THREE ESSAYS ON TECHNICAL EFFICIENCY IN TURKISH MANUFACTURING INDUSTRIES

A Ph.D. Dissertation

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by

PELİN KALE

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in

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I certify that I have read this thesis and have found that it is fully adequate, in scope and in quality, as a thesis for the degree of Doctor of Philosophy in Economics.

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ABSTRACT

THREE ESSAYS ON TECHNICAL EFFICIENCY

TURKISH MANUFACTURING INDUSTRIES

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This study includes three essays on technical efficiency in Turkish manufacturing industries during 1983-1994. The first one, presented in Chapter III, investigates the sources of inefficiency in the food, textiles, machinery, chemicals and the aggregate manufacturing industries within a stochastic frontier (SF) framework. Panel data sets with four-digit industries are used. Among possible sources of inefficiency, industry-specific structural and organizational factors are considered. Results suggest that public ownership is detrimental to technical efficiency while higher real wages or engagement in international trade enhances it. Regarding the effects of domestic competition, no common pattern emerges.

The second essay, presented in Chapter IV, investigates the time pattern of technical efficiency and technological change. Parametric SF and nonparametric data envelopment analysis (DEA) techniques are applied to five panel data sets used in the first essay. Results suggest that mean efficiency increased in the chemicals industry, declined in the machinery industry and remained time-invariant in the food, textiles and the aggregate manufacturing industries. Malmquist productivity indices show that sources of productivity growth differed across industries. In the food and machinery industries, technological progress accounted for productivity improvements while the chemicals and textiles industries witnessed significant efficiency improvements.

The third essay, presented in Chapter V, uses semiparametric methods to construct an efficient frontier for the aggregate manufacturing industry. The benchmark technology is estimated by kernel regressions and efficiency scores calculated by fixed effects models. Comparison of results to those from DEA and SF models suggest that semiparametric and SF models not only yield close mean efficiency estimates but also are highly consistent in ranking industries.

Keywords: Technical Efficiency, Stochastic Frontier Analysis, Data Envelopment Analysis, Semiparametric Frontiers, Turkish Manufacturing Industries

ÖZET

TÜRKİYE İMALAT SANAYİİNDE TEKNİK ETKİNLİK

Kale, Pelin

Doktora, Ekonomi Bölümü

Tez Yöneticisi: Doç. Dr. Osman Zaim

Mart 2001

Bu çalışmada Türkiye imalat sanayiinde teknik etkinlik üzerine üç makale yer almaktadır. III. Bölümde yer alan ilk makalede 1983-1994 yılları arasında panel verileri kullanılarak gıda, tekstil, kimya, makina ve toplam imalat sanayiinde dörtlü ana iktisadi faaliyet kollarında etkinliği belirleyen yapısal ve organizasyonel fakrörler bir stokastik üretim sınırı yaklaşımı çerçevesinde araştırılmaktadır. Sonuçlar kamu mülkiyetinin tüm sektörlerde etkinliği düşüren bir faktör olduğuna işaret ederken, yüksek reel ücret düzeyi ve dış ticarete açıklığın etkinliği artırdığını göstermektedir. İç rekabet düzeyi - teknik etkinlik ilişkisinde sektörler arasında ortak bir sonuca varılamamaktadır. IV. Bölümde sunulan ikinci makalede, ilk makalede incelenen sektörlerde teknik etkinliğin zaman içindeki davranışı ve teknolojik değişimin yön ve büyüklüğü iki farklı yöntemle araştırılmaktadır. Sözkonusu yöntemler parametrik olmayan (nonparametrik) veri zarflama analizi (DEA) ve parametrik stokastik üretim sınırı yöntemleridir. Elde edilen bulgular, 1983-1994 döneminde teknik etkinliğin yalnızca kimya sanayiinde arttığı; makine sanayiinde azaldığı; incelenen diğer sektörlerde ise zaman değişkeninden bağımsız olduğu (sabit kaldığı) yönündedir. Teknolojik değişimim nonparametrik tahminine olanak sağlayan Malmquist indeks yaklaşımı, tüm sektörlerde, incelenen dönemde verimlilik artışı olduğuna ve bu artışın kaynaklarının sektörler arasında farklılık gösterdiğine işaret etmektedir. Gıda ve makina sektörlerinde teknolojik gelişme verimlilik artışına yol açarken kimya ve tekstil sektörlerinde teknik etkinlik artışları verimliliği artırmıştır. V. Bölümde sunulan son makalede yarı-parametrik (semiparametric) yöntemler kullanılarak toplam imalat sanayi için bir etkin sınır oluşturulmaktadır. Bu yaklaşımda tüm üretim birimleri için ortak olduğu varsayılan sınır fonksiyonu çekirdek kestirim (kernel estimation) yöntemiyle oluşturulmuş, etkinlik düzeyleri ise sabit-etkiler regresyonları aracılığıyla hesaplanmıştır. Elde edilen sonuçlar, klasik yöntemlerle (DEA ve stokastik üretim sınırı yöntemleri) çeşitli kriterlere göre karşılaştırılmaktadır. Yarı-parametrik ve parametrik stokastik üretim sınırı modellerinden elde edilen etkinlik düzeyleri oldukça yakın olup, sözkonusu iki yöntemin sektörleri etkinlik düzeylerine göre sıralamada da yüksek derecede tutarlı oldukları gözlenmiştir.

Anahtar Kelimeler: Teknik Etkinlik, Stokastik Üretim Sınırı, Veri Zarflama Yöntemi, Türkiye İmalat Sanayi, Yarı-parametrik üretim sınırı

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CHAPTER I

INTRODUCTION

The concept of economic efficiency is central to the measurement of the performance of producing units. However, among its two components, technical and allocative efficiency, measurement of the former was ignored by the productivity literature for many years. Researchers (e.g. Lovell, 1993 and Kalirajan and Shand, 1999) attribute this to the fact that neoclassical production theory assumed full technical efficiency. It was Leibenstein (1966) who drew attention to the gap that exists between the theoretical assumption of full technical efficiency and empirical reality. Later on, a separate literature on the measurement of technical efficiency emerged from the productivity literature providing a range of tools to quantify technical efficiency measures.

Measurement of technical efficiency is essential for at least three reasons. As put forward by Lovell (1993), inefficiency measures are performance indicators; thus, their measurement enables comparisons across similar units. Second, once variations in efficiency levels are quantified, hypotheses concerning the sources of efficiency and productivity differentials can be explored. Finally, efficiency analyses provide policy implications for the improvement of efficiency by granting the management a control mechanism with which they can monitor the performance of production units.

Efficiency measurement tools evolved along two major methodological paths. The first one includes nonparametric deterministic[1] approaches [usually referred to as data envelopment analysis (DEA)] while the second line covers parametric approaches based on econometric techniques.

Deterministic models builded upon Farrell's (Farrell, 1957) work who formally defined technical efficiency as using the minimal level of inputs given the output and input mix.[2] These models employed linear programming techniques to estimate the best practice technology and to identify the efficient units. The classical deterministic model due to Aigner and Chu (1968) considered a Cobb-Douglas production function that related the frontier output to actual output as $y_i = a_i f(x_i, \beta)$, $0 < a_i \leq 1$ where $i = 1, \ldots, N$ is an index for firms, y_i is the level of observed output, x_i is the i^{th} input and a_i is the degree of (output-based) technical efficiency and β is the vector of the unknown parameters of the frontier function. Aigner and Chu (1968) calculated β by means of linear programming techniques, which later led to the development of non-parametric methods that employ mathematical programming techniques.

[1] By "deterministic", we refer to non-stochastic models which do not accommodate for statistical noise.

[2] Farrell's measure of technical efficiency, inspired by the concepts from Debreu (1951) and Koopmans (1951), is originally defined as one minus the maximum equiproportionate reduction in all inputs that still allows for the production of given outputs. This measure can be converted to equiproportionate output expansion with given inputs.

Nonparametric linear programming methods were suggested by authors such as Boles (1966) and Afriat (1972) but did not gain popularity until Charnes Cooper and Rhodes (CCR) (1978) proposed a formal model they termed as data envelopment analysis (DEA). The CCR model was inspired by Debreu-Farrell measures of efficiency and assumed constant returns to scale.

DEA is based on the construction of a piecewise linear frontier function that envelops the data set as tightly as possible with a notion of inefficiency closely related to that of Pareto optimality. A given economic unit is considered as inefficient if it is dominated by some other unit, or some combination of other units in the sense that they can produce the same amounts of outputs using less of some resources and not more of any other.

Subsequent papers extended the model in various dimensions such as Banker et al. (1984) who allowed variable returns to scale, and Färe and Grosskopf (1983), Färe et al. (1983 and 1985) who analyzed the problem of output congestion and weak disposability of outputs, among others.

A great virtue of DEA is its ability to accommodate multiple outputs. However, it suffers from excess sensitivity to outliers and like the deterministic model of Aigner and Chu (1968), it is non-stochastic. Thus, it cannot disentangle random noise from inefficiency.

The second methodological path, development of estimation procedures that avoid the pitfalls associated with deterministic frontiers, can be traced back to

Afriat (1972) who provided the statistical foundations of frontier estimation. However, the econometric methodology did not become popular until Aigner, Lovell and Schmidt (1977) and Meeusen and Van den Broeck (1977) independently introduced the stochastic frontier methodology.

The stochastic frontier model was a major improvement over deterministic methods due to its ability to distinguish the effects of random noise from inefficiency by adding a composed error term to the usual frontier–actual output relationship. Given a parameterised functional form for the technology, the problem is to estimate the regression model $y_i = f(x_i;\beta)\exp(v_i - u_i)$. The random disturbance term v_i captures the effects of statistical noise and is assumed to be independently and identically distributed as $N(0,\sigma_v^2)$. The random variable u_i, which represents technical inefficiency, is assumed to be independently distributed from v_i, and to satisfy $u_i \geq 0$.

The major issue in stochastic frontier models is the treatment of the inefficiency terms, u_i. They are assumed to have nonnegative distributions, several possibilities being the half-normal, exponential, truncated normal, or gamma. The frontier production function can be estimated by maximum likelihood (ML) methods or simpler corrected OLS estimators and technical efficiency of producers given by $TE_i = \exp\{u_i\}$can be computed using the methodology of Jondrow et al. (1982) that provides a solution to the problem of decomposing the residuals into inefficiency and noise terms.

The choice of the functional form of the frontier and assumptions on the distributions of inefficiency and random noise terms affect the frontier estimates and thus the inefficiency scores (Schmidt and Lin, 1984). The first point constitutes the major drawback in all parametric methods. Imposing a predetermined functional form to the underlying technology may result in misspecification problems and contaminate the efficiency measures. The second problem can be avoided when panel data are available. In such a case, firm-specific technical efficiencies can be estimated within the stochastic frontier framework without any assumptions regarding the distribution of the error term. Furthermore, by observing each producer more than once, better estimates of inefficiency can be obtained.

Although the use of panel data in modelling production behaviour dates back to Mundlak (1961); Pitt and Lee (1981) were the first to use panel data to estimate firm specific efficiency levels using econometric techniques while Schmidt and Sickles, (1984) were the first to establish a link between the frontier and panel data literatures.

Within the DEA framework, benefits of panel data can be exploited to perform multiperiod analysis and to identify the sources of productivity change. Caves, Christensen and Diewert (1982) established the link between Farrell efficiency measures and total productivity indices by proposing a productivity index based on the methods of Malmquist (1953) and named it as the *Malmquist productivity index*. Inspired by this micro-approach to productivity measurement, Färe et al. (1992) proposed the linear programming approach to calculate Farrell measures that are employed in the construction of the Malmquist indexes. Later, Färe and Grosskopf (1994) showed how to decompose the Malmquist index into the product of two terms: change in technical efficiency and change in technology.

To sum up, we can relate the differences between nonparametric methods and stochastic parametric ones to their relative strengths and weaknesses. The DEA and Aigner and Chu approaches are deterministic: they neglect any stochastic variables influencing the producer's behaviour. On the other hand, econometric approaches have the ability to accommodate random noise but they are more prone to specification errors since they require an explicit specification for the functional form of the technology.

Given a wide range of measurement tools, the purpose of this study is to analyze issues related to productive efficiency of Turkish manufacturing industries. Performance of manufacturing industries is a crucial factor influencing the outcome of industrialisation policies and efforts directed towards economic growth. This appeal to manufacturing industry dating back to the early literature on economic development is best observed in Kaldor:

> *It is the rate of growth of manufacturing production (together with the ancillary activities of public utilities and construction) which is likely to exert a dominating influence on the overall rate of economic growth: partly on account of its influence on the rate of growth of productivity in the individual sector itself, and partly also because it will tend, indirectly, to raise the rate of productivity growth in other sectors. And of course it is more generally true that industrialisation accelerates the rate of technological change throughout the economy (Kaldor, 1966: 112).*

Following this line of thought, almost all developing economies pursued industrialisation strategies for four decades with resolution.

As a case in point, the manufacturing industry in Turkey assumed a significant role in the process of economic growth both during the pre-1980 period characterized by import substituting industrialisation policies and post-1980 era during which the relatively protected and highly regulated structure of the economy was transformed into a liberalised one through a series of policies and reforms.

Although a large literature emerged on the analysis of the macroeconomic aspects and effects of these policies and reforms, there have been a few number of studies focusing on the microstructure of the Turkish economy during this transformation period. The purpose of this study is to fill this gap. Our motivation comes from evidence provided by empirical micro studies which point to considerable amount of inefficiency in the use of productive resources in developing economies.

The core of this dissertation consists of three essays on the performance of Turkish manufacturing industries during 1983-1994. Chapter II provides a background on the Turkish economy with an emphasis on the manufacturing industry during the period under study. Remaining chapters are devoted to the analysis of the performance of Turkish manufacturing industries.

Chapter III investigates the determinants of technical inefficiency in the Turkish manufacturing industries using a rich panel data set covering the 1983-1994 period. The cross sectional units are industries defined at the four-digit International Standard Industrial Classification (ISIC) codes. A stochastic frontier methodology is employed to construct efficient frontiers for four broad industry categories: food, textiles, chemicals, machinery and also for the aggregate manufacturing industry.

Theory does not provide a model for the sources of technical inefficiency, and in some cases there are conflicting signals concerning the impact of some phenomena on performance. Hence it is basically an empirical issue to determine the factors that influence efficiency. The empirical literature generally attributes inefficiency to firm or industry specific structural and ornanizational factors such as suboptimal ornanization and agency relationships within the firm; suboptimal oligopoly bargains and related competitive factors within the industry or government interventions. In this chapter, focus will be on the effects on technical efficiency of competitive conditions, including measures of both domestic and international competition, and ornanizational factors that are postulated to exert pressures on management or workers. Results provide insights on the empirical validity of a number of theoretical propositions that have policy implications for the improvement of efficiency.

Chapter IV investigates the time pattern of technical efficiency and technological change in Turkish manufacturing industries during the liberalization period using both parametric and nonparametric methodologies. The techniques are applied to the five panel data sets analyzed in the previous chapter, namely the food, textiles, machinery, chemicals and the aggregate manufacturing industries. Parametric measures of technical efficiencies and rates of technological change are obtained from the estimation of stochastic frontier models as specified by Battese and Coelli (1992). To obtain nonparametric measures of efficiency scores, DEA models are constructed relative to both constant and variable returns to scale technologies. Technological change is measured through the construction of Malmquist productivity indexes and their decomposition into two multiplicative components: technological change and technical efficiency change. Consistency of results from the econometric and mathematical programming approaches are evaluated in terms of the efficiency ranking of producing units, the magnitudes of mean efficiency scores, time pattern of mean efficiency, and estimates of average rates of technical change.

Chapter V adds to the analysis of technical efficiency by the estimation of a semi-parametric model for the Turkish manufacturing industry. This model can be regarded as a compromise between nonparametric and parametric methods. The benchmark technology is estimated by a kernel estimator which has the advantage of a nonparametric model in the sense that it does not impose a functional form to the underlying production technology. Thus, the kernel estimator is less susceptible to misspecification errors than its parametric alternatives. The semiparametric approach computes technical efficiency scores by estimating stochastic fixed effects panel data models as proposed by Schmidt and Sickles (1984). Thus, this new approach also embodies the advantages of a stochastic frontier model.

In Chapter V, we compare the results from the semiparametric approach with those from the classical nonparametric and parametric methodologies, namely, data envelopment analysis and stochastic frontier approach. We use panel data corresponding to four-digit industries in the aggregate manufacturing sector during 1983-1994. With panel data, we consider two more issues: whether the assumption of time-invariant technical inefficiency inherent in most nonparametric and parametric models is valid and whether the production frontier shifts during the observation period i.e. whether technical change occurs. Therefore, we also explore the sensitivity of efficiency estimates to changes in the assumptions on the time pattern of inefficiency and allowance for technical change.

Particularly, we concentrate on models which belong to the following four categories:

Parametric - Fixed effects models estimated with the distribution free approach of Schmidt and Sickles (1984): In models of this type, estimated fixed effects from a parametric production function are used to obtain firm level efficiency scores as suggested by Schmidt and Sickles (1984). Extensions by Cornwell, Schmidt and Sickles (1990) and by Lee and Schmidt (1993) are also considered to allow time-varying inefficiency.

Parametric stochastic models estimated with maximum likelihood techniques: These models attribute some part of the deviation from the frontier to factors that are beyond the control of the producing units. Producer specific (conditional) inefficiency estimates are obtained through imposing a distributional assumption to the one-sided error (inefficiency) term.

Nonparametric deterministic DEA models: Although there is no common agreement on how to handle panel data within a DEA framework there are a couple of alternatives. The first one computes the full period average efficiency scores based on the estimation of year-by-year frontiers. Thus, a separate frontier is estimated for each year in the panel. In the second methodology, sequential frontiers are constructed. For a given year t, all observations generated up to that year are pooled and DEA programs are run which provide T sets of technical efficiency scores for each industry and average of these scores provide the technical efficiency of each firm in period t.

We compare the results both across methodologies (parametric, nonparametric and semiparametric) and also across models that belong to the same category. Finally, in Chapter VI we provide some concluding remarks.

CHAPTER II

AN OVERVIEW OF THE TURKISH ECONOMY AND THE MANUFACTURING INDUSTRY DURING THE POST-1980 PERIOD

II.1. Introduction

While the main purpose of this study is to analyze issues related to the technical efficiency of selected Turkish manufacturing industries, the time span of the study, 1983-1994, corresponds to a structural adjustment and liberalization period of the Turkish economy. Thus, we believe that it will be appropriate to provide an overview of the economy focusing on the manufacturing sector during this period.

Hence, Section 2 is devoted to a brief overview of the Turkish economy during the post 1980 period and Section 3 provides a descriptive analysis of the four industries that will be analyzed in the following chapters.

II.2. An Overview of the Turkish Economy

Turkish industrialisation policy exhibited distinct policy episodes from the formation of the Republic in 1923 till 1994. During 1923 to 1950, public sector assumed a significant role in economic activity. State Economic Enterprises (SEEs) initiated the development of key industries such as minerals, chemicals, and machinery and dominated the production of intermediate goods. During 1950-1980, a protectionist development strategy based on import substitution formed the foundation of economic policy. Due to excessive import protection and the lack of export drive, production was structured to meet the demands of the domestic market. Exports largely consisted of agricultural products, with a small share of manufactured goods. SEEs typically accounted for more than half of the fixed capital formation and accelerated the industrialisation process. However, this rapid industrial growth was excessively dependent on imported intermediate and capital goods. To satisfy the industry's critical dependence on imported raw materials and investment goods[1], import substitution policy was supported by an overvalued exchange rate policy.

During the oil crisis of early 1970s, the current account recorded significant deficits, giving signals of unsustainability, but import substitution policies were continued. As a result, toward the end of 1979, Turkey faced a severe foreign exchange and debt crisis with accelerated inflation, increased

[1] Throughout the import substitution period, imports have exhibited an increasing trend except for the imports of consumption goods.

unemployment and declining industrial output due to shortages of energy, imported machinery and intermediate inputs.[2]

The government introduced a series of policy reforms in January 1980 in the form of a Structural Adjustment and Stabilization Program[3]. Major objectives of the program were to integrate the Turkish economy to the world economy and to achieve export led growth. The new outward oriented growth strategy pursued four related goals for the industry: Increasing the role of market signals in decision making; expanding manufacturing exports; enlarging the share of private sector and reforming the SEEs to reduce their monopoly power and their burden on government financing. Furthermore, the concept of privatization was put into agenda with the expressed intention of the government to provide the legal and structural environment for the operation of free enterprises and to ensure the efficient allocation of resources. Included in numerous measures, were a sharp currency devaluation[4] and adoption of a realistic exchange rate regime to encourage exports. Main macroeconomic prices such as the interest rates,[5]

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[2] During 1974-1979, average annual growth rate of GNP was realized as 4.4 percent. The ratio of the public sector deficit to GNP expanded from 2 percent in 1974 to over 8 percent in 1979. Deficits were primarily financed through the Central Bank. The rate of inflation averaged 34 percent during 1974-1979, which led to higher wage settlements. Wage increases further deteriorated public finances and led to a sizeable anti-export bias.

[3] See Celasun and Rodrik (1989), Onis and Reidel (1993), Baysan and Blitzer (1990) on various aspects of the program.

[4] Until January 1980 the exchange rate was not used as a flexible instrument. The 1980 program relied on the usage of the exchange rate as a stabilizing mechanism as well as an instrument to restrict domestic demand and encourage a shift in production towards exports. The flexible exchange rate policy and gradual real depreciations provided incentives for exporters while restricting imports. Starting from January 1980; the Turkish Lira depreciated continuously against major currencies. The real effective exchange rate depreciated by about 30 percent in 1980, 15 percent in 1981, 12 percent in 1982, 1 percent in 1983 and 1984, 6 percent in 1985 and 12 percent in 1986.

[5] Institutional interest rates were increased strongly from 1979 to 1982. With accelerated inflation, real interest rates had become negative in 1980, declining to –80 percent to –100 percent. In 1982, they became positive at a level of 11 percent and 20 percent for bank loans and deposits

exchange rates and prices of SEEs were adjusted and the flexibility of the real wages in the labor market was attained.

Regarding the sequencing of the program, among the three successive phases of liberalization, the first one, encompassing 1980-1983 was characterised by deregulation of industrial product markets and liberalization of exports. During the second phase, 1984-1988, major reforms in the trade regime came into effect. Imports were liberalised in 1984,[6] quantitative restrictions were eliminated and export subsidies were significantly lowered. Finally during the post-1988 period, the capital account liberalization process initiated in 1980 was fully completed in 1989.

From 1981 onwards, Turkey became a success story. The industrial sector was quick to respond to measures which fostered competition. Starting from 1980s the share of industry in the composition of GDP marked an important increase as a consequence of rapid industrial growth. The value added of the industrial sector grew at an average annual rate of 7.1 percent during the 1980-1990 period and the share of industry in GDP reached 27.1 percent in 1990 from 22.3 percent in 1980.

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respectively. In 1983 and 1984, the effects of increased inflation were not fully covered by increases in the nominal interest rates, so the real interest rates for bank loans and deposits approached to zero. In 1985, an upward adjustment in the nominal interest rates with a decline in the rate of inflation brought the real interest rates up to 13 percent.

[6] Until 1984, positive lists for imports that itemised the commodities eligible for importation were used. In the January 1984 import program, a negative list for imports was introduced (all items not specifically mentioned could be imported) and thus many commodities were freed from quantitative restrictions. The number of items prohibited for importation was reduced to three in 1985 (Krueger and Aktan, 1992; Togan, 1996).

Increased industrial growth coupled with the effects of outward oriented economic policies had significant effects on the trade of manufactured goods. Impressive export performance was achieved in advance of the completion of the import liberalization process. Exports almost quadrupled by 1987 and the share of manufactured goods in total exports increased to almost 90 percent.

What is more striking is that, the success story of the manufacturing industry after 1980s was in spite of declining real investments.[7] With the expressed intention of the government to reduce its role in economic activity, public investments were channelled away from the manufacturing industry toward service industries, mainly communication, transportation and energy sectors which directed public enterprises in the manufacturing sector to the credit market for day-to-day financing. This increased debt burden on the public sector resulted in lower levels of investment in an attempt to reduce public sector borrowing. However, low levels of government investment were not offset by the private sector either. Soaring real interest rates as a consequence of financial liberalization coupled with macroeconomic instability and the crowding out effect of government borrowing depressed private investments in manufacturing industry below the levels of the previous decade.[8]

By the end of 1980s, despite high economic growth rates and reasonable current account positions, the basic structural deficit of the economy, large fiscal

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[7] The share of manufacturing industry in total investments declined from a period average of 26.98 percent during 1980-1984 to 18.74 and 18.88 percent during 1985-1989 and 1990-1994 respectively.

[8] The share of manufacturing industry in private sector's total fixed investments declined from an average level of 40.76 percent during 1970-1974 to 32.69 and 26.05 percent during the periods 1980-1984 and 1985-1989 respectively.

imbalances remained unaddressed. Besides, no significant progress was made towards privatization. From 1989 onwards, the increase in short-term capital inflows expanded the magnitude of macroeconomic instability and the degree of currency substitution. By April 1994, which corresponds to the last period covered in this study, Turkey was hit by a severe financial crisis which revealed itself as a major balance of payments disequilibrium. This led to another stand-by agreement with the IMF and a massive real depreciation of TL in 1994[9].

II.3. Selected Manufacturing Industries: The Food, Textiles, Chemicals and Machinery Sectors

In the following chapters of this study, we used data sets constructed from the annual surveys of the manufacturing industry conducted by the State Institute of Statistics (S.I.S). During the time span of this study (1983-1994) these surveys covered the private sector establishments with 25 or more employees and all public sector establishments regardless of the number of their employees. Processed data on some variables, although not fully inclusive of all the questions included in the surveys, are published annually as "Annual Manufacturing Industry Statistics".

To track the activities of private establishments that employ 10-24 people, S.I.S uses a "simple" questionnaire. However, the two questionnaires designed for the private sector are not compatible for constructing some of the variables used in

[9] For an evaluation of the 1994 crisis, see Ozatay (2000).

empirical analysis. Therefore, to achieve congruency, we compiled our data sets from questionnaires that form the basis of publications.

However, analysis presented in this section is based on data that cover all the manufacturing establishments in the public sector and establishments with 10 or more employees in the private sector. Data on selected variables such as average number of persons employed, wages, input, output and value added were available from the S.I.S. at the level of two-digit industries (according to ISIC). As our intention in this section is to provide a synopsis of the structural aspects and the operating environments of the four broad industries, we used the more comprehensive data set.

As for the four industries we chose to analyze in this study, summary Table II.1 shows that their structure and performance displayed considerable variation during 1983-1994. Starting with four-firm concentration ratios (CR4), the food industry with a relatively high percentage of four digit industries that had concentration ratios in the range 25-50 appear as the most competitive industry over the period analyzed. The textiles industry has become increasingly competitive as the percentage shares of industries with CR4 ratios greater than 50 declined considerably during 1983-1994. The chemicals industry on the other hand was the most concentrated one with almost 80 percent of four digit industries having CR4 ratios greater than 50. Concentration ratios of most of the subsectors in the machinery industry on the other hand fall into the 25-50 or 75-100 range. Regarding the aggregate manufacturing industry, most of the subsectors (about 35 percent) lie in the 25-50 range while there are approximately equal number of subsectors within the 50-75 and 75-100 ranges amounting to 25 percent.

In terms of sectoral contributions to total employment and output of the manufacturing industry (See Figures II.1 and II.2), the chemicals industry accounted for the largest share in manufacturing output (with an average of 27.3 percent) but the smallest share in employment (averaging 9.7 percent during 1983-1994). The average share of food and machinery industries in output during 1983-94 were equal, around 18.3 percent, while the latter contributed more to manufacturing employment with its average share of 21.5 percent compared to the 19.5 percent share of the former. The textiles industry increased its share in total output during the period from 13 percent in 1983 to an average of 15.9 percent during 1983-1994. As a consequence, its share in manufacturing employment increased from 23.4 percent to 30 percent.

Regarding the sectoral shares in total manufacturing industry's capital measured by the total capacity of installed equipment (in kilowatt hours), it is observed from Figure II.3 that the food and textiles industries accounted for about 16 and 15 percent of total capital throughout the period under study. The capital intensive chemicals and machinery industries on the other hand increased their shares during 1983-1994. The former accounted for an average of 14.4 percent of total capital in the manufacturing sector during 1983-1985 increasing its share to 17.3 percent during 1992-1994. The corresponding values for the machinery industry were realized as 14.1 and 15.7 percent during 1983-1985 and 1992-1994 respectively.

The shares of public sector in industries' output, capital and employment are presented in Figures II.4 to II.6. We observe that public share in output and employment declined in all industries during 1983-1994. In the total manufacturing industry, public sector accounted for 38.7 percent of output and 32.5 percent of employment during 1983-1985, which declined to 26.1 and 24.1 percent respectively during 1983-1994. In the chemicals industry, public sector produced almost 60 percent of output and employed 27.1 percent of the sector's labor force during 1983-1985 and decreased its share in output and employment to 50 and 25.9 percent respectively during 1992-1994. During 1983-1985, public shares in output and employment of the food industry were as high as 47 and 55 percent respectively. These shares declined to period averages of 36 and 42.5 percent respectively during 1992-1994. In the textiles and machinery industries, public sector accounted for only 5.6 and 4 percent of output and 10.9 and 13.3 percent of employment respectively, during 1992-1994.

Although the shares of public sector in employment and output followed a declining trend in all industries, it is observed that the public-private mix of industries' capital (measured in kilowatt-hours) did not change very much. Public share in capital declined only in the food industry, from a period average of nearly 49 percent in 1983-1985 to a corresponding value of 32.5 percent in 1992-1994. In the textiles and machinery industries, public shares in capital remained quite stable during the period under study, averaging 12.3 percent in the textiles industry and slightly declining in the machinery industry from a period average of 20.1 percent in 1983-1985 to 15.6 percent in 1992-1994.

Besides their industrial structure, export performances of these industries were also very different in the 1980s and 1990s. The textiles industry began exporting during the 1970s and achieved an impressive performance in 1980s. Exports in this industry amounted to 88 percent of its trade volume during 1983-1994. The food industry also recorded high export-import ratios averaging 72.6 percent of its volume of trade. The chemicals and machinery industries on the other hand were in a deficit situation in terms of their trade balance throughout the 1980s and early 1990s.

Regarding the level of real wage rates, the highest per capita real wage rate in the private manufacturing sector was paid in the chemicals industry. The machinery industry was ranked second followed by the food and textile industries. From 1983 to 1988, real wages in all industries were suppressed. Average annual growth rates of real wages were negative in all sectors during 1983-1985 and slightly increased in the textile and machinery industries during 1986-1988.

The post-1988 period, on the other hand, witnessed substantial increases in real wages in all industries. The average annual growth rate of the real wage rate for the total private manufacturing sector was 32.8 percent. Furthermore, the gap between the real wage rates paid by the public and private sectors increased significantly from 1989 onwards in favour of the public sector (See Figures II.7 to II.11).

Table II.1: Manufacturing Industries

	PERIOD AVERAGES				
	1983-85	1986-88	1989-91	1992-94	**1983-1994**
31-FOOD					
Sectoral Share in Total Manuf. Output (%)	19.4	17.0	18.2	18.5	18.3
Sectoral Share in Total Manuf. Employment (%)	21.3	19.4	19.0	18.3	19.5
Sectoral Share in Total Manuf. K (%)	16.6	16.8	14.9	14.6	15.7
Share of Wages in Value Added of the sector (%)	21.8	15.3	20.7	22.0	19.9
Public	23.0	14.3	22.8	34.7	23.7
Private	20.5	16.3	18.8	15.7	17.8
Input/Output Ratios	0.66	0.64	0.63	0.63	0.64
Public	0.54	0.48	0.51	0.57	0.53
Private	0.75	0.73	0.70	0.65	0.71
Share of Public Sector in industry's Output (%)	47.1	39.1	35.0	35.7	39.2
Share of Public Sector in industry's Employment (%)	55.1	49.4	43.8	42.5	47.7
Share of Public Sector in industry's K (%)	48.7	32.3	29.9	32.5	35.8
Exports / Imports	5.58	2.99	2.01	2.10	3.17
Trade Balance / Volume of Trade	63.8	49.6	32.8	34.6	45.2
Percentage distribution of 4-Digit Industries with respect to Concentration Ratios					
0-25	17	16	19	21	18
25-50	48	54	42	33	44
50-75	25	21	31	28	26
75-100	10	9	9	17	11
32-TEXTILES					
Sectoral Share in Total Manuf. Output (%)	14.3	15.6	15.9	17.8	15.9
Sectoral Share in Total Manuf. Employment (%)	25.1	26.2	28.3	30.0	27.4
Sectoral Share in Total Manuf. K (%)	14.8	14.5	14.6	14.9	14.7
Share of Wages in Value Added of the sector (%)	30.0	23.8	28.5	22.4	26.2
Public	51.9	44.9	74.5	83.6	63.7
Private	27.3	21.7	25.1	19.4	23.4
Input/Output Ratios	0.66	0.66	0.64	0.62	0.64
Public	0.61	0.66	0.61	0.52	0.60
Private	0.67	0.66	0.64	0.63	0.65
Share of Public Sector in industry's Output (%)	10.9	9.5	8.5	5.6	8.6
Share of Public Sector in industry's Employment (%)	16.4	15.2	12.7	10.9	13.8
Share of Public Sector in industry's K (%)	12.8	11.8	12.7	12.0	12.3
Exports / Imports	12.05	7.25	8.74	5.16	8.30
Trade Balance / Volume of Trade	84.1	75.5	78.5	67.1	76.3
Percentage distribution of 4-Digit Industries with respect to Concentration Ratios					
0-25	25	33	33	33	31
25-50	22	17	17	25	20
50-75	25	25	25	22	24
75-100	28	25	25	19	24

Table II.1 (Cont'd)

	PERIOD AVERAGES				
	1983-85	1986-88	1989-91	1992-94	**1983-1994**
35-CHEMICALS					
Sectoral Share in Total Manuf. Output (%)	30.6	28.6	27.2	22.9	27.3
Sectoral Share in Total Manuf. Employment (%)	9.5	9.8	9.8	9.6	9.7
Sectoral Share in Total Manuf. K (%)	14.4	16.6	17.6	17.3	16.5
Share of Wages in Value Added of the sector (%)	10.6	7.6	11.2	11.0	10.1
Public	5.8	3.6	5.7	6.7	5.5
Private	16.0	12.9	19.3	16.2	16.1
Input/Output Ratios	0.72	0.62	0.59	0.51	0.61
Public	0.75	0.57	0.52	0.46	0.57
Private	0.68	0.67	0.66	0.55	0.64
Share of Public Sector in industry's Output (%)	58.6	57.6	49.3	50.8	54.1
Share of Public Sector in industry's Employment (%)	27.1	26.0	24.9	25.9	26.0
Share of Public Sector in industry's K (%)	42.6	48.3	53.7	54.8	49.9
Exports / Imports	0.34	0.41	0.37	0.29	0.35
Trade Balance / Volume of Trade	-49.3	-42.3	-46.3	-55.3	-48.3
Percentage distribution of 4-Digit Industries with respect to Concentration Ratios					
0-25	7	7	7	7	7
25-50	33	24	22	20	25
50-75	20	24	24	24	23
75-100	40	44	47	49	45
38-MACHINERY					
Sectoral Share in Total Manuf. Output (%)	16.7	17.4	18.5	20.8	18.3
Sectoral Share in Total Manuf. Employment (%)	21.6	21.6	21.0	21.7	21.5
Sectoral Share in Total Manuf. K (%)	14.1	14.1	15.1	15.7	14.7
Share of Wages in Value Added of the sector (%)	30.6	22.3	26.6	22.6	25.5
Public	53.6	52.5	77.4	72.7	64.0
Private	27.1	19.6	23.3	19.9	22.5
Input/Output Ratios	0.65	0.62	0.60	0.57	0.61
Public	0.61	0.54	0.48	0.39	0.51
Private	0.65	0.63	0.60	0.58	0.62
Share of Public Sector in industry's Output (%)	13.4	9.9	6.5	4.0	8.4
Share of Public Sector in industry's Employment (%)	19.9	18.6	17.6	13.3	17.4
Share of Public Sector in industry's K (%)	20.1	16.9	18.3	15.6	17.7
Exports / Imports	0.18	0.22	0.15	0.18	0.18
Trade Balance / Volume of Trade	-69.5	-65.0	-74.3	-69.7	-69.7
Percentage distribution of 4-Digit Industries with respect to Concentration Ratios					
0-25	10	6	8	8	8
25-50	29	39	25	22	29
50-75	29	19	29	29	27
75-100	32	36	38	40	36

Table II.1 (Cont'd)

	PERIOD AVERAGES				
	1983-85	1986-88	1989-91	1992-94	**1983-1994**
3					
Sectoral Share in Total Industry Output	85.8	85.6	85.6	84.3	85.3
Sectoral Share in GNP	18.5	22.3	22.4	21.5	21.2
Sectoral Share in Total Gross Fixed Investments	24.6	18.6	17.7	18.7	19.9
Sectoral Share in Public Gross Fixed Investments	14.2	7.4	4.7	3.9	7.5
Sectoral Share in Private Gross Fixed Investments	32.6	26.1	23.5	24.5	26.7
Share of Wages in Value Added of the sector (%)	23.3	23.4	21.9	23.8	20.3
Public	23.3	14.3	22.5	26.1	21.6
Private	23.3	17.4	21.7	17.6	20.0
Input/Output Ratios	0.68	0.63	0.61	0.69	0.62
Public	0.67	0.57	0.54	0.51	0.57
Private	0.68	0.66	0.64	0.60	0.65
Share of Public Sector in industry's Output (%)	38.7	34.2	28.3	26.1	31.8
Share of Public Sector in industry's Employment (%)	32.5	29.7	26.0	24.1	28.1
Share of Public Sector in industry's K (%)	39.7	38.1	36.5	35.0	37.3
Exports / Imports	0.89	0.85	0.78	0.73	0.81
Trade Balance / Volume of Trade	-16.3	-22.7	-60.0	-43.1	-35.5
Percentage distribution of 4-Digit Industries with respect to Concentration Ratios					
0-25	13	12	14	14	13
25-50	37	39	33	31	35
50-75	27	24	27	28	26
75-100	23	25	26	27	25

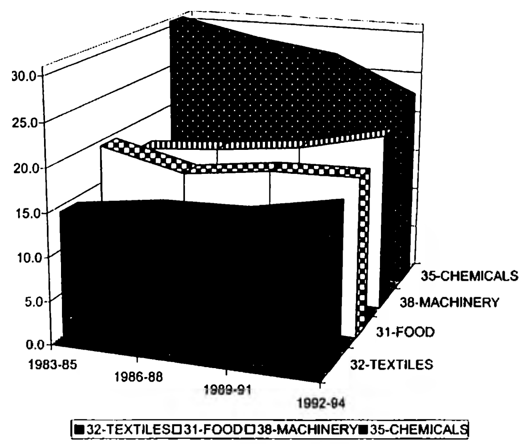


Figure II.1: Sectoral Shares in Manufacturing Output

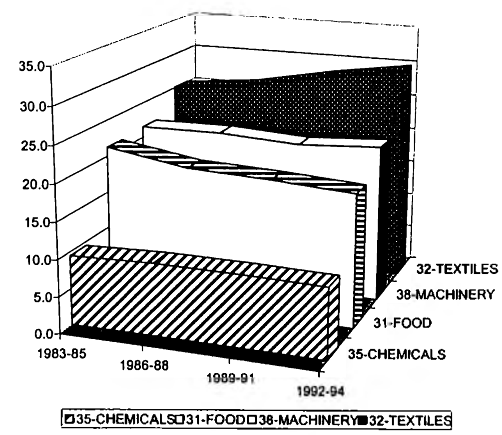


Figure II.2: Sectoral Shares in Manufacturing Employment

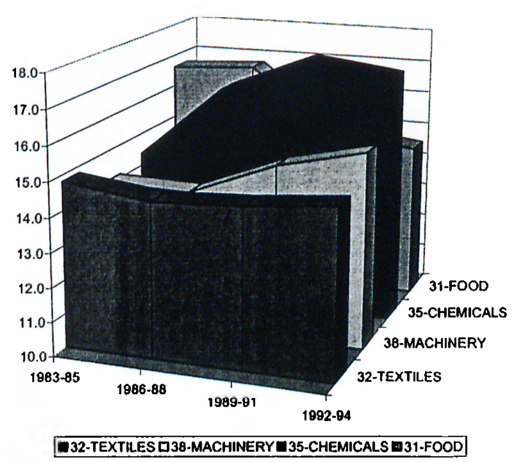


Figure II.3: Sectoral Shares in Manufacturing Capital (Horsepowers)

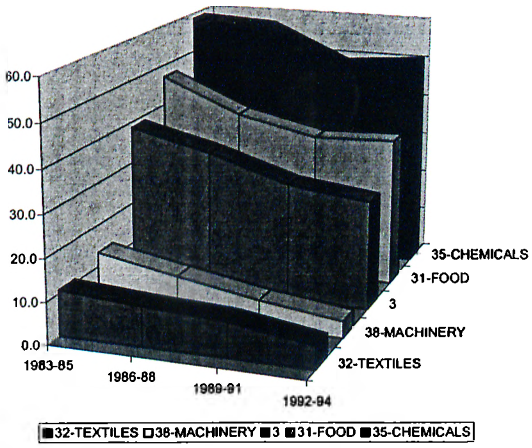


Figure II.4: Share of Public Sector in Output

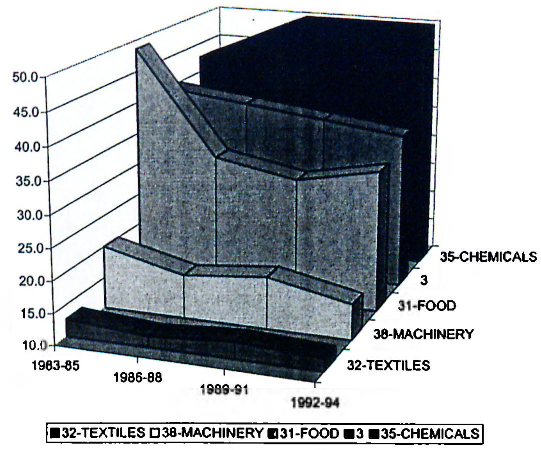


Figure II.5: Share of Public Sector in Capital (Horsepowers)

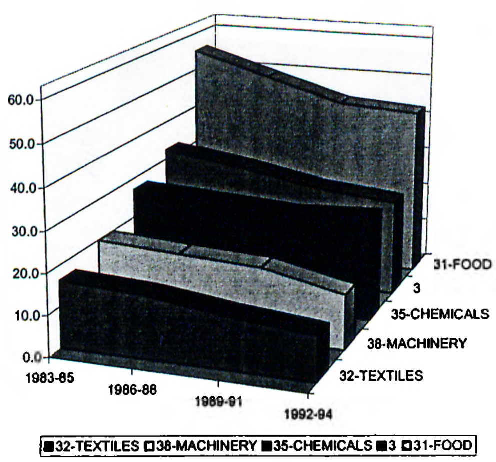


Figure II.6: Share of Public Sector in Employment

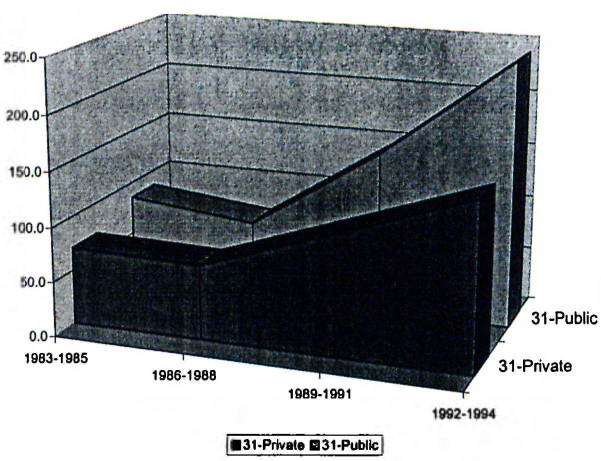
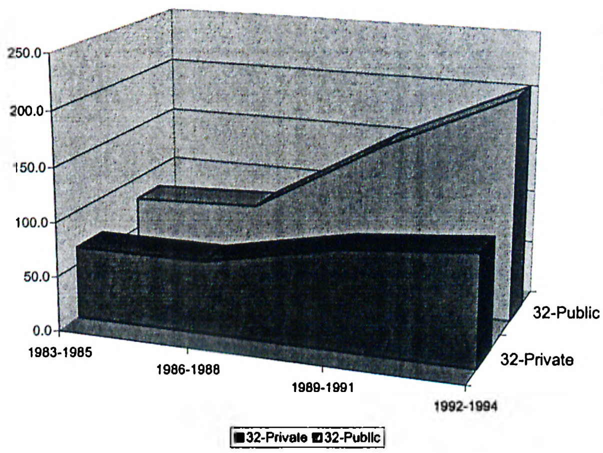


Figure II.7: Real Wages in the Food Industry



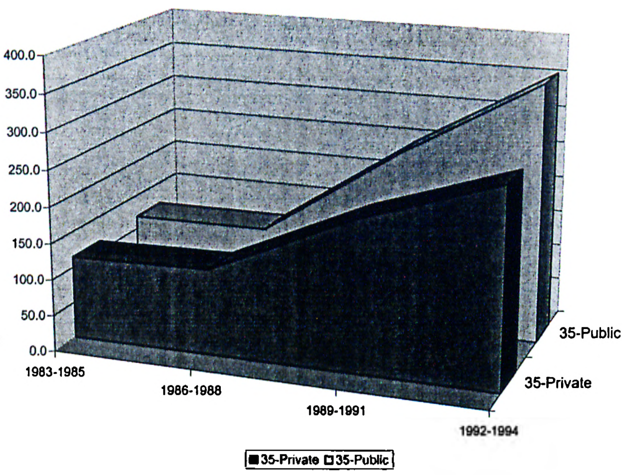


Figure II.8: Real Wages in the Textiles Industry

Figure II.9: Real Wages in the Chemicals Industry

Figure II.10: Real Wages in the Machinery Industry

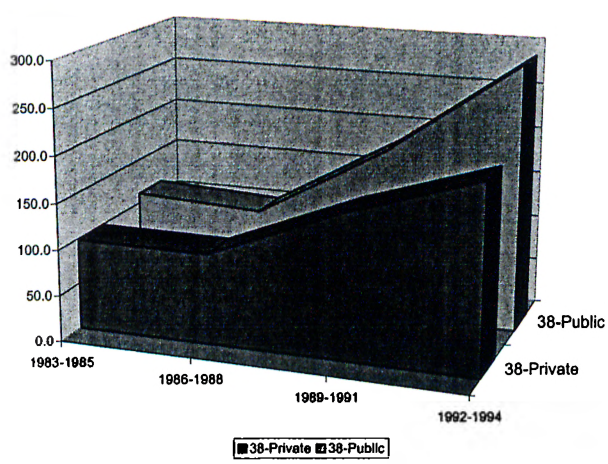


Figure II.11: Real Wages in the Total Manufacturing Indust

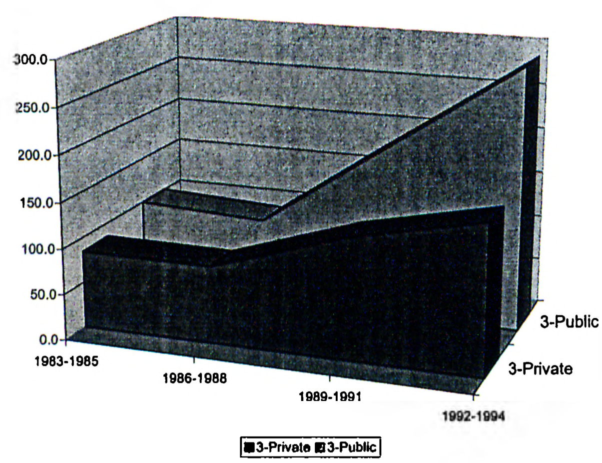


Figure II.10: Real Wages in the Machinery Industry

Figure II.7: Real Wages in the Total Manufacturing Industry

CHAPTER III

DETERMINANTS OF TECHNICAL INEFFICIENCY IN TURKISH MANUFACTURING INDUSTRIES

III.1. Introduction

In this chapter, our purpose is to investigate the sources of technical inefficiency in Turkish manufacturing industries using a rich panel data set covering the post reform era. Our data span the 1983-1994 period with cross sectional units being industries defined at the four-digit International Standard Industrial Classification (ISIC) codes. We estimate stochastic production frontiers (SPFs) for four broad industry categories: food, textiles, chemicals, machinery and also for the aggregate manufacturing industry.

The SPF specification we employ is due to Battese and Coelli (1995) which allows for the explicit modeling of technical inefficiencies through the incorporation of variables that effect efficiency into the frontier model. In the choice of these variables, theory does not provide a compact model. However, empirical literature suggests that inefficiency differentials across producing units are in general attributable to firm or industry specific structural and organizational factors such as suboptimal organization and agency relationships within the firm, suboptimal oligopoly bargains and related competitive factors within the industry or government interventions.

We will focus on the effects on technical efficiency of competitive conditions including measures of both domestic and international competition, and organizational factors that are postulated to exert pressures on management or workers. Results form this study provide insights on the empirical validity of a number of theoretical propositions which might be valuable to both policy makers in developing economies in their pursuits of increased productive efficiency and to researchers that perform comparative studies on industrially advanced countries and newly industrialising ones.

This chapter unfolds as follows: Section 2 provides an overview of existing studies that analyze technical efficiency in Turkish manufacturing industries. Section 3 presents a brief survey of the estimation methodology. Section 4 is devoted to model specification and estimation results, and finally, Section 5 concludes.

III.2. Recent Studies on Technical Efficiency in Turkish Manufacturing Industries

The revival of manufacturing industries during the liberalization period initiated a few number of micro-studies. Among them, Zaim and Taskin (2000) focused on the time pattern of technical efficiency and investigated whether public and private enterprises exhibited different performances. They estimated parametric and nonparametric production frontiers for a panel of 28 subsectors of the manufacturing industry (defined at the three digits according to the ISIC) for years 1974 to 1991 and concluded that public and private enterprises did not differ considerably in their efficiency levels over the entire sampling period and the time pattern of technical efficiency displayed a declining trend.

Taymaz and Saatçi (1997) explored the relationship between technical efficiency and variables such as the use of subcontracted inputs, amount of working time, degree of regional agglomeration, advertisement and telecommunication intensity, structure of ownership (domestic versus foreign, public versus private) and plant size. They constructed stochastic production frontiers for the textile, cement, and motor vehicles industries with panel data of plants for years 1987 to 1992 and reported that determinants of technical inefficiency varied significantly across sectors.

This article can be related to the works of Zaim and Taskin (2000) and Taymaz and Saatçi (1997) regarding the stochastic frontier methodology used. However, our data set, the period we consider and our choice of variables whose effects on technical (in)efficiency will be explored differ significantly from these two studies. Our data cover subsectors of the Turkish food, textiles, chemicals, and machinery industries at a more disaggregated level than Zaim and Taskin (2000) and span a longer period than Taymaz and Saatçi (1997). Furthermore, our explanatory variables reflect a wider range of industry specific and organizational factors such as the degree of domestic competition, openness to foreign trade, the type of ownership and the level of real wage rates. In the next section, we present a methodological overview of the estimation procedure we apply.

III.3. Methodology : An Inefficiency Frontier Model

Technical efficiency defined either as producing the maximal level of output given inputs or as using the minimal level of inputs given output and input mix can be measured through the construction of "best practice" frontiers. The stochastic frontier[1] methodology originally proposed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977) independently is based on the econometric estimation of a parametric frontier production function. Unlike deterministic methods, (for example, nonparametric data envelopment analysis or the parametric approach of Aigner and Chu, 1968), it has the ability to accommodate the variation in output due to factors that are beyond the control of productive units, measurement and reporting errors or "unimportant" variables omitted from the specified production technology.

The model for panel data is given by:

$$Y_{it} = f(X_{ti}, \beta) + E_{it}; \qquad i = 1,2,\ldots,N;\ t = 1,2,\ldots,T \tag{1}$$

where Y_{ti} is the logarithm of the output, X_{it} is a vector of inputs and other explanatory variables for the i^{th} firm in period t; and β is a vector of unknown parameters to be estimated. The error term, E_{it} is composed of two components:

$$E_{it} = V_{it} - U_{it}, \quad U_{it} \geq 0, \tag{2}$$

where V_{it} and U_{it} are independent and unobservable random variables. The V_{it} are random disturbance terms that are assumed to have a symmetric distribution, typically normal with mean zero and variance σ_V^2. The U_{it} are asymmetrically distributed non-negative random variables associated with technical inefficiency.

Given certain distributional assumptions on V_{it} and U_{it}, the parameters of the stochastic frontier model can be estimated and technical efficiencies can be predicted by either maximum likelihood (ML) estimation or corrected ordinary least squares (COLS) methods proposed by Richmond (1974) and Greene (1980).

When the focus is not only on the prediction of technical efficiency levels but also on the investigation of factors that are responsible for inefficiency, most empirical studies employ a two-stage methodology. The first stage consists of constructing a production frontier and obtaining a set of efficiency scores. In the second stage, these scores are regressed upon some explanatory variables. However, there are some drawbacks of this procedure (See Lovell, 1993). First, efficiency scores assume a value of either zero or one or lie between them. Therefore, they must be transformed before they are regressed on explanatory variables in the second stage or limited dependent variable regression techniques must be employed.

[1] Surveys of literature on frontier production functions and efficiency measurement include Fφrsund, Lovell and Schmidt (1980), Schmidt (1985-86), Lovell and Schmidt (1988), Bauer (1990), and Greene (1993).

Furthermore, when the stochastic frontier model is used, the two-stage approach suffers from a theoretical inconsistency: Estimating a regression model for the predicted inefficiency effects contradicts the first stage's assumption that they are identically distributed. Nevertheless, with recent models that allow for the simultaneous estimation of the parameters of the production frontier and the inefficiency effects model,[2] this pitfall can be avoided. Among these models, we employ the Battese and Coelli (1995) specification which assumes the random disturbance terms, the V_{it}, to be iid $N\left(0, \sigma_V^2\right)$ variables and the inefficiency terms, the U_{it}, to be independently distributed as truncations at zero of the normal distribution with mean $m_{it} = z_{it}\delta$ and variance σ_u^2.

In the above specification, z_{it} is a $p \times 1$ vector of explanatory variables associated with technical inefficiency of production and δ is a $1 \times p$ vector of unknown coefficients of the firm-specific inefficiency variables. The unknown parameters of the frontier function (β) and the inefficiency effects model (δ) can be estimated simultaneously by ML techniques.[3] Given the estimates of the variance parameters $\sigma^2 = \sigma_V^2 + \sigma_U^2$ and $\gamma = \sigma_U^2 / \left(\sigma_U^2 + \sigma_V^2\right)$ that enter the likelihood function, technical efficiency scores can be predicted as $TE_{it} = E\left(U_{it} \middle| V_{it} - U_{it}\right)$, following the propositions of Jondrow et al. (1982).

[2] Models of this type include Kumbhakar, Ghosh, and McGuckin (1991), Reifschneider and Stevenson (1991), Huang and Liu (1994), and Battese and Coelli (1995).

III.4. Model Specification and Results

In this section, we investigate the determinants of technical inefficiency in Turkish manufacturing industries. Our productive units are subsectors defined at four-digit ISIC codes, which belong to the following four broad industry categories:

31: Manufacture of food, beverages and tobacco,

32: Textile, wearing apparel and leather industries,

35: Manufacture of chemicals and of chemical, petroleum, coal, rubber and plastic products,

38: Manufacture of fabricated metal products, machinery and equipment, transport equipment, professional and scientific and measuring and controlling equipment.

We first estimate separate frontier production functions for each industry using the computer software FRONTIER 4.2 to determine the industry specific factors that influence technical inefficiency. However, one cannot make inference on the ranking of the four industries in terms of their measured levels of technical efficiency unless an aggregate model, serving as a benchmark for efficiency comparisons is estimated. For this purpose, we also estimate a frontier for the aggregate manufacturing industry using the data set constructed through pooling the data sets of the four subsectors.

We assume the translog functional form for the technology since it does not impose any prior restrictions on the production structure, unlike the Cobb-Douglas or constant elasticity of substitution (CES) specifications. Moreover, selection of

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[3] The likelihood function is presented in Battese and Coelli (1993).

the translog function reduces the possibility that a functional form misspecification could lead to error that is incorrectly taken for technical inefficiency.

Four categories of factor inputs are identified; which are labor, capital, electricity and raw material use.[4] The output of an industry as a function of these inputs and an allowance for non-neutral technical change (is) can be written as:

$$\begin{aligned}\ln(Y_{it}) &= \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 \ln(K_{it}) + \beta_4 \ln(E_{it}) + \beta_5 \ln(L_{it}) + \beta_6 \ln(RM_{it}) + \beta_7 \ln(K_{it})^2 \\ &+ \beta_8 \ln(E_{it})^2 + \beta_9 \ln(L_{it})^2 + \beta_{10} \ln(RM_{it})^2 + \beta_{11} \ln(K_{it})\ln(E_{it}) + \beta_{12} \ln(K_{it})\ln(L_{it}) \\ &+ \beta_{13} \ln(K_{it})\ln(RM_{it}) + \beta_{14} \ln(E_{it})\ln(L_{it}) + \beta_{15} \ln(E_{it})\ln(RM_{it}) + \beta_{16} \ln(L_{it})\ln(RM_{it}) \\ &+ \beta_{17} \ln(K_{it})t + \beta_{18} \ln(E_{it})t + \beta_{19} \ln(L_{it})t + \beta_{20} \ln(RM_{it})t + v_{it} - u_{it},\end{aligned}$$

$$i = 1,2,\ldots,N, \quad t = 1,2,\ldots,T \tag{3}$$

where Y_{it} is the real output of sector i in year t, K_{it} is capital input measured by the total capacity of power equipment installed at the end of year t, E_{it} is electricity consumed measured in kWh, L_{it} is labor input measured by number of hours worked, RM_{it} is raw material used by industry i in period t. Time trend that accommodates for technological change is represented by t. Finally, v_{it} are iid $N(0,\sigma_v^2)$ random errors and u_{it} are technical inefficiency terms that follow a truncated (at zero) normal distribution with mean μ_{it} and variance σ_u^2. The mean, μ_{it}, is defined as a linear combination of variables whose effects on technical inefficiency will be explored.

[4] Details on the sources and definitions of these variables are presented in the Data Appendix.

Conceptually, we model the inefficiency effects through the following specification which includes a set of dummy and explanatory variables[5] that accommodate for industry specific and organizational factors:

$$\mu_{it} = \delta_0 + \delta_1 DUMMYOWN_i + \delta_2 COMP.DOM_{it} + \delta_3 COMP.INT_{it} + \delta_4 ADOP_{it}$$

$$+ \delta_5 RWAGE_{it} + \delta_6 RESOLD_{it} \qquad (4)$$

In Eq. (4), δ_0 is the constant term (an intercept dummy) accounting for differences in production that cannot be attributed to any organizational or structural aspect of an industry.

DUMMYOWN is a dummy variable indicating the type of ownership (public versus private) in industry i. It takes the value 0 for private ownership and 1 for public ownership. The sign of the coefficient of this variable is expected to be positive (ie. efficiency is expected to increase as we move from public to private ownership) within the theoretical framework of the property rights and public choice literatures. The property rights literature argues that private sector organizations will outperform public sector organizations since the managers in the former are provided with incentives to achieve higher productivity and lower costs.[6] The public choice literature contributes to this view asserting that politicians and state bureaucrats pursue their own interest rather than 'public interest' (Downs, 1967; Niskanen, 1971; Tullock, 1965; and Buchanan et al., 1978) which leads to non-optimal pricing, employment and investment policies in the public sector.

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[5] Sources and definitions of the variables are presented in the Data Appendix.

[6] This is attributed to the fact that rights to profits are clearly defined in private sector organizations whereas they are diffused and uncertain in public sector organizations (Alchian, 1965; Furubotn and Pejovich, 1974; De Alessi, 1980).

COMP.DOM and *COMP.INT* are measures of domestic and foreign competition respectively. We include these variables not only to explore their effects on inefficiency but also to control for the possibility of attributing inefficiencies resulting from monopolistic or oligopolistic market structures to those directly related to the type of ownership in an industry.

Competition may improve efficiency by effecting firms' incentives, by letting only the efficient firms survive or by reducing inefficiencies associated with rent-seeking behavior. The effects of competition on firms' incentives are discussed by Vickers (1995) and Nickell (1996). They suggest two mechanisms through which competition may improve efficiency. The first one, referred to as "discovery and selection" is described within the framework of a model of entry into a homogenous good market with Nash-Cournot competition where the ranking of the entrant is revealed in terms of relative costs. A low cost entrant may force some high cost incumbents out and thus provide an incentive for firms to operate more efficiently. The second mechanism works through the positive link between the number of players and the degree of competition in the market. An increase in the number of players will also lead to an increase in comparisons between the performance of managers and thus serve as an explicit incentive scheme to reduce any inherent managerial slack.

Hart (1983), Hermalin (1992), Horn et al (1994), Martin (1991), and Scharfstein (1988) also examine the same issue, focusing on implicit managerial incentives provided by increased competition. They state that in a setting where there exist internal inefficiencies that result from informational asymmetries in principal-agent relations, the effect of competition operates through altering the information structure and increasing the possibilities of the principal to control managers' actions so that superior managerial performance can be distinguished.

However, in most empirical research, including this study, the degree of competition in an industry is proxied by a measure of domestic producers' concentration,[7] which might lead to some complications especially for the case of developing economies. In developing economies with non-competitive market structures, concentration is inversely related to market size and large firms enjoy more market power than their counterparts in developed economies (see, Tybout, 1998 and Lee, 1992). Thus, higher concentration ratios in LDCs might result from smaller markets. In such a setting, when there exist economies of scale in managerial control, i.e., if the marginal cost of managerial effort per output is a decreasing function of output, Torii's "managerial model of technical efficiency" (Torii, 1992) predicts that the more competitive is an industry, the less efficient it becomes since each firm's output decreases as the number of firms in the market increases.

Furthermore, when concentration, market power and monopoly rents are positively associated,[8] Schumpeter's famous argument should not be overlooked. Nearly sixty years ago, he proposed that large firms operating in concentrated markets are mainly responsible for technical progress. The well-known arguments

[7] In this study, the degree of domestic competition is proxied by the four-firm concentration ratio in all industries and by the number of firms in the textile industry. We also include the squared values of measures of domestic competition to allow for possible U-shaped interactions between measures of concentration and technical efficiency.

[8] See Tybout (1998) for an overview of the link between concentration and market power in the LDCs.

justifying his views are based on the fact that large firms have better access to external finance and they can minimize their risks of R&D by being able to undertake and manage a larger portfolio of projects. Thus, a positive relationship between increased concentration and technical efficiency is more likely to be detected in developing economies with imperfect capital markets favoring large firms. Easier access to external finance is expected to promote efficiency for at least a couple of reasons. First, firms with non-binding financial constraints have the opportunity to invest in and make use of new technologies embodied in new vintages of capital. Secondly, they are expected to be affected less by economic shocks as they can compensate for an increase in the requirement for working capital or a fall in turnover by borrowing more. Finally, flexibility in obtaining financial inputs is likely to enhance the efficiency with which these non-measurable inputs are combined with measurable ones.

To explore the effects of international trade on technical efficiency we construct the variables $XTOTV_{it}$ or X_MTOTV_{it} for each industry as the ratio of exports and the ratio of trade balance to the volume of trade respectively. Engagement in international trade, especially import competition, tends to limit domestic industries' departures from "optimal" price-cost margins and has beneficial impacts on productivity growth through embodiment of new technology in imports and knowledge transfer through contracts. Empirical evidence suggests that international competition limits productive inefficiency that is viable in domestic firms (Caves and Baldwin, 1997). However, one other effect of international competition, which has been more recently detected operates through increased turbulence within domestic industries. Turbulence, measured by the entry and exit of firms, the turnover among incumbents or the frequency of changes in control of business units is expected to increase with trade exposure[9] This channel renders the effect of increased trade on productive efficiency ambiguous when turbulence is associated with increased costs of adjustment or increased uncertainty surrounding irreversible investments.

The variable $ADOP_{it}$, defined as the ratio of administrative to operative personnel, accommodates for the effect of the composition of labor force on technical efficiency. The literature on labor hoarding implies that a higher proportion of nonproduction workers might depress efficiency since white-collar workers are associated with larger recruitment and overhead costs which discourage instantaneous downward adjustment of labor input. On the other hand, an increase in nonproduction workers who make up for the more skilled proportion of the work force might enhance efficiency if removal of internal inefficiency requires a higher ratio of skilled labor.

The variable $RWAGE_{it}$, corresponding to the real wage rate in industry i at period t, is included for the purpose of testing the implications of efficiency wage models. We expect a negatively signed coefficient for $RWAGE_{it}$, i.e. technical efficiency is expected to be positively related to real wage rates if higher real wage rates reduce shirking by employees, increase the quality of job

[9] Caves and Baldwin (1997) predict that the amounts of adjustment observed in various industries should increase with the closeness of their international competition. This prediction originates from a recent contribution of Forsyth (1995) who found that trade exposure is a source of disturbance to the values of business assets and thereby a trigger for their organization through a merger.

applicants, or augment the level of effort supplied by workers through improved morale.

Finally, $RESOLD_{it}$ accommodates for inter-industry heterogeneity that is due to different degrees of concentration of operations on production based sales versus sales of goods without further processing. A negatively signed coefficient indicates that industries that are mostly engaged in sales of goods that are not processed further can organize their operations more efficiently and achieve higher technical efficiency levels compared to the ones that are more production oriented.

Having determined the factors that might influence inefficiency, we estimate the stochastic frontier model given in Eq. (3) for the four industries and the aggregate manufacturing industry. Although the maximum likelihood estimates of the parameters might suggest that some variables are redundant, deciding on the significance of each variable considering the t-tests can be misleading due to possible multicollinearity that may result from the presence of squared and interaction terms in the translog form. Therefore, we test the assumed translog functional form against the null hypotheses of a translog model with Hicks-neutral technical change and with no technical change at all through joint tests for the significance of a group of parameters. Furthermore, Cobb-Douglas forms are also tested.

The test results are presented in the first three rows of Table III.3. The null hypotheses of Hicks-neutral technical change are rejected in all industries except for the chemicals industry. Tests on whether there has been any technical change at all reveal that null hypotheses of no technical change can be rejected in all industries and the pooled model. Finally, the null hypothesis of a Cobb-Douglas functional form is also rejected in all industries. Thus we conclude that the unrestricted translog specification is appropriate for describing the production technology in the food, textiles, machinery and the pooled industries, whereas a translog form with Hicks-neutral technical change describes best the technology in the chemicals industry.

Regarding the inefficiency effects, we estimate various models constructed through different linear combinations of the variables that enter Eq. (4). This allows us to check the robustness of the signs of the coefficients of the explanatory variables and to minimize the problems that might arise due to multicollinearity. An examination of the estimates of the variance parameters γ (See Table III.1) reveals that the extent of the variation in output that is attributable to inefficiency effects is significant in all industries. Furthermore, we perform hypothesis tests to decide whether there was no technical inefficiency in a given industry. The null hypothesis formulated as $\gamma = \delta_i = 0, \forall i$ is rejected in all industries implying that neither the sub-sectors nor the aggregate manufacturing sector cannot be assumed as technically efficient during 1983-1994 (See Table III.3, Row 4). This result supports that OLS estimation of Eq. (3) would not be appropriate since the U_{it} are significant and therefore cannot be ignored.

We report the parameter estimates of the stochastic frontier and inefficiency effects models in Table III.1 and present the calculated input elasticities of production[10] and rates of technical change in each industry in Table III.2. Capital elasticity of output is insignificant in the food, textile, machinery and pooled industries. Its value is close to zero and negative in the food and pooled industries. Thus a positive significant value (0.11) is observed only in the chemicals industry. Low and negative levels of capital elasticity of output might be a reflection of excess capacity in installed equipment which is our proxy variable for capital.

Elasticities of production with respect to labor are positive in all industries, and significant for the food, textile and pooled industries. Labor elasticity is highest in the food industry, followed by the pooled and textile industries. Raw material elasticities of production are positively signed and significant in all industries, attaining the highest value in the chemicals industry followed by the machinery, food, pooled and textiles industries. Finally, production elasticities with respect to electricity are positive in all industries except for the chemicals industry where it is also insignificant. Among the four input elasticities of production, raw material elasticities are highest followed by labor elasticities in all industries.

Regarding the sectoral rates of technological change during 1983-1994, the food industry exhibited neither progress nor regress. In all other industries, estimates of technical change are statistically significant. The machinery industry experienced the highest rate of technical progress (2.7 percent per annum) while the textiles and chemicals industries witnessed almost equal rates of technical

[10] Input elasticities of production are evaluated at sample means.

progress; 2.3 and 2.4 percents per annum respectively. In the aggregate manufacturing industry, average annual rate of technical progress was 1.4 percent.

Concerning the factors that influence technical (in)efficiency, the most striking result common to all industries is that public ownership is detrimental to technical efficiency. The public-private dummy variable is statistically significant and positive in all sectoral models of inefficiency.

The results with respect to the real wage rate variable are also particularly interesting. This variable is negatively signed and significant in all sectoral models except for that of the machinery industry suggesting a positive association between real wage rates and technical efficiency as set forth by the efficiency wage hypothesis.

We obtain mixed evidence on the relationship between the composition of labour force and technical efficiency. This is not an uncommon outcome in empirical literature. For example, Caves and Barton (1990), Torii (1992) and Baldwin (1992) who investigate the issue for United States, Japan and Canada respectively, report that higher proportions of nonproduction workers depress technical efficiency while Mayes and Green (1992) present opposite results for Britain. In our case, an increase in the ratio of administrative to operative personnel leads to an improvement in efficiency in the food, textile and pooled industries while it has a detrimental effect on efficiency in the machinery industry and no significant effect in the chemicals industry. This finding might be attributed to different sectoral production structures that give rise to different optimal mix of skilled and unskilled personnel. In the labor-intensive food and textile industries, an increase in skilled labor might improve the production process and contribute to the reduction of managerial slack while in capital intensive industries, the opposite situation might hold.

The variable *RESOLD*, ratio of the value of goods resold without further processing to receipts obtained from sales from production, positively affects technical efficiency in the food and chemicals industries.

Openness to trade is found to improve technical efficiency in all sectors except in the food and chemicals industries where it has no significant effect. This finding is parallel to the results of Nishimizu and Page (1982), Tybout et al. (1991), and Harrison (1996) who report positive effects of foreign competition on the efficiency of firms in developing countries.

Concerning the relationship between measures of domestic competition and technical efficiency, we do not find a common pattern across industries. In the food industry, a u-shaped association between technical efficiency and four-firm concentration ratio is detected. Technical efficiency declines as the market becomes more concentrated but after a certain critical level, increased concentration favors efficiency. In the textiles industry, which includes a larger number of small and medium sized firms relying on labor intensive technologies, efficiency improves with an increase in the number of firms. Within the oligopolistic, highly capital intensive and import dependent structure of the chemicals industry, market concentration seems to have no significant effect on technical efficiency. In the machinery industry which is also capital intensive, a quadratic relationship implies that technical efficiency improves with increased concentration up to a critical level and then exhibits a declining pattern. This result points to the presence of an optimal concentration ratio in the pursuit of minimization of managerial slack in that industry.

Results from the pooled model suggest that increased market concentration favors technical efficiency. This might be explained by the presence of economies of scale in the managerial pursuit of efficiency as suggested by Torii (1992).

Furthermore, the combination of a monopolistic or oligopolistic market structure and a small market size which leads to high concentration levels might be putting an upward pressure on the optimal scale of a firm. Since we do not have data on the average firm size/scale, we cannot control for the effects of this variable on technical efficiency. If higher concentration ratios signal higher average firm size/scale; than a positive association between technical efficiency and higher concentration might be reflecting the advantages of "being large" in obtaining funds necessary to meet the required levels of working and human capital or investment in newer vintages of physical capital.

An alternative explanation for this finding is related to Schumpeter's argument that higher concentration favors economic growth. In highly concentrated industries, larger profits accruing as a result of scale economies or barriers to entry might be leading to allocation of more resources to efficiency enhancing activities such as research and development, or procurement of new technologies.

To assess the relative performance of the four industries, we take the pooled model as a benchmark for our comparisons. Calculated descriptive statistics of technical efficiency scores are presented in Table III.4 which show that the highest and lowest mean technical efficiency levels are recorded in the chemicals and textiles industries, equaling to 0.66 and 0.51 respectively. In the food and machinery industries, estimates of mean technical efficiency are very close (0.56 and 0.57 respectively).

As for the distribution of efficiency scores within industries, technical efficiency scores in the textiles industry are normally distributed with skewness and excess kurtosis close to zero. In all other industries, efficiency distributions are positively skewed with peaked patterns in the food, machinery and pooled industries and a flat pattern in the chemicals industry. These properties lead to the rejection of the null hypothesis that inefficiency effects are normally distributed in the chemicals, food, machinery and pooled industries.

The 1983-1994 period averages of efficiency scores of the cross sectional units reflect that 46.7 percent of the subsectors of the textiles industry were below 50 percent level of efficiency while this ratio was equal to 29.6 percent in the food industry. In the capital intensive chemicals and machinery industries, only 9.5 and 12.1 percent of subsectors operated below 50 percent level of efficiency.

Regarding the evolution of mean technical efficiency scores over time (see Table III.5), it is observed that mean efficiency remained quite stable until 1989 and substantially improved during the post-1989 period in all industries. Throughout the period under study, the chemicals industry dominated others in terms of mean technical efficiency while the textiles industry was ranked last. During 1983-1990, the machinery industry lagged behind the food industry while the situation was reversed from 1991 onwards.

III.5. Conclusions

The manufacturing industry assumed an important role in the industrialization process of Turkey especially from 1980 onwards. During that period, import substituting industrialization policies were replaced with outward oriented, export-promoting strategies. While the structure of the economy was transforming from a highly protected, inward-oriented one into a more competitive and liberalized one, issues like productivity and efficiency in manufacturing gained importance.

In this paper, we aimed at identifying the sources of technical inefficiency in the Turkish food, textiles, machinery and chemicals industries during 1983-94. We used panel data, the cross-sectional units being manufacturing industries defined at the four-digit ISIC codes. We estimated stochastic frontier production functions as specified by Battese and Coelli (1995) which enabled us to model the inefficiency effects in terms of several variables accommodating the industry specific organizational and structural factors.

Among our basic findings, three of them are especially important in providing insights to policymakers in the design and evaluation of industrialization policies. The first one is related to the effects of public versus private ownership on technical efficiency. The results from the sectoral and the aggregate manufacturing (pooled) models suggest that public ownership is harmful to technical efficiency in all industries. This finding constitutes a supporting argument for the privatization efforts of governments.

Our second finding is related to the positive link between real wages and technical efficiency. In all industries except for the machinery industry, higher real wages promote technical efficiency suggesting that given a fixed level of labor input measured by the number of hours worked, higher real wages augment the level of effort supplied.

The third finding is associated with mixed empirical evidence we obtained regarding the effects of domestic competition on technical efficiency. In the food industry, a u-shaped association between technical efficiency and four-firm concentration ratio is detected while in the machinery industry, the coefficients of the quadratic term implies an inverted u-shaped relationship. In the chemicals industry, we do not find any significant relationship between measures of domestic competition and technical efficiency. In the textiles industry, we find evidence on the positive effects of enhanced competition on technical efficiency. Finally, findings from the estimation of the pooled model seem to support a positive link between increased market concentration and technical efficiency in the Turkish manufacturing industry.

Table III.1: Parameter Estimates of the Inefficiency Effects Models

Variable	FOOD ISIC 31		TEXTILES ISIC 32		CHEMICALS ISIC 35		MACHINERY ISIC 38		POOLED	
A.Frontier Functions	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Constant	0.76	9.26	0.30	4.81	-0.23	-3.59	0.11	1.22	0.42	7.58
T	0.04	1.96	0.00	0.11	0.04	2.62	-0.05	-2.36	0.02	1.62
T^2	0.00	-1.76	0.00	1.42	0.00	-1.11	0.01	4.08	0.00	-0.53
K	-0.01	-0.15	0.01	0.09	0.11	2.15	0.02	0.23	-0.01	-0.15
E	-0.04	-0.54	0.15	1.99	-0.02	-0.58	-0.01	-0.11	-0.01	-0.20
L	0.27	4.03	0.16	3.00	0.05	0.91	-0.02	-0.16	0.22	6.94
RawM	0.79	11.43	0.49	5.25	0.84	38.70	0.97	16.90	0.75	28.17
K^2	-0.08	-2.87	-0.04	-1.10	0.07	1.68	-0.01	-0.77	-0.02	-1.59
E^2	-0.02	-0.50	-0.01	-0.18	-0.01	-0.26	-0.04	-2.36	-0.01	-1.27
L^2	0.16	4.74	0.07	2.80	0.06	1.56	0.13	1.83	0.10	6.72
$RawM^2$	0.17	6.55	0.10	4.72	0.10	6.31	0.10	7.75	0.10	13.16
*K*E*	0.06	1.13	0.08	1.49	-0.04	-0.65	0.08	1.86	0.04	2.13
*K*L*	0.01	0.23	-0.09	-1.08	-0.25	-4.68	-0.09	-1.72	-0.07	-2.79
*K*RawM*	0.07	1.70	0.06	0.89	0.09	2.36	-0.02	-0.91	0.02	1.20
*E*L*	0.05	1.33	0.10	1.88	0.21	4.35	0.05	0.57	0.06	3.03
*E*RawM*	-0.09	-2.63	-0.13	-2.15	-0.14	-5.32	-0.02	-0.57	-0.06	-3.58
*L*RawM*	-0.33	-5.39	-0.18	-4.58	-0.11	-3.70	-0.17	-4.05	-0.18	-10.60
*K*t*	0.00	-0.43	0.01	0.83			0.00	0.15	0.00	-0.34
*E*t*	0.01	1.35	0.00	-0.01			0.02	1.58	0.01	1.73
*L*t*	0.01	1.32	0.01	0.69			0.01	1.13	0.01	1.81
*RawM*t*	-0.01	-1.34	0.00	-0.46			-0.03	-5.27	-0.01	-2.66
B.Inefficiency Effects Model										
Constant	1.19	10.90	0.96	8.56	0.19	2.06	-1.37	-1.98	0.93	18.56
DUMMYOWN	0.10	2.49	0.18	3.00	0.18	4.05	1.36	2.42	0.21	9.59
ADOP	-0.38	-4.60	-0.90	-5.28			0.43	2.13	-0.21	-9.40
RWAGE	-0.08	-4.83	-0.07	-2.59	-0.04	-4.95			-0.08	-15.08
CR4	0.01	3.20			0.00	-0.21	-0.03	-3.00	0.00	-7.77
$(CR4)^2$	0.00	-6.85					0.00	3.01		
NOFIRMS			0.00	-9.11						
RESOLD	-0.60	-3.60			-0.25	-17.22				
XTOTRV			-0.15	-2.22						
X_MTOTRV					-0.04	-0.99	-0.57	-6.52	-0.07	-4.90
C. Variance Parameters, Log-likelihood values and mean technical efficiency										
$\sigma^2 = \sigma_u^2 + \sigma_v^2$	0.05	12.73	0.02	6.85	0.03	12.02	0.15	3.40	0.08	24.89
$\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$	0.12	3.86	0.98	11.67	0.00	1.80	0.63	4.77	0.09	4.57
Log-likelihood	45.95		133.56		74.51		-34.65		-191.68	
Mean TE	0.48		0.64		0.88		0.88		0.58	
Number of cross-sections	27		15		21		33		96	
Number of observations	324		180		252		396		1152	

Table III.2: Input Elasticities of Production and Rates of Technical Change

	FOOD ISIC – 31		TEXTILES ISIC – 32		CHEMICALS ISIC - 35		MACHINERY ISIC - 38		POOLED	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Capital	-0.03	-0.80	0.05	1.00	0.11	2.15	0.02	0.46	-0.02	-0.56
Electricity	0.03	0.82	0.14	2.83	-0.02	-0.58	0.09	2.23	0.04	2.02
RawMaterial	0.73	15.12	0.47	6.96	0.84	38.70	0.79	19.71	0.70	37.38
Labor	0.34	7.44	0.19	4.24	0.05	0.91	0.06	0.69	0.27	13.23
TechnicalChange	0.00	0.61	0.02	4.79	0.02	4.64	0.03	3.25	0.01	3.69

Table III.3: Hypothesis Tests on the Models

Null Hypothesis	FOOD	TEXTILES	CHEM.	MACH.	POOLED	Critical Value
Hicks-Neutral technical change [(1)]	20.75*	23.04*	3.71	28.94*	250.70*	9.49
No technical change [(2)]	21.67*	32.98*	32.96*	101.75*		12.59
Cobb-Douglas [(3)]	142.64*	96.36*	113.15*	123.34*	297.58*	24.99
No inefficiency effects [(4),(5)]	260.86*	77.49*	284.50*	34.33*	314.63	

Notes:

(1) $\beta_{17} = \beta_{18} = \beta_{19} = \beta_{20} = 0$

(2) $\beta_1 = \beta_2 = \beta_{17} = \beta_{18} = \beta_{19} = \beta_{20} = 0$

(3) $\beta_2 = \beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = \beta_{12} = \beta_{13} = \beta_{14} = \beta_{15} = \beta_{16} = \beta_{17} = \beta_{18} = \beta_{19} = \beta_{20} = 0$

(4) $\gamma = \delta_0 = \delta_1 = \ldots = \delta_7 = 0$

(5) The null hypothesis involves $\gamma = 0$ and since $\gamma = 0$ is a value on the boundary of the parameter space for γ, the generalized likelihood-ratio statistic has mixed Chi-square distribution. The critical values of this test, which differ for each model are obtained by use of Table 1 in Kodde and Palm (1986)

Table III.4: Descriptive Statistics on Technical Efficiency Scores *

	FOOD	TEXTILES	CHEMICALS	MACHINERY	POOLED
Observations	324	180	252	396	1152
Cross sections	27	15	21	33	96
Mean	0.56	0.51	0.66	0.57	0.58
Median	0.54	0.50	0.63	0.54	0.54
Maximum	0.97	0.67	1.00	0.99	1.00
Minimum	0.38	0.39	0.41	0.37	0.37
Std. Dev.	0.11	0.06	0.16	0.13	0.13
Skewness	1.51	0.30	0.57	1.35	1.33
Kurtosis	6.02	3.03	2.26	4.73	4.46

* The benchmark model is the stochastic frontier function estimated for the aggregate manufacturing industry

Table III.5: Mean Technical Efficiencies Over Time

	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
Food	0.54	0.53	0.52	0.52	0.52	0.51	0.53	0.55	0.58	0.59	0.61	0.57
Textiles	0.49	0.49	0.50	0.49	0.49	0.49	0.50	0.50	0.52	0.52	0.53	0.51
Chemicals	0.56	0.56	0.57	0.59	0.59	0.59	0.64	0.68	0.74	0.77	0.79	0.69
Machinery	0.50	0.50	0.51	0.49	0.51	0.49	0.51	0.55	0.63	0.66	0.72	0.67
Pooled	0.52	0.52	0.53	0.52	0.53	0.52	0.54	0.57	0.62	0.64	0.67	0.62

CHAPTER IV

TIME PATTERN OF TECHNICAL EFFICIENCY AND TECHNOLOGICAL CHANGE IN TURKISH MANUFACTURING INDUSTRIES

IV.1. Introduction

The aims of the stabilization and structural adjustment program implemented in Turkey following the economic crisis of late 1979 was not restricted to short term concerns like addressing macroeconomic disequilibria in the product, money and foreign exchange markets but also implied a radical departure from old practices of import substituting industrialization policies Turkey had been pursuing for almost 50 years.

The new development philosophy relied on market–oriented policies and an outward oriented export led-growth strategy. Thus, 1980s and early 1990s correspond to a transformation period for the Turkish economy during which trade and capital account liberalization processes were initiated and completed, the significant role of state economic enterprises in economic activity was questioned and the concept of privatization was put into agenda.

Hence, Turkey provides a good example for evaluating the impact of a shift from import substituting industrialization policies to outward oriented ones on the performance of manufacturing industries. We believe that liberalization of foreign trade and capital flows must have altered the incentives for firms, by bringing about (or increasing the role of) concepts like productivity and efficiency in a more liberalized economy.

The primary purpose of this chapter is to study the performance of manufacturing industries focusing on the time pattern of efficiency and rate of technological change during 1983-1994[1]. We use four panel data sets constructed to cover the food, textiles, chemicals and machinery industries as well as a pooled data set that represents the aggregate manufacturing industry. The cross sectional units are subsectors defined at the four-digit International Standard Industrial Classification (ISIC) codes.

We employ both mathematical programming and econometric estimation methods, namely data envelopment analysis (DEA) and stochastic frontier (SF) models, to construct the best practice frontiers in each industry. Then, we compare their results with respect to magnitudes of efficiency scores, efficiency rankings of production units, time pattern of efficiency and calculated rates of technological

[1] We do not attempt to investigate the effect of the structural adjustment program of 1980 on the performance of industries since it would require data from the pre-1980 period which is not available at disaggregated level.

change. Thus, as a secondary contribution, this study provides new information on the performance of two alternative methods for the measurement of technical efficiency and technological change.

The organization of the chapter is as follows: Section 2 overviews the methodologies employed. First, the stochastic production frontier specification due to Battese and Coelli (1992) is presented, followed by a brief discussion of the DEA methodology. Next, DEA based Malmquist productivity indices are illustrated. Section 3 is devoted to a discussion of estimation results from the two alternative approaches followed by a comparison of them. Finally, Section 4 concludes.

IV.2. Methodology

The two pioneering contributions to the literature on the measurement of technical efficiency are the data envelopment analysis (DEA)[2] and the stochastic frontier approaches[3] which employ mathematical programming and econometric estimation techniques respectively.

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[2] DEA was first formulated by Charnes, Cooper, and Rhodes (1978); and subsequently modified by Banker, Charnes, and Cooper (1984) and Byrnes, Färe, and Grosskopf (1984), among others.

[3] The stochastic frontier production was originally specified by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977) independently and extended in various ways regarding both specification and estimation. For a survey of the econometric approach to efficiency analysis, see, Greene (1993).

DEA, the nonparametric deterministic approach to frontier estimation[4], unlike the stochastic frontier analysis, does not require any restrictive assumptions for the functional form of the frontier or distributional assumptions for the inefficiency term. Thus, it is less susceptible to specification errors. However, it is non-stochastic. It attributes random deviations from the frontier to inefficiency. The stochastic frontier approach on the other hand is regarded as a major improvement over DEA due to its ability to make a clear distinction between white noise and inefficiency.[5]

Both of these alternative methodologies were originally specified for cross sectional data but developed rapidly in last fifteen years finding applications on panel data as well.[6] Schmidt and Sickles (1984) pointed out that with panel data, consistent estimates of firm efficiencies can be obtained and the restrictive assumption of cross-sectional models that technical inefficiency is independent of the inputs can be relaxed. Moreover, with recently suggested methods that allow technical efficiency to be time varying, benefits of panel data can be fully utilised.

In the stochastic frontier literature, simultaneous investigation of technical change and the time pattern of efficiency is made possible through the extensions of Cornwell et al. (1990), Kumbhakar (1990), Battese and Coelli (1992) and Lee and Schmidt (1993) to the original SF model.

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[4] Reviews of DEA methodology include Seiford and Thrall (1990), Lovell (1993), Ali and Seiford (1993), Charnes et al.(1994) and Seiford (1996), among others.

[5] The strengths and weaknesses of the DEA and stochastic approaches are reviewed by Fφrsund, Lovell and Schmidt (1980), Bauer (1990), Bjurek, Hjalmarsson and Fφrsund (1990), Seiford and Thrall (1990), Fried, Lovell and Scmidt (1993); among others.

[6] Pitt and Lee (1981), and Schmidt and Sickles (1984) were the first to apply stochastic frontier analysis while Charnes et al. (1985) were the first to apply DEA to panel data.

Within the mathematical programming literature, Färe et al. (1994) broadened the range of applications on panel data by showing how a Malmquist productivity index can be computed by DEA techniques and can be decomposed into two components that measure the rate of technological change and technical efficiency change.

The stochastic frontier analysis performed in this chapter employs the time-varying efficiency model of Battese and Coelli (1992) while the nonparametric analysis utilises constant returns to scale (CRS) and variable returns to scale (VRS) DEA models to compute technical efficiency scores. Nonparametric measures of technical change are obtained through the construction and decomposition of Malmquist productivity indexes as described by Färe et al. (1994). The following subsections are devoted to a brief presentation of these models and approaches.

IV.2.1. A Stochastic Frontier Model with Time-Varying Efficiency

Let Y_{it} and X_{it} be the output and the vector of inputs of firm $i\,(i=1,2,\ldots,N)$ at time $t\,(t=1,2,\ldots,T)$ respectively. Given the production technology $f(\cdot)$ the general stochastic frontier production function for panel data is represented by:

$$\ln(Y_{it}) = \ln f(X_{it}, \beta) + V_{it} - U_{it}, \qquad U_{it} \geq 0 \tag{1}$$

where β is the vector of unknown parameters to be estimated and V_{it} and U_{it} are independent, unobservable random variables.

The Battese and Coelli (1992) specification assumes that V_{it}s, which capture statistical noise are normally distributed with mean zero and variance σ_V^2 and the U_{it}s, non-negative random variables associated with technical inefficiency, are allowed to vary over time as described by the relationship:

$$U_{it} = \{\exp[-\eta(t-T)]\}U_i \qquad i=1,\ldots,N, \quad t=1,\ldots,T \tag{2}$$

Above, η is an unknown parameter to be estimated and U_i, $i=1,2,\ldots,N$, are independent and identically distributed non-negative random variables whose distributions are obtained by a truncation of the normal distribution with unknown mean μ and variance σ_U^2.

Note that in this model, $U_i = U_{iT}$, which implies that technical inefficiencies are modeled as a function of the inefficiency terms for the corresponding units in the last period of the panel. This allows one to decide whether the inefficiency terms decrease, increase or remain constant over time. If $\eta > 0$, one can infer that technical efficiency has increased at a decreasing rate. If $\eta < 0$, it has decreased at an increasing rate, and if $\eta = 0$, it has remained constant.

The stochastic frontier model, using the parametrization of Battese and Corra (1977), is estimated jointly with the parameters of the inefficiency term by maximum likelihood methods[7]. In this parametrization, the variance parameters σ_V^2 and σ_U^2 are replaced with $\sigma^2 = \sigma_V^2 + \sigma_U^2$ and the parameter, γ, is defined as:

[7] The log-likelihood function is presented in Battese and Coelli (1992).

$\gamma = \sigma_U^2 / (\sigma_U^2 + \sigma_V^2)$. And technical efficiency estimates are obtained from $TE_{it} = \exp(-U_{it})$ which is $E[\exp(-U_{it} \mid E_{it})]$, the conditional expectation of $\exp(-U_{it})$ given E_{it}.

Some important hypotheses that can be formulated and tested[8] include the null hypotheses that estimated efficiency scores are time invariant and that they have half-normal distribution which are formulated as $H_0 : \eta = 0$ and $H_0 : \mu = 0$ respectively.

IV.2.2. DEA and the Malmquist Productivity Index

Nonparametric measures of technical efficiencies were obtained through the construction of output-oriented CRS and VRS DEA models. More formally, in a setting with K producing units, each producing single output by using N different inputs; for each period $t, t = 1, \ldots, T$, there are $k = 1, \ldots, K$ observations on inputs, $X^{k,t} = (X_{k,1}^t, \ldots X_{k,N}^t)$ and outputs, Y_k^t.

Technical efficiency score of an observation $k^{0,t}$, relative to a CRS frontier technology is computed by solving the following linear programming (LP) problem

[8] The generalized likelihood-ratio test statistic, λ, is computed from: $\lambda = -2[LLF(H_0) - LLF(H_1)]$ where $LLF(H_0)$ and $LLF(H_1)$ are the log-likelihood values under the null and alternative hypotheses. If H_0 is true, then the distribution of this statistic is Chi-square (or mixed Chi-square). If the null hypothesis involves $\gamma = 0$ then λ is asymptotically distributed as a mixed Chi-square random variable and the critical values are presented in Kodde and Palm (1986).

$$\max \Phi$$

subject to

$$\sum_{k=1}^{K} z_k Y_k^t \geq \Phi Y_{k^0}^t ,$$

$$\sum_{k=1}^{K} z_k X_{k,n}^t \leq X_{k^0,n}^t , \qquad n = 1,2,\ldots,N \text{ inputs} \qquad \text{(LP1)}$$

$$z_k \geq 0 \qquad k = 1,2,\ldots,K \text{ producing units}$$

where z_k is an intensity variable and Φ^{-1} ($1 < \Phi < \infty$) is the proportional increase in outputs that could be achieved with fixed input quantities. Thus, Φ^{-1} which varies between zero and one, provides a measure of the output-based Farrell technical efficiency of observation $k^{0,t}$ relative to the reference technology of the same period. The VRS DEA model is obtained simply by imposing the convexity restriction $\sum_{k=1}^{K} z_k = 1$ to (LP1).

With panel data, the mathematical programming approach provides an index-based procedure for the measurement of technological change. First, an output oriented Malmquist index is constructed as:

$$m_o^{t+1}\left[X^{t+1}, Y^{t+1}, X^t, Y^t\right] = \left[\frac{d_o^t\left(X^{t+1}, Y^{t+1}\right)}{d_o^t\left(X^t, Y^t\right)} \times \frac{d_o^{t+1}\left(X^{t+1}, Y^{t+1}\right)}{d_o^{t+1}\left(X^t, Y^t\right)}\right]^{1/2} \qquad (3)$$

where $d_o^t\left(X^t, Y^t\right)$ and $d_o^{t+1}\left(X^t, Y^t\right)$ are output distance functions[9] in period t defined relative to constant returns to scale technologies prevailing in periods t and $t+1$ respectively. Note that of the four different output distance functions in Eq. (3), $d_o^{t+1}\left(X^t, Y^t\right)$ and $d_o^t\left(X^{t+1}, Y^{t+1}\right)$ are mixed-period functions. The former uses period $t+1$ technology, while the latter uses period t technology in evaluating the data from periods t and $t+1$ respectively.

Next, following the methodology of by Färe et al.(1994) the Malmquist index is decomposed into two components of productivity change as follows:

$$m_o^{t+1}\left[X^{t+1},Y^{t+1},X^t,Y^t\right]=\frac{d_o^{t+1}\left(X^{t+1},Y^{t+1}\right)}{d_o^t\left(X^t,Y^t\right)}\times\left[\frac{d_o^t\left(X^{t+1},Y^{t+1}\right)}{d_o^{t+1}\left(X^{t+1},Y^{t+1}\right)}\times\frac{d_o^t\left(X^t,Y^t\right)}{d_o^{t+1}\left(X^t,Y^t\right)}\right]^{1/2} \quad (4)$$

The first term in Eq. (4) provides a measure of technical efficiency change while the second one measures the rate of technical change between two adjacent time periods.

Regarding the computation of the output distance functions in Eq. (4), four LP problems need to be solved for each observation. The first two, used to calculate $d_o^t\left(X^t,Y^t\right)$ and $d_o^{t+1}\left(X^{t+1},Y^{t+1}\right)$, are identical in structure to (LP1). The maximized value of the objective function in (LP1), i.e. the Farrell output-based technical efficiency of each observation relative to the CRS reference technology of the same period, provides $\left[d_o^t\left(X^t,Y^t\right)\right]^{-1}$. Similarly, $\left[d_o^{t+1}\left(X^{t+1},Y^{t+1}\right)\right]^{-1}$ can be computed by substituting $t+1$ for t in LP1.

Of the two components of the Malmquist index which involve calculation of the technical efficiency of an observation relative to the technology of a different period, $d_0^t\left(X^{k^0,t+1},Y^{k^0,t+1}\right)$ is computed by solving the following LP problem:

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9 $d_o^t\left(X^t,Y^t\right)$ measures the reciprocal of the maximal ray expansion of the observed outputs, Y^t, given inputs, X^t, such that outputs are feasible with the production technology of period t.

$$\left[d_o^t\left(X^{k^0,t+1}, Y^{k^0,t+1}\right)\right]^{-1} = \max \Phi ,$$

subject to

$$\sum_{k=1}^{K} z_k Y_k^t \geq \Phi Y_{k^0}^{t+1} , \qquad \text{(LP2)}$$

$$\sum_{k=1}^{K} z_k X_{k,n}^t \leq X_{k^0,n}^{t+1} ,$$

$$z_k \geq 0$$

Computation of $d_o^{t+1}\left(X^t, Y^t\right)$ is similar to that of $d_o^t\left(X^{t+1}, Y^{t+1}\right)$ and can be performed by interchanging t and $t+1$ in LP2.

IV.3. Empirical Results

In this section, we report the results from the stochastic frontier methodology first, followed by those obtained from the construction of CRS and VRS DEA models and Malmquist productivity indices. Finally, we provide a comparison of the two methodologies with respect to the magnitude of efficiency scores, efficiency ranking of units, time pattern of efficiency and rate of technological change.

IV.3.1. Stochastic Frontier Analysis

Assuming the translog functional form[10] for the frontier technology, we estimate models of the form:

[10] The translog form does not impose prior restrictions on the production structure, unlike the Cobb-Douglas or constant elasticity of substitution (CES) specifications. Moreover, selection of the translog function reduces the possibility that a functional form misspecification could lead to error that is incorrectly taken for technical inefficiency.

$$
\begin{aligned}
\ln(Y_{it}) = {} & \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 \ln(K_{it}) + \beta_4 \ln(E_{it}) + \beta_5 \ln(L_{it}) + \beta_6 \ln(RM_{it}) + \beta_7 \ln(K_{it})^2 \\
& + \beta_8 \ln(E_{it})^2 + \beta_9 \ln(L_{it})^2 + \beta_{10} \ln(RM_{it})^2 + \beta_{11} \ln(K_{it})\ln(E_{it}) + \beta_{12} \ln(K_{it})\ln(L_{it}) \\
& + \beta_{13} \ln(K_{it})\ln(RM_{it}) + \beta_{14} \ln(E_{it})\ln(L_{it}) + \beta_{15} \ln(E_{it})\ln(RM_{it}) + \beta_{16} \ln(L_{it})\ln(RM_{it}) \\
& \beta_{17} \ln(K_{it})t + \beta_{18} \ln(E_{it})t + \beta_{19} \ln(L_{it})t + \beta_{20} \ln(RM_{it}) + V_{it} - U_{it},
\end{aligned}
$$

$$
i = 1,2,\ldots,N, \quad t = 1,2,\ldots,T \qquad (5)
$$

for each industry. Above, Y_{it} is the output of an industry measured at 1987 prices, K_{it} is the capital input measured by the total capacity of power equipment installed at the end of period t, E_{it} is electricity consumption measured in kWh, L_{it} is the labor input (number of hours worked) and RM_{it} is raw material use measured at 1987 prices.

To see whether simpler functional forms are sufficient to model the prevailing technology in each industry, we test for Cobb-Douglas specifications and translog functional forms with Hicks-neutral technical change and without any technical change.

Results presented in rows 2-4 of Table IV.1 show that a translog model with Hicks-neutral technical change is strongly rejected in all industries except for the textiles industry. The remaining two null hypotheses are also rejected in all industries, leading to the conclusion that the assumed translog models appropriately describe the technologies in the food, chemicals, machinery and pooled industries.

We also conduct hypothesis tests on the distributional assumptions imposed on the inefficiency term. These include a test of the null hypothesis that technical inefficiency is time-invariant ($\eta = 0$); a test of the null hypothesis that U_{it} s have half normal distribution ($\mu = 0$) and finally, a joint test of both assumptions ($\eta = \mu = 0$). Based on the relevant test statistics, which are reported in the last three rows of Table IV.1, we fail to reject the null hypothesis that technical inefficiency effects are time-invariant $(H_0 : \eta = 0)$ in the food, textiles and pooled industries.

The null hypothesis that inefficiency effects have half-normal distribution $(H_o : \mu = 0)$ cannot be rejected in the food and pooled industries and the joint test of time invariant technical inefficiency effects and their distribution being half-normal cannot be rejected in the food, textile and pooled industries.

Maximum likelihood estimates of the parameters of the preferred models, i.e. models obtained after imposing the restrictions that could not be rejected through formal hypotheses tests are reported in Table IV.2 together with the calculated input elasticities of production[11] and returns to scale (RTS) for each industry. In all industries, except for the chemicals industry, we observe almost constant returns to scale, values of RTS ranging from 0.95 to 1.00. In the chemicals industry, RTS is approximately equal to 0.85, which implies decreasing returns to scale.

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[11] The elasticity of mean production with respect to the k-th input variable for the translog non-neutral stochastic frontier production function is given by: $\beta_k + 2\beta_{kk} x_{kit} + \sum_{j \neq k} \beta_{kj} x_{jit}$. It is observed from Table 2 that all mean input elasticities of production are positive except for the labor elasticity of production in the chemicals industry which is also statistically insignificant. Among the four input elasticities of production, elasticities of raw material dominate others in all industries.

The estimated value of η is positive in the chemicals industry and negative in the machinery industry. Given the assumption that inefficiency effects change exponentially over time, our findings suggest that technical efficiency increased at a decreasing rate in the chemicals industry and decreased at an increasing rate in the machinery industry during 1983-1994. This leads to the prediction that technical efficiencies of producing units diverged over time in the machinery industry which is supported by the increasing time pattern of the variances of efficiency scores in that industry (See column 12, Table IV.3).

IV.3.2. DEA and the Malmquist Index

CRS and VRS output-oriented DEA frontier with four inputs: capital, labor, raw material and electricity are constructed for the food, textiles, machinery, chemicals and the aggregate manufacturing industries. Average efficiency scores are presented in Table IV.3 and plotted against time in Figures IV.1 to IV.5.

In all industries, the CRS and VRS scores follow the same pattern over time and as expected, the efficiency scores obtained under the CRS assumption are less than those obtained under the VRS assumption.[12]

From Figures IV.1 to IV.5, it is observed that the time pattern of mean technical efficiency differed substantially across industries during 1983-1994. In the food industry, it exhibited a time invariant pattern during the whole period while in the textiles industry, a similar pattern was observed from 1987 onwards, following a sharp increase in technical efficiency from 0.71 in 1983 to 0.93 in 1986. In the chemicals and pooled industries, a U-shaped pattern was observed. Mean technical efficiency declined during the early periods and after remaining time-invariant for up to nearly four periods, it increased from 1989 onwards. In the machinery industry, mean technical efficiency exhibited an upward trend during 1983-1988 while a declining one was observed from 1989 onwards.

To investigate the sources of cumulated productivity change in each industry between 1983-1994, Malmquist productivity indices are computed and decomposed into efficiency change and technological change. The summary results are reported in Table IV.4.[13] It is evident that productivity improved in all industries during 1983-1994 but sources of productivity growth differed substantially across industries.

For the food and machinery industries, recorded cumulative productivity growth rates of 32 and 55 percent are mainly attributable to technological progress. Contribution of improvement in efficiency accounted for only 2.6 percent in the food industry while in the machinery industry, a cumulative 41 percent deterioration in technical efficiency contributed negatively to productivity growth. An opposite case is observed in the chemicals and textiles industries. These industries witnessed technological regress at cumulative rates of approximately 36

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[12] The VRS frontier envelops the data more tightly than the CRS frontier.

[13] For the Malmquist index or any of its multiplicative components, a value greater than one indicates improvement in performance while values smaller than one denote deterioration in performance relative to best practice in each industry.

and 2 percents respectively. However, improvements in efficiency led to cumulative productivity growth rates of 19 and 17 percent between 1983 and 1994.

IV.3.3. Comparison of the Two Approaches

IV.3.3.a. Magnitudes and Time Patterns of Mean Efficiency Scores

Average efficiency scores obtained from the stochastic frontier and DEA approaches presented in Table IV.3 reveal that these two alternative methodologies yield substantially different results in terms of the magnitudes of average efficiency scores. However, results from the CRS DEA frontier are closer to those obtained from the stochastic frontier models. This finding supports the stochastic frontier estimates of RTS which imply almost constant returns to scale in all industries except for the chemicals industry.

Regarding the intertemporal behavior of mean efficiency scores, to test whether the CRS DEA and the stochastic frontier models produced consistent results, we regress the logarithms of CRS DEA efficiency scores on time[14]. Results are presented in Table IV.5. Panel regressions with fixed effects, that allow for cross-section specific constant terms, provide supporting evidence on our findings from the stochastic frontier models of the food, machinery, textiles and pooled industries. The trend variable is insignificant in all sectoral regressions except in

[14] The time-varying technical efficiency model of Battese and Coelli (1992) estimated in logarithmic form specifies inefficiency effects as an exponential function of time. However, the data we use in constructing the CRS and VRS DEA frontiers are not in logarithms. So, while making comparisons on the time pattern of efficiency, we regress the logarithms of obtained efficiency scores on time.

that of the machinery industry, where it attains a negatively signed coefficient indicating a declining trend in technical efficiency.

IV.3.3.b. Consistency of Models in Ranking Industries

One other criterion for comparing the parametric and nonparametric methodologies is the consistency of models in ranking the production units in terms of their efficiency levels. We measure the association between measures of technical efficiency obtained from DEA and stochastic frontier models through Spearman rank correlation coefficients. We calculate them using the mean efficiency measures of production units during two sub-periods, 1983-1988 and 1989-1994 and the whole time span of the study, 1983-1994. Results reported in Table IV.6 show that rank correlation coefficients based on the second period (1989-1993) averages of efficiency scores are noticeably higher than those based on the first period (1983-1988) averages.

During the first sub-period, pairwise rank correlation coefficients between the two mathematical programming models are higher than those between the stochastic frontier and the VRS and CRS DEA models in the food, textiles, and machinery industries. However, in the chemicals and pooled industries, the rank correlations between the stochastic frontier and the CRS DEA models dominate others in magnitude.

During 1989-1994, the stochastic frontier and the CRS DEA models produce highly consistent results in ranking the producing units. Pairwise rank correlation coefficients between the SF and CRS DEA models are higher than those between the two mathematical programming models.

Given the mean efficiency scores for the full period (1983-1994), the rank correlations between the SF and the CRS DEA approach are higher than or equal to those between the two mathematical programming models and substantially higher than those between the stochastic frontier and VRS DEA models in all industries. What is more surprising is that the rank correlations between the two DEA models are lower than those between the stochastic frontier and VRS DEA models in the chemicals, machinery and pooled industries.

Regarding the magnitudes of these coefficients, they are lowest in the chemicals industry; in the range of 15 to 29 percent during 1983-1994; and even lower during 1983-1988. In all other industries, correlations between the stochastic frontier and CRS DEA models range from 61 to 73 percent during 1983-1994; 46 to 54 percent during 1983-1988 and 68 to 75 percent during 1989-1994. The correlations between the stochastic frontier models and the VRS DEA models on the other hand are in the range of 46 to 63 percent during the whole time span of the study.

The magnitudes of rank correlation coefficients between the stochastic and deterministic frontiers in all industries excluding the chemicals industry are close to those obtained by Hjalmarsson, Kumbhakar, and Heshamati (1996) in their study of Colombian cement plants[15] and higher than those reported by Cummins and Zi (1998) in their study of U.S. life insurers.[16]

IV.3.3.c. Rates of Technical Change

Rates of technical change calculated from the parameter estimates of the sectoral stochastic frontier models[17] and those obtained from the decomposition of the DEA based Malmquist indices are reasonably close.

In the food industry, the nonparametric and parametric measures of technical change are 2.3 and 2.5 respectively while the corresponding values for the pooled and machinery industries are 3.7 - 3.1 and 9.7 - 7.1 respectively. In the chemicals industry, the stochastic frontier estimates of technical change is both statistically insignificant and close to zero while the nonparametric estimate is –3.9 percent. In the textiles industry, findings from the stochastic frontier imply technical progress at a rate of 1.8 percent per annum while the nonparametric estimates suggest no technical progress, or even technical regress at a rate of –0.2 percent per annum.

Regarding the ranking of the industries in terms of average rates of technical change, the two approaches produced equivalent results. The machinery

[15] Hjalmarsson et al. (1996) report correlations ranging from 50 to 75 percent between the efficiency scores obtained from DEA and stochastic frontier models

[16] Cummins and Zi (1998) report rank correlations between mathematical programming and econometric models ranging from 50 to 52 percent

industry is ranked first, followed by the pooled, food, textiles and chemicals industries.

IV.4. Conclusions

In this study, we applied both parametric stochastic and nonparametric deterministic methodologies to estimate technical efficiency and technological change in Turkish manufacturing industries during the period 1983-1994. Industries covered in our analysis were the food, textiles, chemicals, machinery and the aggregate manufacturing industry, the cross sectional units being subsectors defined at four digits according to ISIC.

The parametric stochastic methodology involved econometric estimation of technical efficiencies and rates of technological change through the construction of stochastic frontier production functions that allow technical inefficiency to be time varying. The deterministic nonparametric analysis on the other hand involved estimation of CRS and VRS output-based DEA models which provided two sets of efficiency scores for each producing unit. To obtain nonparametric measures of technological change, we constructed Malmquist productivity indices and then decomposed them into efficiency change and technological change as proposed by Färe et al.(1994).

[17] Given the estimated parameters of the stochastic frontier production functions, the rate of technical change is obtained as the logarithmic derivative of the production function with respect to time.

The two alternative approaches yielded substantially different results in terms of the magnitudes of estimated average efficiency scores but in all sectoral models, results of the CRS DEA frontier were close to those of the stochastic frontier models.

Regarding the time pattern of average efficiency scores, the stochastic frontier methodology implied that mean technical efficiency remained time-invariant in the food, textiles and pooled industries while it exhibited a declining pattern in the machinery and an increasing one in the chemicals industries during 1983-1994. These findings were largely supported by statistical evidence obtained from panel regressions of nonparametric estimates of technical efficiency scores on time. The trend variable was found insignificant in all sectoral regressions except for that of the machinery industry, in which it assumed a negatively signed coefficient.

Another criterion used for evaluating the performance of the two alternative methodologies was the consistency of models in ranking industries in terms of estimated efficiency scores. Given the full period (1983-1994) average efficiency scores, rank correlations between the stochastic frontier methodology and the CRS DEA approach were the highest among the three set of pairwise rank correlation coefficients. They exceeded not only those between the stochastic frontier and VRS DEA models but also those between the two DEA models.

Finally, the two approaches yielded reasonably close estimates of average rates of technical change in the food, machinery and pooled industries and produced equivalent results in ranking the industries in terms of average rates of technical change. The machinery industry was ranked first, followed by the pooled, food, textiles and chemicals industries.

Table IV.1: Generalized Likelihood Ratio Tests

Null Hypothesis	Log-likelihood Value	Test Statistic, λ (a)	Critical Value (5%)
None			
Food	84.73		
Textiles	131.71		
Chemicals	17.67		
Machinery	-19.467		
Pool	-51.75		
Hicks-Neutral technical change, $H_0 : \beta_{17} = \beta_{18} = \beta_{19} = \beta_{20} = 0$			
Food	74.76	19.95*	9.49
Textiles	128.37	6.67	9.49
Chemicals	11.91	11.53*	9.49
Machinery	-35.34	31.75*	9.49
Pool	-67.91	32.33*	9.49
No technical change, $H_0 : \beta_1 = \beta_2 = \beta_{17} = \beta_{18} = \beta_{19} = \beta_{20} = 0$			
Food	74.37	20.73*	12.59
Textiles	122.13	19.15*	12.59
Chemicals	5.97	23.41*	12.59
Machinery	-63.04	87.14*	12.59
Pool	-76.97	50.44*	12.59
Cobb-Douglas, $H_0 : \beta_2 = \beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = \beta_{12} = \beta_{13} = \beta_{14} = \beta_{15} = \beta_{16} = \beta_{17} = \beta_{18} = \beta_{19} = \beta_{20} = 0$			
Food	41.09	87.27*	24.99
Textiles	105.53	52.37*	24.99
Chemicals	-50.03	135.41*	24.99
Machinery	-69.72	100.50*	24.99
Pool	-126.90	150.30*	24.99
OLS, $H_0 : \gamma = \mu = \eta = 0$			
Food	-84.48	338.41*	7.81
Textiles	94.81	67.12*	7.81
Chemicals	-65.89	167.11*	7.81
Machinery	-51.82	64.70*	7.81
Pool	-348.99	594.49*	7.81
Inefficiency effects have half normal distribution, $H_0 : \mu = 0$			
Food	82.99	3.48	3.84
Textiles	125.98	4.79*	3.84
Chemicals	12.66	10.03*	3.84
Machinery	-23.24	7.54*	3.84
Pool	-51.74	-0.02	3.84
Time-invariant inefficiency, $H_0 : \eta = 0$			
Food	83.69	2.07	3.84
Textiles	128.09	0.56	3.84
Chemicals	-4.29	43.92*	3.84
Machinery	-27.20	15.46*	3.84
Pool	-51.76	0.03	3.84
Inefficiency effects are time invariant and have half normal distribution , $H_0 : \mu = \eta = 0$			
Food	81.95	5.56	5.99
Textiles	125.80	5.16	5.99
Chemicals	3.62	28.10*	5.99
Machinery	-30.87	22.80*	5.99
Pool	-51.760	0.03	5.99

NOTES: (a) In all sectoral models except for that of the textiles industry, the null hypotheses on μ and η are tested against the unrestricted translog functional form which cannot be rejected through the first three restrictions. For the textiles industry, the null hypotheses are tested against the Hicks-neutral translog functional form that cannot be rejected.
* indicates rejection of the null hypothesis

Table IV.2: Maximum Likelihood Estimates of the Parameters of the Stochastic Frontier Models, Input Elasticities of Production, Rates of Technological Change and Returns to Scale

A. Parameter estimates of the stochastic frontier models

		FOOD		TEXTILES		CHEMICALS		MACH		POOLED	
Variable	**Parameter**	**Coeff.**	**t-ratio**	**Coeff.**	**t-ratio**	**Coeff.**	**t-ratio**	**Coeff.**	**t-ratio**	**Coeff**	**t-ratio**
Constant	β_0	0.44	5.87	0.44	4.61	0.78	3.66	0.26	2.54	0.13	2.50
T	β_1	0.04	3.12	-0.01	-0.98	0.06	2.33	-0.06	-2.94	0.02	2.31
t^2	β_2	0.00	-0.94	0.00	2.62	-0.01	-3.23	0.01	5.86	0.00	1.41
K	β_3	0.07	1.64	0.09	2.06	-0.04	-0.35	0.11	1.52	0.07	2.06
E	β_4	-0.10	-1.79	0.20	4.24	0.14	1.46	-0.07	-1.02	-0.01	-0.24
L	β_5	0.22	3.86	0.07	1.67	-0.12	-0.80	0.03	0.23	0.10	2.53
RM	β_6	0.71	12.93	0.63	12.27	0.79	10.08	0.96	16.93	0.76	25.07
K^2	β_7	-0.04	-2.36	-0.02	-0.65	-0.05	-0.76	-0.01	-0.37	0.00	0.06
E^2	β_8	-0.10	-4.25	-0.01	-0.55	-0.02	-0.56	-0.06	-3.22	-0.02	-1.73
L^2	β_9	0.15	5.46	0.08	3.47	-0.09	-1.11	-0.12	-1.99	0.08	4.70
RM^2	β_{10}	0.09	5.21	0.04	2.00	0.19	7.92	0.07	4.97	0.09	11.51
KxE	β_{11}	0.08	2.18	0.08	2.15	0.05	0.65	0.05	1.02	0.06	3.16
KxL	β_{12}	-0.03	-0.80	-0.12	-1.73	0.08	0.89	-0.05	-0.97	-0.06	-2.41
KxRM	β_{13}	0.03	0.92	0.04	0.86	0.00	0.02	0.00	0.15	-0.01	-0.47
ExL	β_{14}	0.04	1.37	0.04	0.71	0.21	2.71	0.21	2.86	0.03	1.01
ExRM	β_{15}	0.02	0.86	-0.03	-0.62	-0.22	-4.87	-0.04	-1.25	-0.06	-3.71
LxRM	β_{16}	-0.24	-6.35	-0.12	-4.31	-0.17	-2.21	-0.10	-2.57	-0.12	-6.79
Kxt	β_{17}	-0.01	-1.14	-		0.02	1.28	-0.01	-1.31	0.00	0.76
Ext	β_{18}	0.02	3.14	-		-0.01	-0.98	0.03	2.85	0.01	3.12
Lxt	β_{19}	0.01	1.24	-		-0.01	-0.48	0.00	-0.14	0.00	0.07
RMxt	β_{20}	-0.01	-1.90	-		0.01	1.22	-0.02	-5.09	-0.01	-4.11
μ		0.00 (Restr.)		0.35	5.00	0.645	4.38	0.58	4.29	0.00 (Restr.)	
η		0.00 (Restr.)		0.00 (Restr.)		0.06	5.50	-0.16	-3.99	0.00 (Restr.)	
Variance Parameters											
σ^2		0.38	4.60	0.04	6.64	0.14	4.36	0.14	8.80	0.23	9.12
$\gamma = \sigma_u^2 / \left(\sigma_u^2 + \sigma_v^2\right)$		0.95	70.88	0.75	13.05	0.75	15.74	0.61	9.43	0.80	34.68
Log-likelihood		81.95		128.09		17.67		-19.47		-51.76	

B. Input elasticities of production, returns to scale and rates of technological change

	FOOD		TEXTILES		CHEMICALS		MACH.		POOLED	
	Value	**t-ratio**	**Value**	**t-ratio**	**Value**	**t-ratio**	**Value**	**t-ratio**	**Value**	**t-ratio**
Input elasticities of production										
Capital elasticity	0.03	0.94	0.09	2.06	0.07	0.88	0.05	0.97	0.08	3.46
Electricity elasticity	0.003	0.08	0.20	4.24	0.09	1.26	0.10	2.37	0.06	2.59
Labor elasticity	0.26	4.53	0.07	1.67	-0.15	-1.45	0.02	0.18	0.10	3.13
Raw material elasticity	0.66	13.17	0.63	12.27	0.84	12.06	0.81	18.05	0.70	26.50
Returns to Scale	0.96		1.00		0.85		0.98		0.94	
Technological change	2.47	5.48	1.82	5.49	-0.82	-0.67	7.06	5.33	3.20	40.42

Table IV.3: Mean efficiency values and standard deviations of efficiency scores across producing units by year.

	FOOD			TEXTILES			CHEMICALS			MACHINERY			POOLED		
	DEA VRS	DEA CRS	SFA	DEA VRS	DEA CRS	SFA	DEA VRS	DEA CRS	SFA	DEA VRS	DEA CRS	SFA	DEA VRS	DEA CRS	SFA
1983															
Mean	0.74	0.55	0.54	0.83	0.71	0.68	0.63	0.45	0.27	0.78	0.68	0.90	0.57	0.44	0.70
Std. Dev.	0.23	0.26	0.19	0.19	0.19	0.13	0.21	0.24	0.19	0.20	0.22	0.04	0.23	0.23	0.13
1984															
Mean	0.78	0.58	0.54	0.90	0.85	0.68	0.81	0.59	0.29	0.77	0.69	0.88	0.62	0.46	0.70
Std. Dev.	0.21	0.25	0.19	0.10	0.12	0.13	0.15	0.21	0.18	0.20	0.20	0.05	0.22	0.22	0.13
1985															
Mean	0.65	0.47	0.54	0.92	0.87	0.68	0.43	0.25	0.31	0.81	0.72	0.86	0.36	0.25	0.70
Std. Dev.	0.27	0.27	0.19	0.10	0.13	0.13	0.24	0.21	0.18	0.17	0.18	0.05	0.25	0.20	0.13
1986															
Mean	0.75	0.58	0.54	0.95	0.93	0.68	0.37	0.19	0.33	0.85	0.68	0.84	0.30	0.17	0.70
Std. Dev.	0.21	0.26	0.19	0.09	0.09	0.13	0.27	0.22	0.18	0.16	0.17	0.06	0.25	0.17	0.13
1987															
Mean	0.71	0.55	0.54	0.96	0.89	0.68	0.32	0.19	0.35	0.87	0.70	0.82	0.28	0.18	0.70
Std. Dev.	0.24	0.26	0.19	0.07	0.09	0.13	0.28	0.19	0.18	0.15	0.19	0.07	0.26	0.14	0.13
1988															
Mean	0.72	0.56	0.54	0.95	0.90	0.68	0.33	0.20	0.37	0.91	0.87	0.79	0.29	0.19	0.70
Std. Dev.	0.24	0.25	0.19	0.07	0.10	0.13	0.28	0.19	0.17	0.10	0.12	0.08	0.24	0.14	0.13
1989															
Mean	0.68	0.52	0.54	0.97	0.92	0.68	0.29	0.18	0.39	0.90	0.84	0.76	0.25	0.17	0.70
Std. Dev.	0.25	0.25	0.19	0.07	0.10	0.13	0.29	0.19	0.17	0.12	0.13	0.09	0.23	0.12	0.13
1990															
Mean	0.75	0.62	0.54	0.93	0.84	0.68	0.31	0.17	0.41	0.83	0.77	0.72	0.27	0.17	0.70
Std. Dev.	0.21	0.21	0.19	0.14	0.18	0.13	0.29	0.19	0.17	0.14	0.14	0.10	0.27	0.12	0.13
1991															
Mean	0.69	0.43	0.54	0.96	0.91	0.68	0.52	0.31	0.43	0.84	0.81	0.68	0.40	0.28	0.70
Std. Dev.	0.25	0.27	0.19	0.08	0.11	0.13	0.28	0.20	0.16	0.15	0.14	0.12	0.25	0.18	0.13
1992															
Mean	0.70	0.50	0.54	0.96	0.90	0.68	0.58	0.34	0.45	0.73	0.52	0.64	0.47	0.32	0.70
Std. Dev.	0.24	0.26	0.19	0.08	0.11	0.13	0.26	0.24	0.16	0.25	0.24	0.13	0.26	0.22	0.13
1993															
Mean	0.77	0.55	0.54	0.97	0.93	0.68	0.85	0.82	0.47	0.81	0.66	0.59	0.61	0.53	0.70
Std. Dev.	0.21	0.25	0.19	0.05	0.10	0.13	0.16	0.17	0.16	0.19	0.20	0.14	0.23	0.22	0.13
1994															
Mean	0.78	0.57	0.54	0.92	0.87	0.68	0.87	0.82	0.49	0.69	0.40	0.54	0.55	0.36	0.70
Std. Dev.	0.22	0.26	0.19	0.11	0.14	0.13	0.12	0.15	0.15	0.23	0.22	0.15	0.25	0.21	0.13

Table IV.4: Malmquist Index Summary - Cumulated Productivity 1983-1994

	Efficiency Change	Technological Change	Productivity Change (Malmquist Index)
FOOD	1.0267	1.2904	1.3239
TEXTILES	1.2195	0.9801	1.1955
CHEMICALS	1.8169	0.6453	1.1692
MACHINERY	0.5954	2.6007	1.5504
POOLED	0.8193	1.4932	1.2232

Table IV.5: Results from Panel Regressions of CRS DEA Technical Efficiency Scores on Time.

Panel Regressions (Fixed Effects)
Method: GLS (Cross Section Weights. iterated to convergence)
Dependent Variable: Log(Technical Efficiency)

	FOOD		TEXTILES		CHEMICALS		MACHINERY		POOLED	
	Coefficient	**t-stat**	**Coefficient**	**t-stat.**	**Coefficient**	**t-stat.**	**Coefficient**	**t-stat.**	**Coefficient**	**t-stat.**
Time	0.0000	0.0004	0.0000	0.0086	0.000	0.001	-0.013	-4.769	0.006	1.510

Table IV.6: Rank Correlation Coefficients Between Models

	1983-94			1983-88			1989-94		
	CRS-DEA	**VRS-DEA**	**SFA**	**CRS-DEA**	**VRS-DEA**	**SFA**	**CRS-DEA**	**VRS-DEA**	**SFA**
FOOD-31									
CRS-DEA	1.00			1.00			1.00		
VRS-DEA	0.74	1.00		0.77	1.00		0.68	1.00	
SFA	0.61	0.50	1.00	0.52	0.37	1.00	0.75	0.59	1.00
TEXTILES-32									
CRS-DEA	1.00			1.00			1.00		
VRS-DEA	0.75	1.00		0.81	1.00		0.63	1.00	
SFA	0.73	0.46	1.00	0.61	0.31	1.00	0.70	0.45	1.00
CHEMICALS-35									
CRS-DEA	1.00			1.00			1.00		
VRS-DEA	0.15	1.00		0.06	1.00		0.34	1.00	
SFA	0.29	0.24	1.00	0.17	0.04	1.00	0.34	0.30	1.00
MACHINERY-38									
CRS-DEA	1.00			1.00			1.00		
VRS-DEA	0.63	1.00		0.61	1.00		0.71	1.00	
SFA	0.74	0.63	1.00	0.46	0.29	1.00	0.72	0.66	1.00
POOLED									
CRS-DEA	1.00			1.00			1.00		
VRS-DEA	0.54	1.00		0.52	1.00		0.69	1.00	
SFA	0.66	0.52	1.00	0.54	0.42	1.00	0.68	0.60	1.00

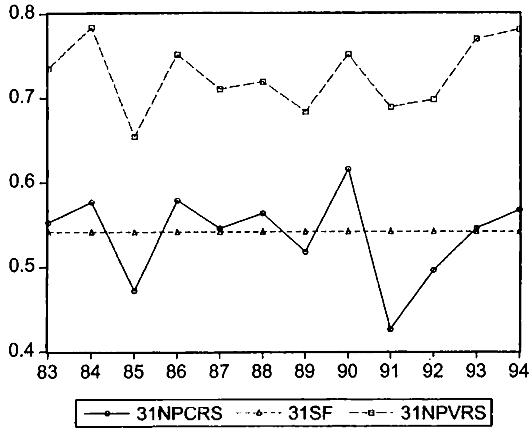

Figure IV.1: Mean Efficiency Scores in the Food Industry – SF and DEA Models

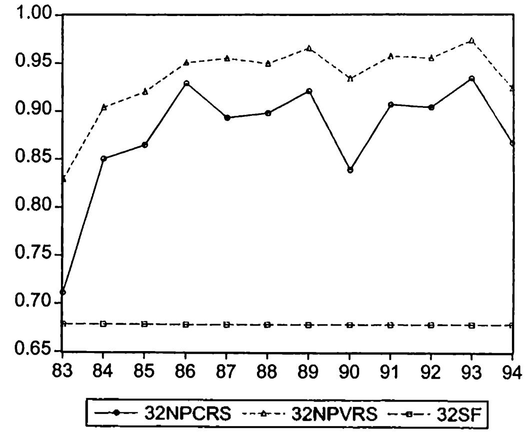

Figure IV.2: Mean Efficiency Scores in the Textiles Industry – SF and DEA Models

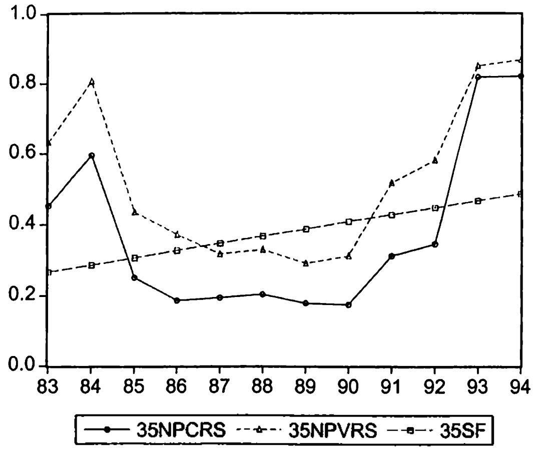

Figure IV.3: Mean Efficiency Scores in the Chemicals Industry – SF and DEA Models

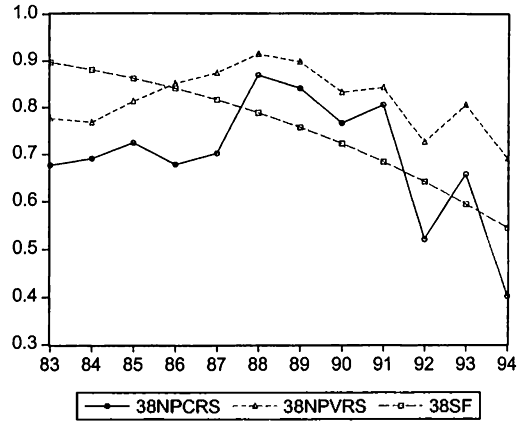

Figure IV.4: Mean Efficiency Scores in the Machinery Industry – SF and DEA Models

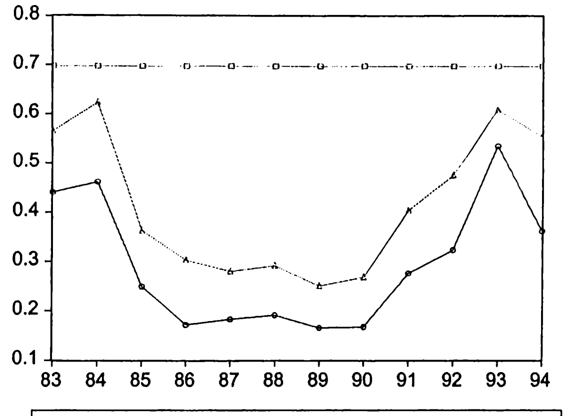

Figure IV.5: Mean Efficiency Scores in the Pooled Industry – SF and DEA Models

CHAPTER V

A COMPARISON OF COMPETING TECHNIQUES FOR FRONTIER ESTIMATION USING PANEL DATA: AN APPLICATION TO TURKISH MANUFACTURING INDUSTRY

V.1. Introduction

The parametric (econometric) and the nonparametric (mathematical programming) approaches are two main alternative methodologies for constructing production frontiers. The former specifies the best-practice technology as an explicit function with constant parameters and generally requires distributional assumptions about the error term(s). Parametric estimation methods include the deterministic approach of Aigner and Chu (1968), the corrected ordinary least squares (COLS) method of Richmond (1974), the shifted ordinary least squares (OLS) methods by Gabrielsen (1975) and Greene (1980) and the most widely used stochastic frontier (SF) method introduced independently by Meeusen and Broeck (1977) and Aigner et al (1977). Stochastic frontier analysis has the advantage of accommodating for both random noise and inefficiency through the incorporation of an additive composed error term to the frontier model. Thus the stochastic frontier model can disentangle inefficiency from white noise.

The nonparametric approach dating back to Farrell (1957) does not require any explicit functional form for the frontier technology and thus, avoids possible errors that might result from functional form misspecification. However, like the parametric approach of Aigner and Chu (1968) it is deterministic.[1] Since inefficiency is measured by the magnitude of the one-sided deviation of observed output from the estimated best-practice frontier, any deviation from the frontier is reported as inefficiency. The most widely used nonparametric technique, data envelopment analysis (DEA) (see, for example, Charnes, Cooper and Rhodes, 1978 and Färe, Grosskopf and Lovell, 1985), employs linear programming techniques to envelop the observed data as tightly as possible with the assumptions of a convex production possibility set[2] and free disposability of outputs and inputs.

Given the strengths and weaknesses of the nonparametric and parametric approaches and two alternative practices for the treatment of the error terms, deterministic versus stochastic, one naturally seeks a method that possesses the virtues of both approaches: flexibility in functional form and ability to account for random noise. A recent semiparametric methodology introduced by Kneip and Simar (1996) addresses this need. The frontier model with a composite error term is estimated without imposing any a priori parametric functional form on the

[1] In recent years some papers have investigated the statistical properties of DEA and FDH estimators. Proofs of the statistical consistency of FDH is provided by Korostelev, Simar, and Tsybakov (1995a); of DEA is provided by Banker (1993) and of DEA and FDH by Korostelev, Simar and Tsybakov (1995b).

[2] The more recent free disposable hull technique (see Deprins, Simar and Tulkens, 1984) allows for nonconvexities in the production possibilities set.

production function or any distributional assumptions on the disturbance and inefficiency terms. The benchmark technology is estimated by a nonparametric kernel estimator while inefficiencies are obtained using a parametric procedure that requires no distributional assumptions on error terms.

Hundreds of applications in the efficiency literature dealt with either DEA or SF methods. However, to our knowledge, the semiparametric method of Kneip and Simar (1996) has not attracted the attention of empirical researchers much. Consequently, there exists no empirical work that compares the parametric, nonparametric and semiparametric methodologies used in efficiency analysis. The primary purpose of this chapter is to fill this gap. We apply these three approaches to evaluate the technical efficiency of producing units in the Turkish manufacturing industry with a rich panel data set spanning the period 1983-1994 with cross-sectional units defined as four-digit industries according to the ISIC.

With panel data, one has to consider two more issues: whether the assumption of time-invariant technical inefficiency inherent in most nonparametric and parametric models is valid and whether the production frontier shifts during the observation period, i.e. whether technical change occurs. When technological change is not adequately controlled for or when there is no strong argument for the assumption of time-invariant inefficiency, measures of technical efficiency and statistical inferences about them might be wrong or misleading.

Therefore, in this study, we also explore the sensitivity of efficiency estimates to changes in the assumptions on the time pattern of inefficiency and allowance for technical change. We compare parametric, nonparametric and semiparametric models that differ in their assumptions regarding the time pattern of technical efficiency and technical progress. Our comparison criteria are the magnitudes and time patterns of estimated efficiency scores and consistency of models in ranking industries in terms of estimated average efficiency scores.

Within the parametric frontier methodology, we consider two approaches that produce point estimates of efficiency. The first one is the stochastic frontier model estimated by maximum likelihood (ML) techniques. It embodies a composed error term with a random part that follows a symmetric distribution and an inefficiency term that is assumed to have an asymmetric distribution. The second parametric approach is the "distribution free" (DF) method of Schmidt and Sickles (1984) proposed for panel data with time-invariant inefficiency. We also consider its extensions by Cornwell et al. (1990) and Lee and Schmidt (1993) that allow for time-varying efficiency. The distribution free approach does not require any assumptions regarding the probability distributions of the inefficiencies or the random errors but only imposes the usual nonnegativity restrictions on inefficiencies.

Our nonparametric analysis is based on the estimation of DEA models under both constant and variable returns to scale assumptions while the semi parametric methodology is adopted from Kneip and Simar (1996).

The paper is organized as follows: In Section 2, we present the methodologies that are employed to construct technical efficiency indices. In

Section 3, we provide model specifications and empirical results. Section 4, is devoted to a comparison of methodologies and finally, Section 5 concludes.

V.2. Methodology

V.2.1. Nonparametric DEA Models

Mathematical programming models utilized in solving DEA models are formulated in a setting with K producing units, each producing single output by using N different inputs. For each period $t, t = 1, \ldots, T$, there are $k = 1, \ldots, K$ observations on inputs, $X^{k,t} = \left(X_{k,1}^{t}, \ldots X_{k,N}^{t}\right)$ and outputs, Y_k^t. Technical efficiency score of an observation $k^{0,t}$, relative to a CRS frontier technology is computed by solving the following linear programming (LP) problem

$$
\begin{aligned}
&\max \Phi \\
&\text{subject to} \\
&\sum_{k=1}^{K} z_k Y_k^t \geq \Phi Y_{k^0}^t , \\
&\sum_{k=1}^{K} z_k X_{k,n}^t \leq X_{k^0,n}^t , && n = 1,2,\ldots,N \text{ inputs} && \text{(LP1)} \\
&z_k \geq 0 && k = 1,2,\ldots,K \text{ producing units}
\end{aligned}
$$

where z_k is an intensity variable and Φ^{-1} ($1 < \Phi < \infty$) is the proportional increase in outputs that could be achieved with fixed input quantities. Thus Φ^{-1}, which varies between zero and one, provides a measure of the output-based Farrell technical efficiency of observation $k^{0,t}$ relative to the reference technology of the same period. The VRS DEA model is an extension of the CRS model obtained simply by imposing the convexity restriction $\sum_{k=1}^{K} z_k = 1$ to (LP1).

There is no common agreement on how to handle panel data within the framework of DEA but there are a couple of alternatives. We have utilized two different methodologies to obtain nonparametric DEA measures of technical efficiency. The first one computes the full period average efficiency scores based on the estimation of year-by-year frontiers. A separate frontier is estimated for each year in the panel. In the second methodology, we construct sequential frontiers. For a given year t, all observations generated up to that year are pooled and DEA programs are run which provides T sets of technical efficiency scores. The j^{th} set, resulting from the j^{th} sequential run produces $N \times j$ efficiency scores. Thus for period t, one has $T+1-t$ scores for each firm, and average of these scores provide the technical efficiency of each firm in period t.

V.2.2. Parametric Production Frontier Models

V.2.2.a. The Stochastic Frontier Model

The stochastic frontier model specified for panel data is given by:

$$\ln(Y_{it}) = \ln f(X_{it}, \beta) + E_{it} \tag{1}$$

where Y_{it} is the real output of firm i $(i = 1,2,\ldots,N)$ at time t $(t = 1,2,\ldots,T)$; $f(.)$ is the production technology; X is a vector of inputs; β is the vector of unknown parameters to be estimated and finally E_{it} is the composed error term:

$$E_{it} = V_{it} - U_{it}, \quad U_{it} \geq 0, \qquad (2)$$

Here, V_{it} and U_{it} are independent, unobservable random errors. They represent the stochastic and inefficiency terms respectively. Assuming a symmetric distribution[3] for the V_{it}s and an asymmetric one [4] for the non-negative U_{it}s, Eq. (1) can be estimated by ML methods. In this study, we employ the ML estimation procedure proposed by Battese and Coelli (1988; 1992) to obtain both time-invariant and time varying estimates of technical efficiency. Thus, we assume U_{it}s to be normally distributed random variables with unknown mean μ and variance σ_U^2 ($N(\mu, \sigma^2)$); truncated at zero and define them as follows:

$$U_{it} = \{\exp[-\eta(t-T)]\}U_i \qquad i = 1, \ldots, N, \quad t = 1, \ldots, T \qquad (3)$$

where η is an unknown parameter to be estimated and $U_i = U_{iT}$. Technical inefficiency of a production unit at time t is modeled as a function of the inefficiency level of the corresponding unit in the last period of the panel. If the estimated value of η is positive, one can infer that technical efficiency has increased at a decreasing rate. If its is negative, it has decreased at an increasing rate, and if $\eta = 0$, it has remained constant. In the last case, when $\eta = 0$, the SF model specification reduces to the common time-invariant technical inefficiency model. The Battese and Coelli (1992) framework provides the advantage of

---

[3] V_{it} s are typically assumed to be normally distributed with mean zero and variance σ_V^2.

[4] Theory provides little guidance on selecting a distribution for U_{it} s (Schmidt and Lovell, 1979 and Lee, 1983). However, researchers have generally picked the half-normal (Aigner, Lovell, and Schmidt, 1977), exponential (Aigner, Lovell, and Schmidt, 1977; Meeusen and van den Broeck, 1977) or gamma distributions.

conducting formal tests on the assumption of time invariance among several other hypotheses[5] through the use of generalized likelihood ratio tests.[6]

Furthermore, both the parameters of the stochastic frontier model and those of the inefficiency terms can be estimated simultaneously by ML methods[7] using the parametrization of Battese and Corra (1977). They define the parameters $\sigma^2 = \sigma_V^2 + \sigma_U^2$ and $\gamma = \sigma_U^2 / (\sigma_U^2 + \sigma_V^2)$ and use them instead of original variance parameters σ_V^2 and σ_U^2.

Technical efficiency for each observation is obtained as $TE_{it} = \exp(-U_{it})$ which is $E[\exp(-U_{it} \mid E_{it})]$, the conditional expectation of $\exp(-U_{it})$ given E_{it}.

V.2.2.b. The Distribution Free Method

The distribution free method of Schmidt and Sickles (1984) is an alternative methodology applicable to panel data. A functional form is specified for the frontier but unlike ML estimation, no distributional assumptions are required for the inefficiency or random error terms. The model is given by:

---

[5] The null hypotheses that estimated efficiency scores have half-normal distribution can be formulated as $H_0 : \mu = 0$

[6] The generalized likelihood-ratio test statistic, λ, is computed from: $\lambda = -2[LLF(H_0) - LLF(H_1)]$ where $LLF(H_0)$ and $LLF(H_1)$ are the log-likelihood values under the null and alternative hypotheses. If H_0 is true, then the distribution of this statistic is Chi-square (or mixed Chi-square). If the null hypothesis involves $\gamma = 0$ then λ is asymptotically distributed as a mixed Chi-square random variable and the critical values are presented in Kodde and Palm (1986).

[7] The log-likelihood function is presented in Battese and Coelli (1992).

$$y_{it} = \alpha + x_{it}'\beta + v_{it} - u_i, \qquad u_i \geq 0 \;\; i = 1,\ldots,N, \quad t = 1,\ldots,T. \tag{4}$$

or equivalently:

$$y_{it} = \alpha_i + x_{it}'\beta + v_{it},$$

$$\alpha_i = \alpha - u_i \tag{5}$$

where y_{it} is the logarithm of real output, x_{it} is a vector inputs, v_{it} is statistical noise and $u_i \geq 0$ is the firm effect representing technical inefficiency. The parameters of the frontier model (β) can be estimated by fixed effects (dummy variable), GLS or Hausman and Taylor instrumental variables estimation methods. With the fixed effects approach, the assumption that technical inefficiency is independent from the explanatory variables can also be relaxed. However, this practical method has a drawback. It assumes time-invariant technical inefficiency, which might give rise to misleading results if inefficiency is not constant over time. Fortunately, as will be discussed later, Cornwell, Schmidt and Sickles (1990) and Lee and Schmidt (1993) extended the distribution free approach to account for time-varying inefficiencies.

Now, turning to the estimation of technical efficiencies, once Eq (4) is estimated, the residuals ($y_{it} - X_{it}'\beta$) provide an estimate of $v_{it} - u_i$ and the firm effects are calculated by averaging these residuals over time. Specifically, the estimate of α_i is

$$\hat{\alpha}_i = \bar{y}_i - \bar{x}_i\hat{\beta}$$

and is consistent as $T \to \infty$.

The frontier intercept α and firm specific level of inefficiencies are given by $\hat{\alpha} = \max_j(\hat{\alpha}_j)$ and $\hat{u}_i = \hat{\alpha} - \hat{\alpha}_i$ respectively. Technical efficiency for the i^{th} firm is computed by:

$$TE_i = \exp(-u_i) = \frac{\exp\hat{\alpha}_i}{\max(\exp\hat{\alpha}_i)}$$

The procedure provided by Cornwell, Schmidt and Sickles (1990) and Lee and Schmidt (1993) that accounts for time varying efficiency is similar to the Schmidt and Sickles (1984) model. The frontier model given in Eq (4) can be put in the form:

$$y_{it} = X_{it}\beta + W_{it}\delta_i + \varepsilon_{it} \qquad (6)$$

$$\delta_i = \delta_0 + u_i \qquad (7)$$

where y_{it}, X_{it} and β are as defined before, and W'_{it} is a vector of firm-specific explanatory variables and u_i is a random vector with zero-mean with covariance matrix Λ. Note that when W_i is constant, this model reduces to the Schmidt and Sickles (1984) model.

We consider two alternative treatments for the time-path of efficiency. When $W_{it}\delta_i = \alpha_{it} = \delta_{i1} + \delta_{i2}t$, technical efficiency is specified to follow a linear trend and when $W_{it}\delta_i = \alpha_{it} = \delta_{i1} + \delta_{i2}t + \delta_{i3}t^2$, it is allowed to behave more freely, allowing for a quadratic trend. The procedure used to estimate technical efficiency scores is analogous to the one used by Schmidt and Sickles (1984). The residuals $(y_{it} - X'_{it})$ from Eq.(4) are regressed on a constant, time (and time-squared). The fitted values from this regression provide an estimate of α_{it}. The frontier intercept of firm i in period t is obtained from

$\hat{\alpha}_t = \max_j (\hat{\alpha}_{jt})$

and

$\hat{u}_{it} = \alpha_t - \hat{\alpha}_{it}$

Technical efficiency of firm i in period t is calculated as: $TE_{it} = \exp(-\hat{u}_{it})$.

For firm i, productivity growth at time t is the time derivative of $\hat{\alpha}_{it}$. However, identification of changes in technical efficiency and technical change requires distributional assumptions regarding the inefficiency terms. Thus, the distribution free method does not permit a satisfactory analysis or decomposition of efficiency change and technical change.

V.2.3. The Semiparametric Model

The semiparametric framework suggested by Kneip and Simar (1996) assumes the same technology for each productive unit but allows for firm-specific location effects α_i. The model of interest is given by:

$$y_{it} = h(x) + \alpha_i + \varepsilon_{it} \tag{8}$$

where h represents a general production function and α_is are individual firm effects with the identifiability condition that the general production technology is the mean of firm specific technologies i.e. $E(\alpha_i) = 0$

In this setup, the common production function is estimated by a nonparametric kernel estimator[8] of the Nadaraya-Watson type using all the N.T observations[9]. The estimator is given by:

$$\hat{h}(x) = \frac{\sum_{i=1}^{N}\sum_{t=1}^{T} K\left(b^{-1} * (x - x_{it})\right) y_{it}}{\sum_{i=1}^{N}\sum_{t=1}^{T} K\left(b^{-1} * (x - x_{it})\right)} \tag{9}$$

Here, K determines the shape of the kernel (the density function). The parameter b, is the bandwidth that balances between the bias and the variance of the estimator. It influences the speed of convergence. In the multidimensional case ($d > 1$), a multidimensional product kernel function[10] is used which is written as $K\left(b^{-1} * (x - x_{it})\right)$. Here, b is a vector of bandwidths and b^{-1} stands for $\left(\frac{1}{b_1}, \ldots, \frac{1}{b_d}\right)$ and $*$ stands for an elementwise vector product.

The main advantage of this estimator is its flexibility. It does not impose any parametric form on the frontier function but only requires h to be a smooth function so that the desired convergence properties are obtained.

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[8] For a review of kernel estimators and a comparison of them to k-NN estimators and splines, see Härdle (1990).

[9] A different production frontier can be specified for each firm. But since nonparametric methods require large data sets, (see, for example, Härdle, 1990 and Silverman, 1986 for a discussion of the curse of dimensionality in nonparametric regression and density estimation), we adopt the approach which uses all the available observations.

[10] $K(u_1, u_2, \ldots, u_d) = \prod_{j=1}^{d} K^*(u_j)$ where K^* is a univariate kernel. Regarding the structure of the kernel function $K : \Re^d \to \Re$, the assumptions are as follows:

(i) There exists a constant c such that $K(x) < c$ for all $x \in D$.

(ii) $K(x) = 0$ if $x \notin [-1,1]^d$.

(iii) $\int_{\Re^d} K(x)dx = 1$ and $\int_{\Re^d} xK(x)dx = 0$.

In estimating Eq (9), the choice of the bandwidth is an important decision. Bandwidths may be chosen in a data-adaptive way using cross validation, i.e., by minimizing the prediction error

$$\sum_{i,t}\left(y_{it} - \hat{h}_{i,-t}(x_{it})\right)^2$$

where $\hat{h}_{i,-t}$ is computed by leaving out the observation ($y_{it}, x_{i,t}$).

Having determined the optimal bandwidths, we obtain estimates $\hat{h}$ of h and predict each α_i by least squares: $\hat{\alpha}_i = \frac{1}{T}\sum_{t=1}^{T}\left(y_{it} - \hat{h}\ (x_{it})\right)$. Once α_is are estimated, efficiency scores are obtained following the method of Schmidt and Sickles (1984) for time-invariant specifications and of Cornwell, Schmidt and Sickles (1990) and Lee and Schmidt (1993) for time varying models, as described before.

V.3. Model Specification and Empirical Results

In all models, we identified four categories of inputs to construct the production frontiers for the aggregate Turkish manufacturing industry. Details on the description and sources of the data are provided in Appendix A. Here, we note that in all models, Y is output at 1987 prices, L is the number of hours worked, E is electricity consumed measured in Kwhs and RM is raw material use at 1987 prices.

V.3.1. Nonparametric Models

Using the year-by-year and sequential frontier methodologies, we obtain technical efficiency scores with respect to both CRS and VRS technologies. In the year-by-year methodology, a different best-practice frontier is estimated for each period and efficiency scores are calculated based on the comparison of actual observations to the best-practice frontier technology of the corresponding year. A shift in the frontier at time t is reflected in the technical efficiency level of a decision making unit at the same period, t.

The sequential methodology, on the other hand, has a smoothing effect on efficiency scores. The r^{th} sequential run $(r:1,2,\ldots,12)$ produces r set(s) of technical efficiency scores for each producing unit. Thus, technical efficiency of unit i in period t is computed by averaging $13-t$ scores. Furthermore, to compute the mean efficiency of a producing over the time span of the study, its efficiency scores are averaged over time so that we obtain 96 mean efficiency scores. Results from the year-by-year and sequential frontier methodologies together with some descriptive statistics on the 1983-1994 average efficiency scores are presented in Table V.1-A.

It is observed that mean technical efficiency estimates from the sequential frontier methodology are lower than those from the year-by-year methodology under both CRS and VRS assumptions which might be due to the smoothing effect of the sequential methodology. Another finding is that technical efficiency scores computed with the CRS assumption are lower than those computed with the VRS assumption regardless of the methodology used. This might be attributable to the fact that the VRS frontiers wrap the data more tightly than the CRS ones due to the additional restriction imposed by the VRS assumption on the linear programming problems.

Values of CRS and VRS mean efficiency scores over 1983-1994 are presented in Table V.4 while their time patterns can be observed in Figure V.1-A. The sequential methodology (SVRS and SCRS) produced more stable time-patterns of mean technical efficiency compared to the year-by-year estimation. The SCRS and SVRS scores range from 0.27 to 0.31 and 0.17 to 0.22 respectively during 1983-1994. Corresponding values for CRS and VRS models estimated with the year by year methodology are 0.30 to 0.66 and 0.18 to 0.57 respectively. Since the range of efficiency scores from the two alternative methods differ to a great extent, we present individual plots of mean efficiency scores for the four DEA models in Figure V.2.

Under the two scale assumptions (CRS and VRS), the sequential and year-by-year methodologies produced U-shaped patterns of mean efficiency during 1983-94. The sequential model with variable returns to scale assumption (SVRS), yielded mean efficiency scores that decline during 1983-1988 and increase from 1989 onwards, restoring their initial value in 1994. Under the same scale assumption, the year-by-year methodology produced the same pattern, with the exception that the minimum point is reached in 1989. The year-by-year methodology with the CRS assumption gave rise to a declining pattern of mean efficiency during 1983-1985, an almost time-invariant one during 1986-1990 and an increasing trend from 1991 onwards (with its maximum value attained in 1993 which is slightly larger than its initial 1983 level). The sequential methodology with the CRS assumption yielded mean efficiency scores that decline until 1987, remain time-invariant till 1989 and increase during 1990-1993 without ever attaining its initial level again.

To check the consistency of methods in ranking industries by their 1983-1994 average efficiency levels, we calculated pairwise Spearman rank correlation coefficients. Results presented in Table V.2 are in the range of 0.49 – 0.91 for DEA models. The lowest value of the coefficient is observed between the CRS model estimated by the year-by-year methodology and the VRS model estimated sequentially. The highest value, on the other hand, is recorded between the two VRS models (VRS and SVRS). These findings imply that the consistency of nonparametric models in ranking cross sectional units in terms of estimated average efficiency scores is most sensitive to the scale assumption inherent in DEA models rather than the estimation methodology (year-by-year versus sequential).

V.3.2. Parametric Models

Econometric estimates of technical efficiency are based on the construction of a four input-single output Cobb-Douglas frontier technology. First, we consider the ML estimation of the stochastic frontier model as specified by Battese and Coelli (1988) under the assumptions of both time-invariant and time-varying inefficiency. Then, we employ the distribution free methods proposed by Schmidt and Sickles (1984) and Cornwell et al. (1990) and Lee and Schmidt (1993). The

Schmidt and Sickles (1984) method is applied when inefficiency is assumed to be time-invariant while the latter approaches are adopted when inefficiency is allowed to vary over time.

V.3.2.a. Stochastic Frontier Analysis with ML Estimation

Assuming the Cobb-Douglas functional form and the truncated normal distribution for inefficiency terms, we construct four SF models that differ by their treatment of technical change [11] and assumptions on the time pattern of inefficiency. The first model, MLETAO, does not allow for technical change and assumes inefficiency effects to be time-invariant. MLTBETAO allows for a linear trend in the production frontier, still maintaining the assumption of time-invariant technical inefficiency. MLETAFREE does not account for technical change but relaxes the assumption of time invariance of inefficiency terms. And finally, MLTBETAFREE controls for shifts in the production frontier and inefficiency terms.

Estimates of the parameters of the production technology and of variance parameters associated with random errors are presented in Table V.3-A. Input elasticities of production are positive in all models except for that of electricity in MLETAO; and among them, raw material elasticity is highest. Furthermore, the parameter γ defined as the ratio of the variance of inefficiency terms to the total variance of random terms is statistically significant which reflects that

[11] In ML estimation of the stochastic frontier models, technical change is accounted for by including a smooth time trend in the production technology and its coefficients are estimated jointly with the parameters of the inefficiency terms.

inefficiencies exhibit a highly random pattern. In the two time-varying efficiency models, MLETAFREE and MLTBETAFREE, η is statistically significant but assumes a positively signed coefficient in former model while its coefficient is negatively signed in the latter one. However, in both models, its magnitude is very close to zero, which implies a very weak trend.

Regardless of the assumptions on the time pattern of efficiency or allowance for technical change, ML models yield approximately equivalent results in terms of average and median technical efficiency levels and standard deviations of scores (See Table V.1-B). In all ML models, mean efficiencies range between 0.45 and 0.48 and the null hypothesis of equality of means across different models cannot be rejected based on the anova F-statistic.

Mean efficiency scores during 1983-1994 are given in Table V.4 and plotted against time in Figure V.1-B. Among MLETAO and MLTBETAO which assume inefficiency to be time-invariant, the latter which includes a smooth time trend in the production frontier yields a lower level of efficiency (0.44) than the former, MLETAO (0.46).

MLTBETAFREE and MLETAFREE which allow for time-varying inefficiency produce opposite time paths as was reflected by the signs of the estimated coefficients for η. The former, which includes a trend in the benchmark technology, predicts a declining pattern of efficiency during 1983-1994 while the latter predicts an opposite pattern with the two time paths crossing in 1991 at an efficiency level of approximately 47 percent. This finding suggests that inclusion of a time trend in the benchmark technology can give different time paths of efficiency scores.

Regarding the consistency of models in ranking industries, pairwise rank correlations between four SF models are very high (See Table V.2), ranging from 0.92 to 0.99. This suggests that the assumptions on the time-pattern of inefficiency or allowance for technical change in the frontier technology do not affect the qualitative consistency of these models.

V.3.2.b. Stochastic Frontier Analysis with the Distribution Free Method

Analysis with the distribution free methods is carried out under the assumptions of time invariant and time-varying efficiency but we are unable to account for technological change since distributional assumptions are required to disentangle technological change and efficiency change.

The time-invariant technical efficiency model is estimated by Schmidt and Sickles' (1984) method while models that allow for time-varying efficiency are estimated following Cornwell et al. (1990) and Lee and Schmidt (1993). Among them, we first consider a model that specifies a linear trend for the time-pattern of efficiency. Next, we allow for an additive quadratic trend to model possible u-shaped time-patterns of technical efficiency. Parameter estimates of the Cobb-Douglas frontier functions are presented in Table V.3-B.

Descriptive statistics on the 1983-1994 averages of efficiency scores of the producing units provided in Table V.1-B suggest that distribution free models yield close results in terms of the magnitudes of mean efficiencies, ranging from 0.20 and 0.24. However, anova F-statistic used to test their equality leads to the rejection of the null hypothesis. Highest mean efficiency score is obtained when a linear trend is included to model the time pattern of inefficiency (OLSEFLT). OLSEFFQT which allows for both a linear and a quadratic trend in inefficiency levels on the other hand yields the lowest mean technical efficiency score.

Time patterns of mean efficiency obtained from the DF models are presented in Table V.4 and plotted in Figure V.1-C. OLSEFFLT that specifies inefficiency effects as a linear function of time predicts that efficiency increased from 0.15 percent to 34 percent during 1983-1994. OLSEFFQT on the other hand, yields a u-shaped path during 1983-1992. Mean technical efficiency declined during 1983-1988 from 0.35 in 1983 to its minimum level of 0.12 in 1988 and increased during the period 1989 - 1992 to a level of 0.30. In 1993 and 1994 efficiency declined with a sharp fall especially in 1994 reaching to 0.14.

Spearman rank correlation coefficients between all pairs of distribution free models are very high, in the range of 0.90 – 0.97. Just like the alternative parametric methodology, this finding points to the unimportance of the assumptions regarding the time pattern of inefficiency on the consistency of models in ranking industries according to mean efficiency scores.

V.3.3. Semiparametric Models

In the semiparametric models, to construct the nonparametric benchmark technology common to all production units, we employ the product Epanechnikov kernel function[12] given by the formula:

$$K(x) = \prod_{j=1}^{d} K(x_j)$$

where

$$K(x_j) = \begin{cases} \frac{3}{4\sqrt{5}}\left(1 - \frac{1}{5}x_j^2\right) & \mathit{if}\ x_j^2 < 5 \\ 0 & \mathit{otherwise} \end{cases}$$

and use cross-validation technique which provides consistent estimators of the optimal bandwidth in many situations[13].

The semiparametric models we estimate can be classified under two groups according to the treatment of technological change. The first group includes a smooth time trend as a separate argument in the benchmark technology, which is estimated by a nonparametric kernel estimator while the second one assumes no technical change. These two groups can be further divided into two subgroups according to the assumptions regarding the time pattern of inefficiency yielding six different models that are briefly described below:

SP: No allowance for technical change, assumes time-invariant technical efficiency.

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[12] It is the optimal kernel based on a calculus of variations solution to minimizing the integrated mean square error of the kernel estimator.

[13] Alternative automatic bandwidth selectors are generalized cross-validation (see, e.g., Craven and Wabha, 1979) or plug-in methods (see, e.g., Gasser, Kneip, and Köhler, 1991).

SPTB: Accounts for technical change with a smooth trend in the benchmark technology, assumes time-invariant technical efficiency.

SPEFFLT: No allowance for technological change, assumes a linear trend for technical efficiencies.

SPEFFQT: No allowance for technological change, assumes both a linear and a quadratic trend term to model time-varying inefficiency.

SPTBEFFLT: Accounts for technical change with a smooth time trend in the benchmark technology, assumes a linear trend for inefficiencies.

SPTBEFFQT: Accounts for technical change with a smooth time trend in the benchmark technology, assumes a linear and a quadratic trend term to capture the time pattern of technical inefficiency.

The semiparametric models which do not allow for technical change (SP, SPEFFLT, SPEFFQT) produce approximately equal mean and median efficiency scores that are around 0.44 (See Table V.1-C). The same result holds for mean efficiency scores from the models that account for technical change. They estimate mean technical efficiency levels around 0.46. This points to the fact that mean efficiency scores are not sensitive to the assumption regarding the time pattern of inefficiency.

Time patterns of mean efficiency, plotted in Figure V.1-D, and their corresponding values presented in Table V.4 show that SPEFFLT and SPTBEFFLT which allow for a linear trend in inefficiency terms produce an increasing time pattern of efficiency during the whole period. The latter model that includes a trend in the benchmark technology produces a higher slope. Turning to

SPEFFQT and SPTBEFFQT, which model the time pattern of inefficiency through a linear and a quadratic time trend respectively, the former yields an inverted u-shaped pattern while the latter which also accommodates for technical change predicts an increasing time pattern of mean efficiency during 1983-1993 with a decline only in the last period of the panel.

Regarding the consistency of models in ranking industries, models which do not account for technical change have rank correlations which are exactly equal to 1.00. The same result is observed between the remaining three models that allow for technical change. Regardless of the assumptions on the time pattern of inefficiency, whether it is modeled as a linear function of a smooth time trend (SPEFFLT), a linear and a quadratic trend (SPEFFQT) or assumed to be time invariant (SP), the semiparametric models that belong to the same category (according to the treatment of technological change) produce identical results in ranking industries in terms of mean efficiencies.

All the rank correlations between two categories (the models that allow for technical change and those that do not) are equal to 0.90; which suggests that allowance for technological change has a small impact on the ranking of industries with respect to average efficiency scores.

V.4. Comparison of Results across Methodologies

V.4.1. Magnitudes of Mean Technical Efficiency Scores

Among the three different methodologies, the parametric DF models produced lowest mean technical efficiency scores. The semiparametric and the alternative parametric methodology based on ML estimation of stochastic frontier functions yielded highest mean efficiency scores that were also very close to each other. Below, we provide pairwise comparisons of the three methodologies in terms of the magnitudes of mean efficiency scores

V.4.1.a.Nonparametric versus Parametric Models

With the exception of the VRS model estimated by the year-by year methodology, average efficiency scores from the nonparametric DEA models are lower than those obtained from ML estimation of stochastic frontier production functions. The difference between mean efficiency scores is in the range of 23 to 13 points (on a scale of 100). This finding can be attributed to the deterministic nature of DEA models which consider any deviation from the best-practice frontier as inefficiency. Stochastic ML models on the other hand are more likely to yield higher efficiency scores due to their ability to disentangle white noise and inefficiency.

Turning to the alternative parametric methodology, distribution free models produced lower estimates of mean efficiency compared to VRS, CRS and SVRS models and approximately equal mean efficiency levels compared to the SCRS model (CRS DEA model estimated by sequential frontiers). Similar to DEA approach, the distribution free approach does not require any (distributional) assumptions for inefficiency terms. However, unlike nonparametric DEA methods, the distribution free models explicitly specify the frontier technology through a parametric best-practice production function. This finding is not unusual if the nonparametric DEA approach wraps the frontier more tightly than parametric specifications.

V.4.1.b. Nonparametric versus Semiparametric Models

When comparing nonparametric and semiparametric models in terms of the magnitude of efficiency scores, one might expect higher efficiencies from the semiparametric models since although both approaches estimate the benchmark technology by flexible techniques that require no explicit specifications of the functional form, the semiparametric models estimate technical efficiencies using parametric methods that allow for two-sided deviations from the frontier production function. We find supporting evidence for this argument with technical efficiency scores ranging from 0.23 to 0.46 in SP models and from 0.23 to 0.33 in DEA models with the only exception of the VRS model.

V.4.1.c. Parametric versus Semiparametric Models

Mean efficiency scores from the semiparametric models and stochastic frontier models estimated by maximum likelihood techniques are almost equal.

This might be due to the trade off between specifying a rigid functional form for the benchmark technology in the SF model and possible weaknesses of the DF methodology employed by the semiparametric models while estimating technical efficiencies. The DF method employs a least squares estimator of the inefficiency terms when estimating both time-invariant and time varying inefficiency models. Furthermore, time-varying models are estimated by a two-step procedure in which residuals from the first step are regressed on trend variables. ML procedure on the other hand estimates the parameters of the stochastic production technology and the inefficiency model simultaneously.

V.4.2. Time Patterns of Mean Technical Efficiency Scores

Comparison of the time paths of parametric, nonparametric and semi parametric efficiency scores may not be very meaningful since the parametric and semiparametric models specify a functional from for the behavior of inefficiency over time, whereas nonparametric DEA models do not restrict the frontier or the inefficiency terms.

Bearing this in mind, when Figures V.1-A to V.1-D are examined, we observe that DEA models and the DF model that allows for a quadratic trend in the time pattern of efficiency produced very similar paths. The stochastic frontier models estimated by ML methods and on the other hand, yielded close time-paths of mean efficiency to those obtained from the semiparametric models.

V.4.3. Consistency of Methods in Ranking the Producing Units

To check the consistency of the three methodologies in ranking industries, we present the ranges of Spearman's rank correlation coefficients in Table V.5. We observe that the CRS DEA models and the stochastic frontier models estimated by ML techniques are highly consistent with the distribution free models.

Pairwise rank correlations between the semiparametric and the parametric models are significantly higher than those obtained between the semiparametric and nonparametric DEA models. VRS DEA models attain the lowest rank correlations among all pairs of methodologies we compare and furthermore, these coefficients are approximately equal, in the range of 0.43-0.65. The distribution free approach is most consistent with the stochastic frontier approach estimated by ML. It is almost equally consistent with the CRS DEA models and the semiparametric models.

V.5. Conclusions

Most of the papers related to the measurement of technical efficiency utilised either parametric or on non-parametric methods. The choice of estimation method has been an issue of debate, with some researchers preferring the parametric approach (e.g. Berger, 1993) and others the non-parametric approach (e.g., Seiford and Thrall, 1990). Critics of the nonparametric approaches argue that since they are deterministic, they cannot no distinguish between technical inefficiency and statistical noise On the other hand, parametric frontier models allow for both inefficiency and measurement error. However, their success depends on both a correctly specified functional form for the production technology and the ability to properly decompose noise and inefficiency.

A recently introduced semiparametric methodology due to Kneip and Simar (1996) avoids the weaknesses of the parametric methodologies by freeing the functional form restrictions on the benchmark technology. Furthermore, by a parametric treatment of the inefficiency terms, it is also immune from the drawbacks of the deterministic approaches.

We believe that neither the parametric nor the nonparametric approach seems to be strictly preferable. Their joint use can improve the accuracy with which productive efficiency is measured. The semiparametric methods on the other hand can serve as a nice alternative to the classical methodologies.

The major concern of this chapter was the comparison of the semiparametric approach to efficiency measurement with the two popular methodologies: nonparametric DEA and parametric stochastic frontiers. Using a panel data set corresponding to a sample of 96 Turkish manufacturing industries (defined at four-digit codes according to ISIC) during 1983-1994, we constructed several frontier production models that differed in their assumptions on the time pattern of efficiency and accommodation for technical change. We obtained efficiency scores using the tools provided by the parametric, nonparametric and semiparametric methodologies. Within the parametric methodology, we employed both maximum likelihood and "distribution-free" estimation techniques to estimate stochastic frontier models. The nonparametric models were based on the construction of constant returns to scale and variable returns to scale DEA models. The benchmark technology semiparametric specifications were constructed by kernel estimators of the Nadaraya-Watson type and inefficiencies were obtained by the parametric distribution free approaches suggested by Schmidt and Sickles (1984) Cornwell et al (1990) and Schmidt and Lee (1993).

With respect to the DEA approaches, given that the constraint set is more restricted under VRS than under CRS, the latter assumption led to lower efficiency scores. CRS models estimated by the sequential frontiers method produced lower estimates of mean efficiency than those estimated by the year-by-year method. CRS and VRS DEA models estimated by the former methodology led to average levels of technical efficiency of 23 and 33 percent respectively while the year-by-year method estimated mean efficiency as 33 and 47 percent for the CRS and VRS case respectively. The DEA approach, which does not restrict the time pattern of efficiencies, produced u-shaped patterns of mean efficiency over the period 1983-1994. All models predicted minimum mean efficiency levels in 1988-1989 and a sharp decline in efficiency in 1994, which corresponds to a crisis year for the Turkish economy. Regarding the consistency of DEA models in ranking industries (in terms of mean efficiency levels), models estimated with the constant returns to scale assumption were not very consistent with those estimated with the variable returns to scale assumption. Pairwise rank correlations between CRS and VRS models were 0.54 for the former and 0.49 for the latter.

Within the parametric models estimated by maximum likelihood techniques, no noticeable differences arose regarding the magnitudes of mean efficiencies. They were in the range of 45 to 48 percent. On the other hand, parametric models estimated by the distribution free approach predicted mean efficiency levels that ranged from 20 to 24 percent. Given that the distribution free approach is based on corrected ordinary least squares methods which also report random disturbances as inefficiency, the ability of ML techniques to disentangle white noise from inefficiency might have led to higher estimates of mean efficiency. The assumptions on the time pattern of efficiency or accommodation for technological change on the other hand, did not have any significant effect on the values of the mean efficiency scores estimated by the distribution free method or by maximum likelihood techniques. Stochastic frontier models estimated by maximum likelihood techniques yielded opposite results regarding the time behavior of efficiency. When technological change was accounted for, a declining trend in mean efficiency was detected while mean efficiency exhibited an increasing trend when the frontier technology was not allowed to shift during the period under study. The distribution free approach employed to a model that allowed for both a linear and a quadratic time trend produced a u-shaped pattern of mean efficiency resembling those obtained from the DEA models. Regarding the consistency of parametric models in ranking industries according to mean efficiency levels, results show that they are extremely consistent. Their pairwise correlation coefficients are not less than 90 percent.

Within the semiparametric models, estimates of mean efficiency were almost identical, around 45 percent regardless of the assumptions on the allowance for technical change and time-varying efficiency. However, the time patterns of mean efficiency were sensitive to the assumptions on the allowance for technical change and time-varying efficiency. Regarding their qualitative consistency, i.e. consistency in ranking industries, the semiparametric models produced almost identical rankings with pairwise rank correlation coefficients not less than 90 percent.

Comparisons across methodologies show that mean efficiency scores obtained from the parametric models estimated by the distribution free approach are lowest while those obtained from parametric maximum likelihood estimation and semiparametric estimation methods are the highest with very close values. The nonparametric models' estimates of mean efficiency lie between them. We attribute this to the fact that the distribution free method is unable to properly decompose the total error into efficiency and noise components. These models suffer from both drawbacks: the problems of a rigid functional form specification for the production technology and the shortcoming of not distinguishing between inefficiency and noise given their deterministic structure.

Regarding the time patterns of efficiency, it would not be appropriate to make comparisons across methodologies. DEA based approaches do not restrict the functional form of the frontier or the time pattern of inefficiencies whereas parametric and semiparametric models put restrictions on either or both of them.
As for the consistency of methodologies in ranking producing units, the correlation coefficients are high between parametric models estimated by maximum likelihood techniques and semiparametric models. They are in the range of 66 and

81 percent. On the other hand, correlation coefficients between DEA and econometric methodologies (ranging between 50 and 78 percent) were higher than those between DEA and semiparametric methods (which were in the range of 45 and 64 percent).

We observed that the assumptions on the time pattern of efficiency or accommodation for technical change has no significant effect in ranking industries according to their mean efficiency scores. Furthermore, choice of parametric or semiparametric techniques is also quite unimportant if one is interested in the ranking of industries or the magnitudes of mean efficiency scores. However, the nonparametric DEA based models and semiparametric models led to different –but still comparable-rankings. Based on these results, we suggest that the semiparametric approach is a good alternative to parametric models in terms of ranking industries and estimated mean efficiency scores.

Table V.1: Descriptive Statistics on 1983-1994 Average Efficiency Scores of Producing Units

	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque -Bera
A- NONPARAMETRIC MODELS								
CRS	0.33	0.29	0.97	0.16	0.14	2.01	7.64	150.39
VRS	0.47	0.42	1.00	0.16	0.19	1.09	3.65	20.59
SCRS	0.23	0.20	0.75	0.11	0.11	2.00	7.80	156.04
SVRS	0.33	0.30	0.98	0.11	0.17	1.52	5.16	55.59
B – PARAMETRIC MODELS								
SF Models with ML Estimation								
MLETAFRE	0.45	0.43	1.00	0.26	0.13	1.93	8.14	165.12
MLETAO	0.46	0.44	1.00	0.23	0.14	1.74	7.20	118.79
MLTBETAFR	0.48	0.45	1.00	0.29	0.13	1.72	6.92	108.80
MLTBETAO	0.45	0.42	1.00	0.24	0.13	1.80	7.65	138.05
SF Models with the DF Approach								
OLS	0.22	0.20	1.00	0.12	0.11	4.77	32.49	3,842.98
OLSEFLT	0.24	0.21	1.00	0.13	0.11	4.66	31.82	3,669.24
OLSEFQT	0.20	0.18	0.87	0.11	0.09	4.80	33.16	4,008.26
C-SEMIPARAMETRIC MODELS								
SP	0.44	0.44	1.00	0.31	0.08	4.05	30.68	3,325.71
SPEFFLT	0.44	0.44	1.00	0.31	0.08	3.98	29.92	3,151.30
SPEFFQT	0.45	0.44	1.00	0.32	0.08	3.93	29.44	3,044.40
SPTB	0.46	0.45	1.00	0.34	0.09	2.91	18.39	1,082.63
SPTBEFLT	0.45	0.45	1.00	0.34	0.09	2.80	17.30	943.27
SPTBEFQT	0.46	0.44	0.99	0.34	0.09	2.80	17.24	936.39

Table V.2: Spearman's Rank Correlation Matrix

	CRS	VRS	S-CRS	S-VRS	MLETAO	MLETA FREE	MLTB ETAO	MLTB ETAFR	OLS	OLSEFF LT	OLSEFF QT	SP	SPEF FLT	SPEF FQT	SPTB	SPTB EFFLT	SPTB EFFQT
CRS	1.00																
VRS	0.54	1.00															
S-CRS	0.89	0.43	1.00														
S-VRS	0.49	0.91	0.49	1.00													
MLETAO	0.78	0.55	0.74	0.50	1.00												
ML-ETA-FREE	0.77	0.63	0.66	0.56	0.94	1.00											
ML-TB-ETAO	0.72	0.65	0.60	0.56	0.92	0.99	1.00										
ML-TB-ETA-FREE	0.75	0.64	0.61	0.55	0.90	0.99	0.99	1.00									
OLS	0.85	0.48	0.79	0.44	0.96	0.90	0.86	0.85	1.00								
OLS-EFF-LT	0.81	0.59	0.68	0.50	0.93	0.96	0.94	0.97	0.90	1.00							
OLS-EFF-QT	0.83	0.56	0.75	0.52	0.93	0.96	0.93	0.95	0.91	0.97	1.00						
SP	0.64	0.54	0.53	0.48	0.73	0.79	0.78	0.80	0.71	0.80	0.78	1.00					
SPEFFLT	0.64	0.54	0.53	0.47	0.73	0.79	0.78	0.80	0.71	0.80	0.78	1.00	1.00				
SP-EFF-QT	0.65	0.55	0.54	0.48	0.73	0.79	0.78	0.80	0.71	0.81	0.78	1.00	1.00	1.00			
SP-TB	0.60	0.57	0.45	0.46	0.66	0.77	0.76	0.81	0.63	0.80	0.77	0.90	0.90	0.90	1.00		
SP-TB-EFF-LT	0.60	0.57	0.44	0.45	0.67	0.77	0.76	0.81	0.64	0.80	0.77	0.90	0.90	0.90	1.00	1.00	
SP-TB-EFF-QT	0.61	0.57	0.45	0.46	0.67	0.78	0.77	0.81	0.64	0.81	0.77	0.90	0.90	0.91	1.00	1.00	1.00

Table V.3: Parameter Estimates of the Stochastic Frontier Models: ML and DF Estimation

A: ML MODELS

	MLETAO		MLTBETAO		MLETAFREE		MLTBETAFR	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Constant	0.85	13.89	0.66	12.68	0.82	16.41	0.54	12.80
Trend			0.02	11.93			0.03	8.81
Capital	0.06	4.27	0.04	2.92	0.05	3.24	0.04	2.43
Labor	0.13	7.70	0.10	6.56	0.09	5.54	0.07	4.30
Electricity	-0.03	-1.94	0.05	2.84	0.06	2.76	0.11	5.44
Raw Material	0.78	68.16	0.72	56.25	0.74	48.56	0.73	55.85
Sigma-squared	0.18	13.94	0.19	12.09	0.16	11.88	0.20	14.14
Gamma	0.69	41.00	0.72	50.67	0.71	42.82	0.74	52.58
Mu	0.72	9.05	0.74	12.52	0.67	9.40	0.77	6.61
Eta	0.00		0.00		0.02	6.34	-0.01	-2.08
LLF	-188.73		-130.51		-147.25		-126.90	

B: DISTRIBUTION FREE MODELS

	OLS		OLSEFFLT and OLSEFFQT	
C	-	-		
TREND				
K?	0.07	4.38	0.07	4.40
ELEC?	0.15	8.03	0.04	2.72
L?	0.01	0.38	0.08	5.16
RM?	0.75	41.86	0.77	61.65
Sum OF fixed Effects	8.56	-		

Table V.4: Average Efficiencies Over Time

	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
CRS	0.48	0.50	0.29	0.20	0.21	0.21	0.18	0.19	0.31	0.37	0.57	0.40
VRS	0.61	0.66	0.42	0.37	0.35	0.35	0.30	0.34	0.46	0.54	0.65	0.61
S-CRS	0.22	0.20	0.18	0.18	0.17	0.17	0.17	0.17	0.17	0.19	0.20	0.18
S-VRS	0.32	0.29	0.27	0.27	0.27	0.25	0.26	0.27	0.28	0.31	0.33	0.31
ML-ETA-FREE	0.42	0.43	0.43	0.44	0.44	0.45	0.46	0.46	0.47	0.48	0.48	0.49
ML-TB-ETA-FREE	0.50	0.50	0.50	0.49	0.49	0.48	0.48	0.47	0.47	0.46	0.46	0.45
ML-TB-ETAO	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45
OLS-EFF-LT	0.16	0.17	0.18	0.19	0.21	0.22	0.24	0.25	0.27	0.29	0.31	0.33
OLS-EFF-QT	0.35	0.27	0.19	0.14	0.12	0.12	0.12	0.15	0.20	0.29	0.28	0.15
SP-EFF-LT	0.43	0.43	0.43	0.44	0.44	0.44	0.44	0.45	0.45	0.46	0.46	0.46
SP-EFF-QT	0.40	0.42	0.43	0.45	0.46	0.46	0.47	0.47	0.46	0.46	0.45	0.44
SPTB	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46
SP-TB-EFF-LT	0.38	0.40	0.41	0.42	0.44	0.45	0.46	0.48	0.50	0.52	0.53	0.55
SP-TB-EFF-QT	0.40	0.40	0.41	0.42	0.43	0.44	0.46	0.48	0.49	0.52	0.54	0.51

Table V.5: Range of Rank Correlation Coefficients Among Parametric, Nonparametric and Semiparametric Models

Nonparametric Models				Parametric Models				Semiparametric Models	
CRS & SCRS		VRS and SVRS		ML Estimation		Distribution Free Approach		Kernel Estimation Approach	
DF	0.75-0.88	ML	0.50-0.65	DF	0.85-0.97	ML	0.91-0.97	DF **	0.64-0.81
ML	0.61-0.78	DF	0.48-0.59	SP *	0.76-0.80	CRS and/or SCRS	0.79-0.88	ML	0.66-0.81
SP	0.60-0.64	SP	0.45-0.57	NP	0.50-0.77	SP	0.74-0.80	NP	0.45-0.65
VRS and SVRS	0.44-0.54	CRS and SCRS	0.43-0.54			VRS and/or SVRS	0.45-0.71		

*SP Models are ranked 2nd in all models except for MLETAO which has higher rank correlations with the CRS and SCRS models (0.74 and 0.78 respectively)

** DF Models are ranked second for SPTB which has the highest correlations with ML models (0.66-0.81)

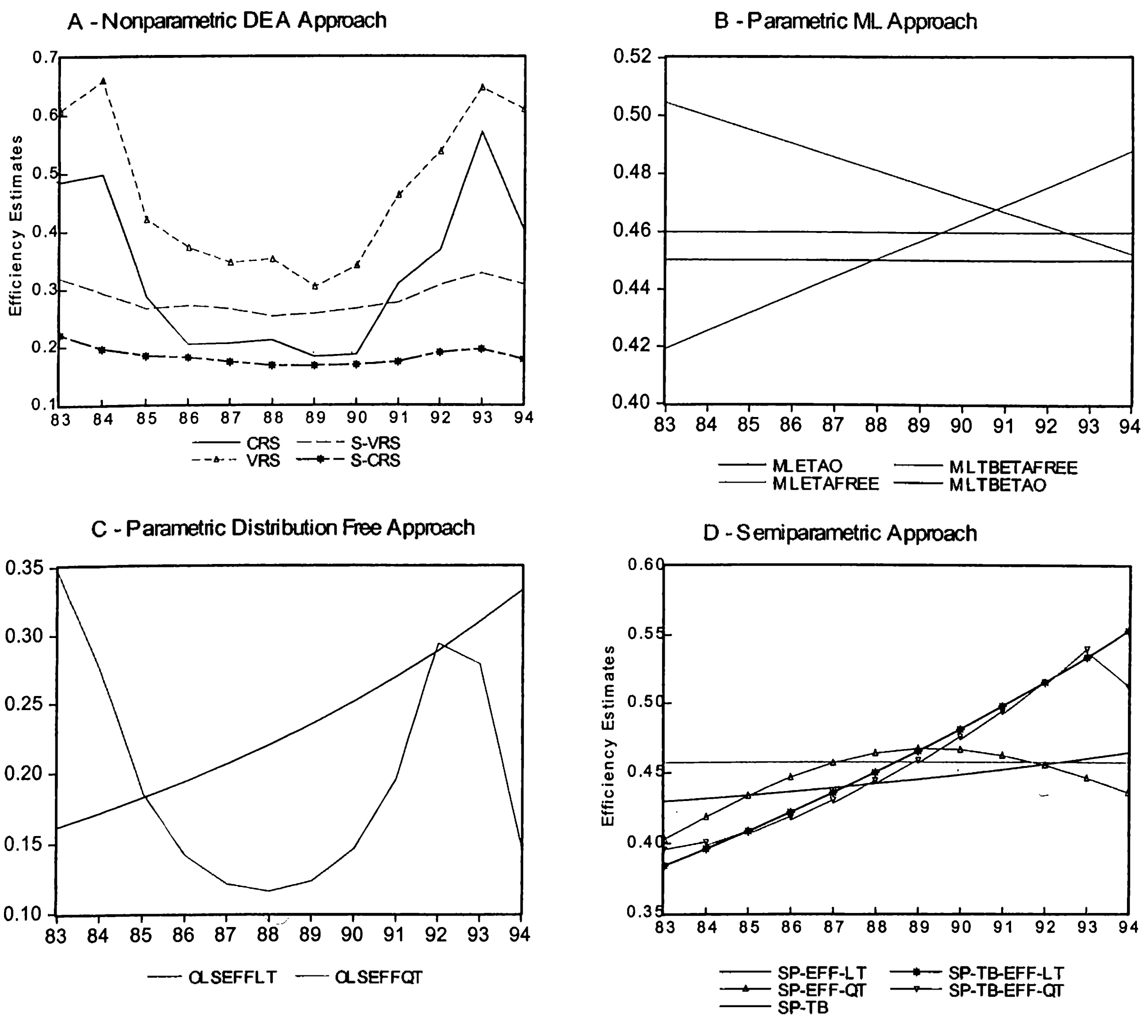

Figure V.1. Time Patterns of Mean Efficiency Scores Obtained from Parametric, Nonparametric and Semiparametric Approaches

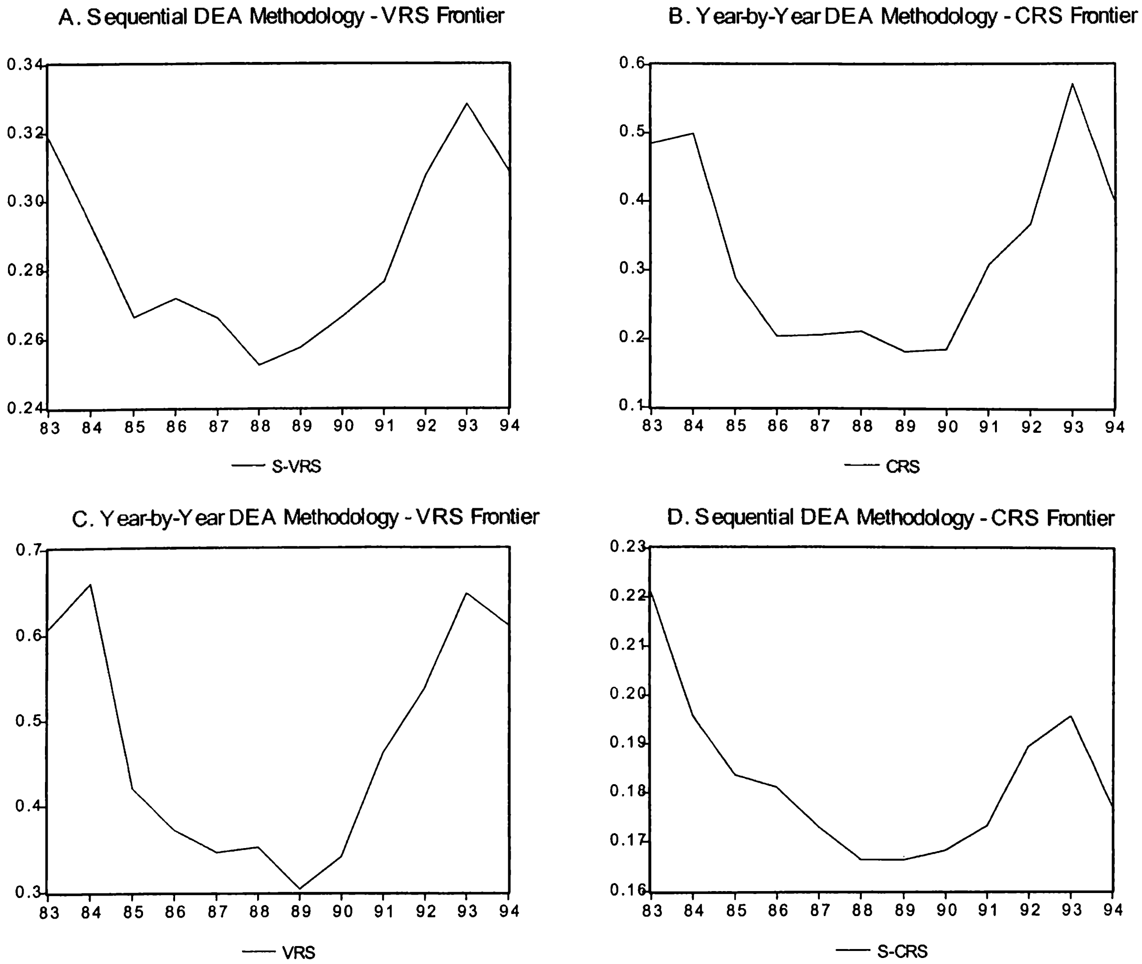

Figure V.2.: Time Pattern of Mean Efficiency Scores Obtained from Nonparametric DEA Models

CHAPTER VI

CONCLUSION

In this study, we analysed issues related to the technical efficiency of Turkish manufacturing industries during 1983-1994, which could be regarded as a liberalization period for the Turkish economy.

In Chapter I, we introduced the methodologies used in the analysis and the significance of the time span of the study for the Turkish economy. Chapter II followed with a brief overview of the economy with an emphasis on the manufacturing industries that were analysed in subsequent chapters.

Chapter III was devoted to the investigation of the sources of technical inefficiency in Turkish manufacturing industries using a rich panel data set spanning the 1983-1994 period with cross sectional units being industries defined at the four-digit International Standard Industrial Classification (ISIC) codes. We estimated stochastic production frontiers (SPFs) for four broad industry categories: food, textiles, chemicals, machinery and for the aggregate manufacturing industry.

We focused on the effects on technical efficiency of competitive conditions including measures of both domestic and international competition, and organisational factors that are postulated to exert pressures on management or workers. More specifically, the following variables were used to describe inefficiency:

$DUMMYOWN$: A dummy variable indicating the type of ownership (public versus private)

$COMP.DOM$: Measures of domestic competition proxied by either four-firm concentration ratios or the number of firms in an industry

$COMP.INT$: Measures of international competition proxied by the ratio of exports or the ratio of trade balance to the volume of trade in an industry.

$RWAGE_{it}$: The real wage rate

$ADOP_{it}$: Ratio of administrative to operative personnel.

$RESOLD_{it}$: Ratio of sales of goods that are not further processed to sales from production.

Although theory did not provide a compact model for inefficiency effects, it shed light on possible effects of the type of ownership, real wages, composition of the labour force and domestic and international competition on the performance of producing units. In some cases there were conflicting signals concerning the impact of some phenomena on efficiency.

Among our basic findings, three of them are especially important in providing insights to policymakers in the design and evaluation of industrialisation policies. The first one is related to the effects of public versus private ownership on technical efficiency. In all industries, public ownership was found detrimental to technical efficiency which constitutes a supporting argument for the privatization efforts of governments.

Our second finding is related to the positive link between real wages and technical efficiency. In all industries except for the machinery industry, we found a positive association between real wages and technical efficiency supporting the views of the efficiency wage literature.

The third finding is associated with the mixed empirical evidence obtained regarding the effects of domestic competition on technical efficiency. In the food industry, a u-shaped association between technical efficiency and four-firm concentration ratio was detected while in the machinery industry; the coefficients of the quadratic term implied an inverted u-shaped relationship. In the chemicals industry, we did not find any significant relationship between measures of domestic competition and technical efficiency. In the textiles industry, we found evidence on the positive effects of enhanced competition on technical efficiency. Finally, in the aggregate manufacturing industry, a positive link was observed between increased market concentration and technical efficiency. We relate this to a couple of factors. The first one might be the presence of economies of scale in the managerial pursuit of efficiency as suggested by Torii (1992).

Secondly, the combination of a monopolistic or oligopolistic market structure and a small market size responsible for high concentration ratios might put an upward pressure on the optimal scale of a firm. Since we did not have data on the average firm size/scale, we could not control for the effects of this variable on technical efficiency. If higher concentration ratios signal higher average firm size/scale; than a positive association between technical efficiency and higher concentration might reflect the advantages of "being large" in obtaining funds necessary to meet the required levels of working and human capital or investment in newer vintages of physical capital.

An alternative explanation is related to Schumpeter's argument. In highly concentrated industries, larger profits accruing as a result of scale economies or barriers to entry might lead to allocation of more resources to efficiency enhancing activities such as research and development, or procurement of new technologies.

After investigating the sources of technical efficiency, in Chapter IV, we analysed its time pattern together with the rates of technological change Turkish manufacturing industries using two alternative approaches: the stochastic frontier and data envelopment analysis (DEA) methodologies. Our motivation was based on the expectation that a radical shift from import substituting industrialisation policies might have exerted transformation pressures on producing units and altered their incentives in a way that leads to improvements in productive efficiency.

However, our results from the stochastic frontier methodology suggested a time-invariant pattern for mean efficiency in the food, textiles and the aggregate manufacturing industries. Efficiency improved only in the chemicals industry while it deteriorated in the machinery industry. These trends were supported by constant returns to scale and variable returns to scale DEA models.

Regarding the rates of technological change, the two approaches yielded close results. A DEA based decomposition analysis performed on sectoral Malmquist productivity indices showed that although productivity improved in all industries during 1983-1994, the sources of productivity growth differed substantially across them.

For the food and machinery industries, recorded cumulative productivity growth rates, 32 and 55 percent respectively, were mainly attributable to technological progress. Contribution of improvement in efficiency accounted for only 2.6 percent in the food industry while in the machinery industry, a cumulative 41 percent deterioration in technical efficiency contributed negatively to productivity growth. An opposite case was observed in the chemicals and textiles industries. These industries witnessed technological regress at cumulative rates of approximately 36 and 2 percent respectively. However, improvements in efficiency led to cumulative productivity growth rates of 19 and 17 percent between 1983 and 1994.

Chapter V added to the analysis of technical efficiency by employing a recent semiparametric methodology to analyse technical efficiency in the aggregate manufacturing industry. This chapter, by providing a comparison of the semiparametric method with classical methodologies (the nonparametric and parametric approaches), filled a gap in the literature. Comparative analysis were performed both across the three methodologies (parametric, nonparametric and semi parametric) and within models that belonged to a specific category.

Comparisons were based on the magnitudes and time patterns of average efficiency scores, efficiency ranking of production units and calculated rates of technological change. Regarding the magnitudes of mean efficiency scores, the parametric models estimated without assuming a distribution for the inefficiency term produced lowest scores while the semiparametric and the stochastic frontier models yielded highest mean efficiency scores that were also very close to each other

Comparison of the time pattern of mean efficient scores across parametric, nonparametric and semi parametric models were not very meaningful since the parametric and semiparametric models specified a functional from for the behaviour of inefficiency over time, whereas nonparametric DEA models did not restrict the frontier or the inefficiency terms.

Bearing this in mind, results suggested that DEA and parametric models estimated by a distribution-free approach with a linear and a quadratic trend for inefficiency terms produced very similar paths while stochastic frontier and semiparametric models yielded close paths.

The consistency of the three methodologies in ranking industries was checked through the calculation of Spearman's rank correlation coefficients. Pairwise rank correlations between the semiparametric and the parametric models were significantly higher than those obtained vis-à-vis nonparametric DEA models. Parametric models estimated using the distribution-free approach were most consistent with stochastic frontier models, and almost equally consistent with the CRS DEA models and semiparametric models.

Comparisons based on various criteria provided evidence that semiparametric models can be a closer alternative to parametric models rather than nonparametric DEA based approaches.

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APPENDIX

DATA

Panel data sets used in this study are compiled from the Annual Manufacturing Industry Statistics published by the State Institute of Statistics (S.I.S) of Turkey unless otherwise stated. These publications are based on the Annual Surveys of the Manufacturing Industry conducted by S.I.S. During the period under study (1983-1994), all the manufacturing establishments in the public sector and establishments with 25 or more persons engaged in the private sector are covered.

Industry groups are determined in accordance with the "International Standard Industrial Classification (ISIC) of all Economic Activities - Manufacturing Industry Classification". Five data sets constructed for the applications in Chapters III and IV include the food, textiles, chemicals and machinery industries and a pooled data set representing the aggregate manufacturing industry. In Chapter V, we focus only on the aggregate manufacturing industry. The cross sectional units are four digit industries as defined by ISIC. The four broad industries include the following subsectors:

Table A-1 : 31-FOOD (Manufacture of Food, Beverages and Tobacco)

Subsectors Included (ISIC)		Public	Private
3111	Slaughtering, preparing and preserving meat	+	+
3112	Manufacture of dairy products	+	+
3113	Canning and preserving of fruits and vegetables		+
3114	Canning, preserving and processing of fish crustacea and similar goods		+
3115	Manufacture of vegetable and animal oils and fats	+	+
3116	Grain mill products fats	+	+

Table 1 (Continued): 31-FOOD (Manufacture of Food, Beverages and Tobacco)

Subsectors Included (ISIC)		Public	Private
3117	Manufacture of bakery products fats	+	+
3118	Sugar factories and refineries	+	
3119	Manufacture of cocoa, chocolate and sugar confectionery		+
3121	Manufacture of food products not elsewhere classified	+	+
3122	Manufacture of prepared animal feeds	+	+
3131	Distilling, rectifying and blending spirits	+	
3132	Wine industries	+	+
3133	Malt liquors and malt	+	+
3134	Non-alcoholic beverages, carbonated fruit juice, natural mineral waters and source origin water	+	+
3140	Tobacco manufactures	+	+
Total Number of Private Sectors Included			14
Total Number of Public Sectors Included			13
Total number of Sectors			27

Table A-2 : 32-TEXTILES (Textile, Wearing Apparel and Leather Industries)

Subsectors Included (ISIC)		Public	Private
3211	Spinning, weaving and finishing textiles	+	+
3212	Manufacture of textile goods except wearing apparel		+
3213	Knitting mills		+
3214	Manufacture of carpets and rugs	+	+
3215	Cordage rope and twine industries		+
3219	Manufacture of textiles not elsewhere classified		+
3221	Manufacture of fur and leather products		+
3222	Manufacture of wearing apparel except fur and leather	+	+
3231	Tanneries and leather finishing		+
3233	Manufacture of products of leather and leather substitutes except footwear and wearing apparel		+
3240	Manufacture of footwear, except vulcanized or moulded rubber of plastic footwear	+	+
Total Number of Private Sectors Included			11
Total Number of Public Sectors Included			4
Total number of Sectors			15

Table A-3 : 35-CHEMICALS (Manufacture of Chemicals and of Chemical, Petroleum, Coal, Rubber and Plastics)

Subsectors Included (ISIC)		Public	Private
3511:	Manufacture of basic industrial chemicals except fertilizers	+	+
3512:	Manufacture of fertilizers and pesticides	+	+
3513:	Manufacture of synthetic resins, plastic materials and manmade fibers, except glass	+	+
3521:	Manufacture of paints, varnishes and lacquers		+
3522:	Manufacture of drugs and medicines (including veterinary medicine)	+	+
3523:	Manufacture of soap and cleaning preparations perfumes, cosmetics and other toilet preparations		+
3529:	Manufacture of chemical products not elsewhere classified	+	+
3530:	Petroleum refineries	+	
3541:	Manufacture of asphalt paving and roofing materials		+
3542:	Manufacture of coke coal and briquettes	+	
3543:	Compounded and blended lubricating oils and greases	+	+
3544:	Liquid petroleum gas tubing		+
3551:	Tyre and tube industries		+
3559:	Manufacture of rubber products not elsewhere classified		+
3560:	Manufacture of rubber products not elsewhere classified		+
Total Number of Private Sectors Included			13
Total Number of Public Sectors Included			8
Total number of Sectors			21

Table A-4 : 38-MACHINERY (Manufacture of Fabricated Metal Products, Machinery and Equipment, Transport Equipment, Professional and Scientific and Measuring and Controlling Equipment)

Subsectors Included (ISIC)		Public	Private
3811	Manufacture of cutlery, hand tools and general hardware		+
3812	Manufacture of furniture and fixtures primarily of metal		+
3813	Manufacture of structural metal products	+	+
3819	Manufacture of fabricated metal products except machinery and equipment not elsewhere classified	+	+
3821	Manufacture of engines and turbines	+	+
3822	Manufacture of agricultural machinery and equipment and repairing	+	+
3823	Manufacture of metal and wood working machinery and repairing (Public and private)	+	+
3824	Manufacture of special industrial machinery and equipment except metal and wood working and repairing machinery	+	+

Table A-4 (Cont'd)

Subsectors Included (ISIC)		Public	Private
3825	Manufacture of office, computing and accounting machinery and repairing		+
3829	Manufacture of machinery and equipment, except electrical, not elsewhere classified	+	+
3831	Manufacture of electrical industrial machinery and apparatus	+	+
3832	Manufacture of radio, television, and communication equipment and apparatus	+	+
3833	Manufacture of electrical appliances and housewares		+
3839	Manufacture of electrical apparatus and supplies not elsewhere classified	+	+
3841	Ship building and repairing	+	+
3842	Manufacture of assembly of railroad equipment and repairing	+	
3843	Manufacture, assembly of motor vehicles and repairing		+
3844	Manufacture of motorcycles and bicycles and repairing		+
3851	Manufacture of professional, scientific measuring and controlling equipment not elsewhere classified	+	+
3852	Manufacture of photographic and optical goods		+
3854	Other		+
Total Number of Private Sectors Included			13
Total Number of Public Sectors Included			20
Total number of Sectors			33

The definitions of the output and input variables included in the construction of production frontiers of Chapters III, IV and V are presented below. For simplicity, we avoid referring to the subscripts of the variables, but one must consider that each variable has both an industry specific index and an index that accommodates for the time dimension (i.e. x_{ij} refers to the value of variable x in industry i, at time t).

Variables that enter the frontier functions:

Y : Output at 1987 prices (TL). It is constructed through dividing the nominal output by the whole sale price index (in natural logarithms).

L : Labour, measured as number of hours worked (in natural logarithms).

E : Electricity consumed, measured in kilowatt-hours. It is obtained by subtracting the value of electricity sold from the total sum of electricity purchased and electricity generated (in natural logarithms).

RM : Raw material used at 1987 prices (TL.). Firstly, raw material use at current prices is constructed through adding the raw material stocks at the beginning of each period to purchases of raw materials and fuels in the current period and subtracting the value of the raw material stocks at the end of the period. To obtain the raw material use at constant (1987) prices, we have deflated the nominal values by the corresponding sectoral whole sale price indices (in natural logarithms).

Variables used in the inefficiency effects model of Chapter III:

$RWAGE$: Real wages (at 1987 prices). It is constructed through dividing the total payments made to workers to the total number of hours worked. The nominal hourly wage rate obtained like this is then deflated by the whole sale price index of the corresponding industry.

$RESOLD$: The ratio of the value of sales from goods that are directly purchased without being processed any further to the value of sales from goods produced within the industry.

$ADOP$: It is calculated as the ratio of administrative personnel to operatives (i.e. personnel who are directly engaged in production)

$CR4$: It is the four-firm concentration ratio. The data are obtained from the S.I.S of Turkey.

$NOFIRMS$: It represents the number of firms.

$XTOTRV$: Ratio of exports to volume of trade.

X_MTOTRV : The ratio of the trade balance to the volume of trade.

Here, we should note that since separate data on the foreign trade of private and public sector enterprises were not available, foreign trade variables assume the same values for both the public and private sectors of a given industry. A similar treatment holds for the $CR4$ variable.