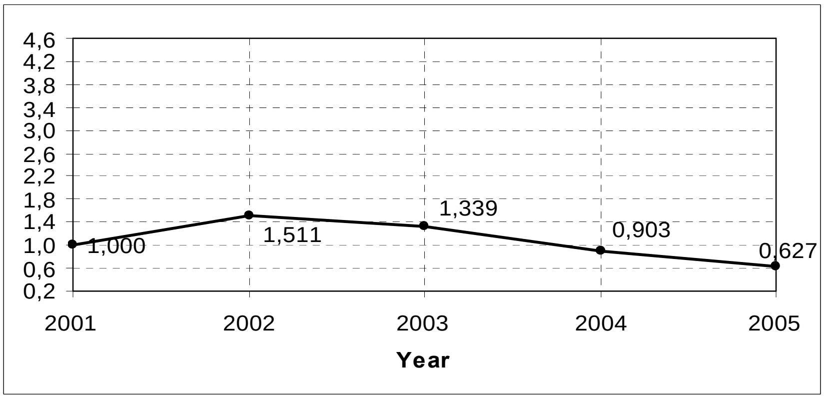

Figure B-38 Technical Change of TOFAŞ

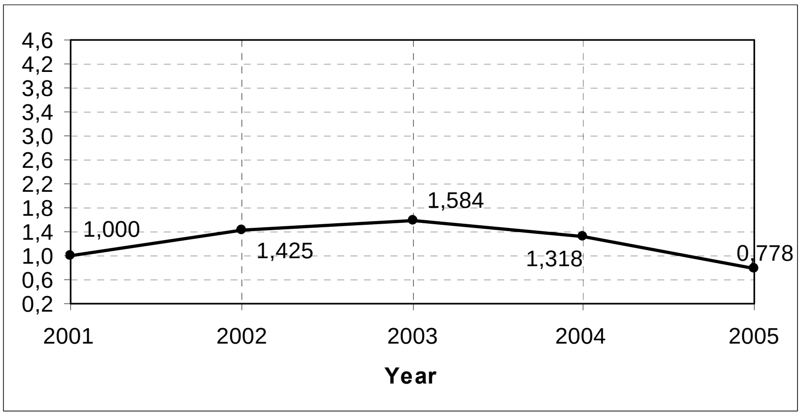

Figure B-39 Malmquist TFP Index of TOFAŞ

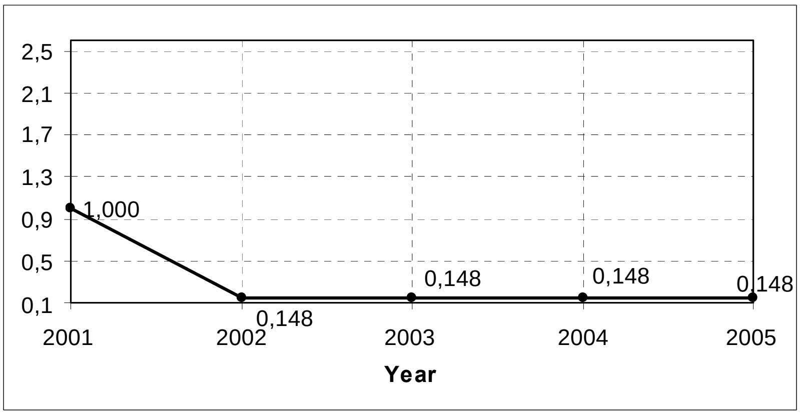

Figure B-40 Efficiency Change of TOYOTA

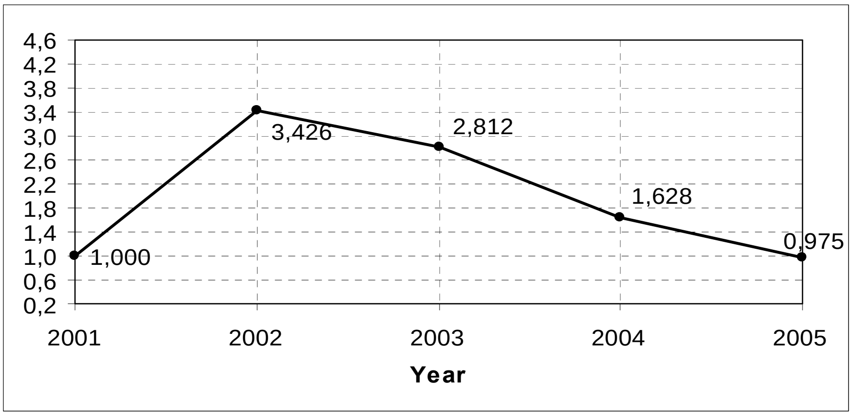

Figure B-41 Technical Change of TOYOTA

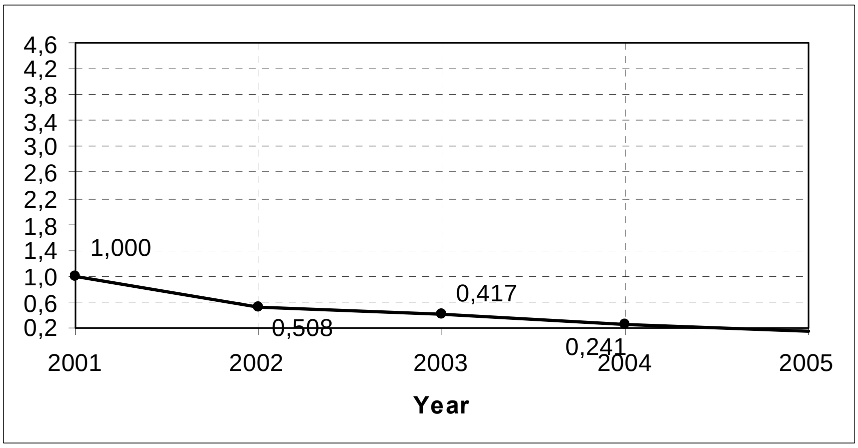

Figure B-42 Malmquist TFP Index of TOYOTA

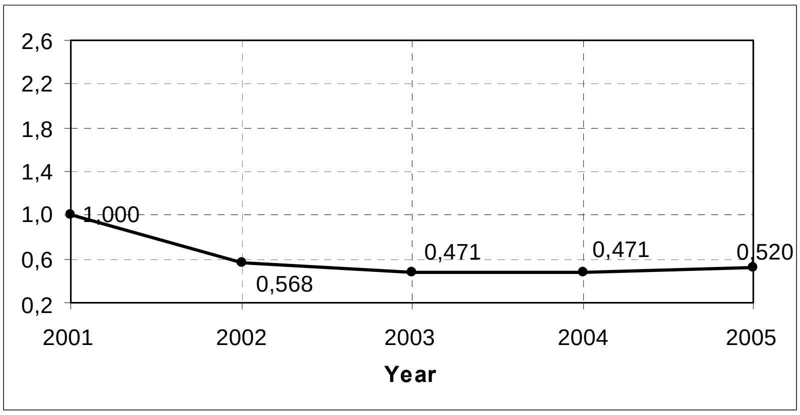

Figure B-42 Efficiency Change of TÜRK TRAKTÖR

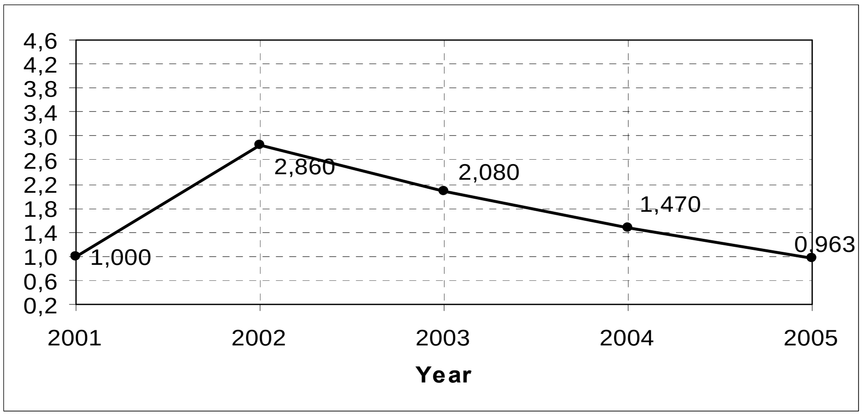

Figure B-43 Technical Change of TÜRK TRAKTÖR

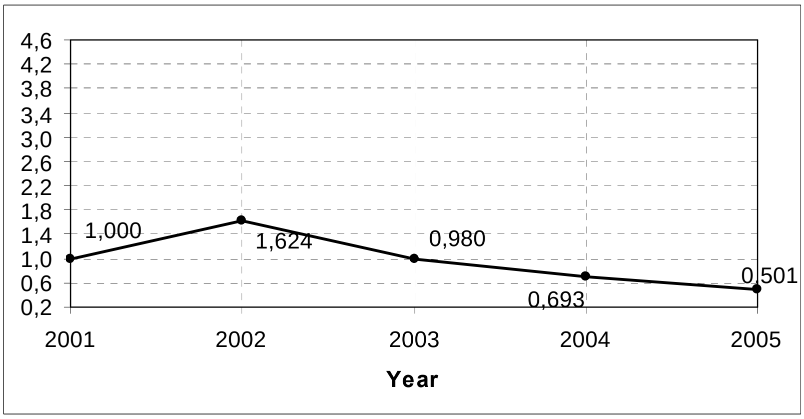

Figure B-44 Malmquist TFP Index of TÜRK TRAKTÖR

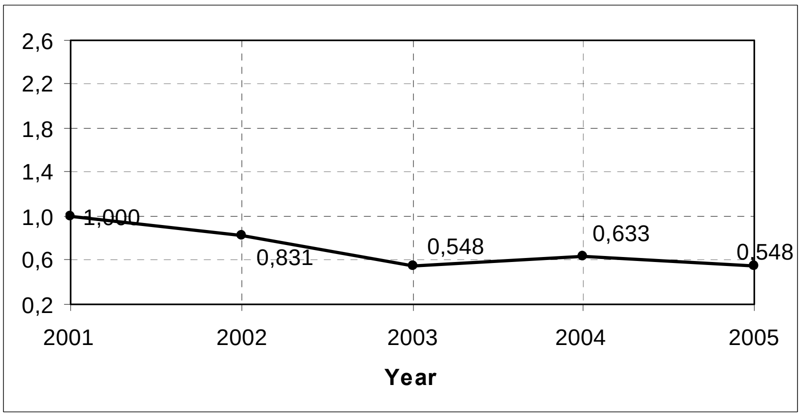

Figure B-45 Efficiency Change of UZEL

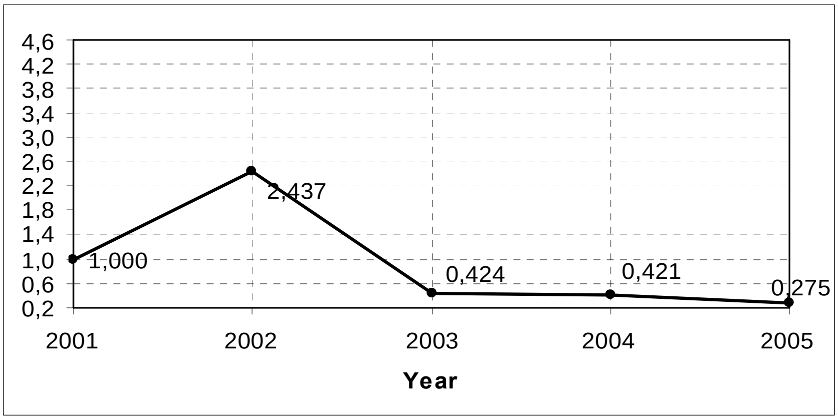

Figure B-46 Technical Change of UZEL

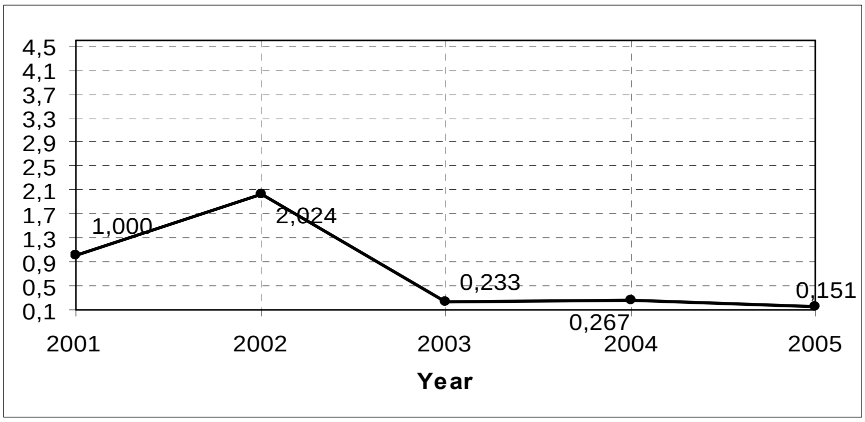

Figure B-47 Malmquist TFP Index of UZEL