SELECTED ASPECTS OF PERFORMANCE OF INDIAN INDUSTRIES:

AN EMPIRICAL INVESTIGATION

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Dedicated to

My Parents

Preface

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I am the only responsible person for any error that may remain in this thesis.

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Chapter 1

Introduction and Plan of the Thesis

1.1 Introduction

At the time of India's independence the need of the hour was to develop the economy at a fast pace so as to achieve a reasonable standard of living for the masses within a short period of time. India's first Industrial Policy Resolution was adopted in 1948 which put emphasis on the expansion of production of both agricultural and industrial goods to satisfy the basic needs of the masses, a large proportion of whom lived well below a subsistence level of living. Hence, emphasis was given on agricultural expansion in the First Five Year Plan and on building up the industrial sector in the Second Five Year Plan. The Second and Third Five Year Plans sought to advocate and also promote the establishment of core and basic industries; the underlying objective was to expand the industrial base of the economy in order to facilitate its rapid growth as early as possible. Policy makers were also in favour of promoting cottage and small scale industries to meet demands for the relatively cheaper industrial goods coming particularly from the lower-end consumers (Little, Mazumdar and Page, 1987, pp. 22-23). Thus cost rather than quality of the product appeared to be the main concern at that time. In this way a quality compromising mind set-up, with relatively less concern for competitiveness of the Indian industries in the international market, had its beginning in India around the mid-fifties.[1] In addition to the policy of promoting small scale industries which might even produce poorer quality output, the tariff policy of the government was also so designed as to prevent (the so called) unfair foreign competition and promote utilisation of India's own resources. In other words, the desire to develop a socialistic pattern of society became the guiding principle behind social and economic policies of the government at that time.

[1] There were, of course, some positive aspects of such policies. For instance, it was argued that a developed cottage and small scale industrial sector could provide immediate large scale employment, offer a method of ensuring an equitable distribution of income and effectively mobilise productive resources like capital and skill which might otherwise have remained unutilised.

However, a healthy expansion of cottage and small scale industries depended upon a number of factors like adequate availability of raw materials, cheap power and technical advice, efficient and organised marketing of their produce, and wherever necessary, protection from intensive competition from large scale manufacturing. (This last aspect, needless to say, would restraint large-scale industrial units from attaining their optimal scales of operation (Ahluwalia, 1985, pp. 160)). However, in view of the urgent need for planned and rapid economic development, industries which were of basic and strategic importance and/or in areas of public utility services, were sought to be developed under the public sector. Of course, state's declared policy was to give fair and non-discriminatory treatment to private and public enterprises when both operated within the same industry. (But such efforts, to a large extent, had remained inoperative in practice.) In addition, having realised the economic rationale of existence of big industries, the government wanted to take steps so that some such industries could co-exist with small industries.[2] Thus the desire to steer the country's industrial development along these directions perhaps prompted the government to adopt a system of industrial licensing – a system which involved the use of a wide variety of instruments and controls.

The system of industrial licensing and several other controls on export-import, capital issues, foreign exchange, transport, prices of essential items etc. which evolved in India had, therefore, had their origins in a combination of nationalistic feeling and socialistic views of some of the founding fathers of the country. Interestingly, the private sector at that time was also in favour of strong governmental assertion. However, the licensing system, whose original intention was to use this power judiciously for the promotion of selected industries on a priority basis, was later used to control almost all industries. As a result, regulation rather than economic rationale became the more important feature of the system, pushing into the background any question of accountability and efficiency of enterprises.[3]

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[2] For example, the government agreed to take initiative to examine how the textile mill industry could be made complementary to, rather than competitive with, the handloom industry which was the country's largest and the best organised cottage industry at that time.

[3] A comprehensive description, evaluation and indictment of this system can be found in Bhagwati and Desai (1970).

The authority gradually realised that the system of industrial licensing – at least in the form it was being introduced – was not well suited for bringing investments into the desired areas. Government appointed one committee after another in the 1960s to examine the industrial licensing system in detail, but did not succeed to channelise investments into the desired directions. As a matter of fact, the authority seemed to be lacking in serious efforts, until quite recently, to bring any substantive changes to this licensing system. Presumably, the promotion of a sheltered home market had a common appeal to all – the bureaucratic authoritarian state, domestic industrial houses and even the multinationals that supplied technology and capital. Thus, interests of all agents coincided to keep Indian industry sheltered and under control system and any question or attempt to attain efficiency was lost in the background (Kapila, 2006, pp. 453-454).

Of course, to meet new challenges Industrial Policy Resolution of 1956 has been modified, from time to time, through various Industrial Policy Statements. However, it became clear and was also admitted officially that the results of actual implementation of policies in the industrial field had not been quite up to expectations nor had it fulfilled the declared objectives.[4] Although the new industrial policy regarding the cottage and small scale industries remained basically the same as stated earlier, the government, perhaps for the first time, showed its concern for quality of products as well as efficiency of production processes. It was stated officially that "….whatever can be produced by small and cottage industries must only be so produced.…*However, it must also be ensured that production in this sector is economic and of acceptable quality*….It is also essential that development of indigenous technology is responsive to the objective of efficient production in increasing quantities of goods that society urgently needs" (GOI, 1977). The next Industrial Policy Resolution came in 1980 which emphasised the need for technological upgradation and modernisation of domestic industries as well as the need for promoting competition among them. It also remarked that the public sector be seen as 'people's sector' and *not* as 'no body's sector'. The policy laid the foundation for an

[4] To quote from the Industrial Policy Statement, 1977, "Unemployment has increased, rural-urban disparities have widened and the rate of real investment has stagnated. The growth of industrial output in the last decade has been no more that 3 to 4 per cent per annum on an average. The incidence of industrial sickness has become widespread and some of the major industries are the worst affected" (Government of India (GOI), 1977).

increasingly competitive export base and for encouraging inflow of foreign investment in the high technology areas. These ideas found expression in the Sixth Five Year Plan also.

The year 1991 is an important landmark in the economic history of post-independent India. The country had to go through a severe economic crisis triggered by a serious balance of payment problem. The crisis, however, provided an opportunity to introduce some fundamental changes in the content and nature of economic policies pursued. Indeed, the response to the crisis came in the form of a set of policies aimed at overcoming the crisis and bringing some fundamental changes in the economic system. The structural reforms introduced in the early 1990s broadly covered the areas of industrial licensing, foreign trade, foreign investment, finance and exchange rate management. Some argued that reforms were solidly based on an understanding of what went wrong with the Indian development strategy since 1950 that delivered neither rapid growth nor any appreciable reduction in inequality (Srinivasan, 1993).

Economic reforms, which were sought to be introduced in industries in areas of licensing, foreign trade and foreign investment, had important implications. Without going into details it may be argued that one common objective of various policy measures introduced since 1991 is to improve the system's efficiency. The thrust of the *New Economic Policy* has been towards creating a more competitive environment in the economy as a means for improving productivity and efficiency of the system. This was to be achieved by removing the barriers to entry and the restrictions on the growth of firms. While the Industrial Policy Resolution of 1991 sought to bring about a greater competitive environment domestically, its counterpart on the external front, the Trade Policy, set out in the same year, aimed at improving international competitiveness of the domestic firms subject to the degree of protection offered by tariffs. For instance, the private sector has been allowed to operate in areas reserved earlier exclusively for the public sector. In these areas the public sector would have to compete with the private sector even if the former might continue to play the dominant role in near future. What has been sought to be achieved through all these is to improve the functioning of the various entities irrespective of whether they are in the private or the public sector. Good performance of a unit is being emphasised now, as it is supposed to be a prerequisite for growth or even mere survival.

Several aspects of India's industrialisation process have been studied in the literature (see, e.g., Gokarn and Vaidya, 1993; Majumdar, 1996a; Aggarwal, 2002) and may surely be studied further to assess the impact of new economic policies adopted since the early 1990s. These aspects include, among other things, pattern of industrial growth, the kind of its diversification desired/to be attempted, the extent of labour absorption and capacity utilisation, any perceptible improvement in total factor productivity and efficiency in selected industries/industrial sector as a whole, effect on profitability of industrial enterprises, kind of growth of manufacturing exports and so on.[5]

The objective of the present dissertation is to take up a couple of these aspects for a detailed analysis. The *first aspect* which the dissertation wants to examine is efficiency of industrial units. To be specific, the study attempts to measure, applying two very well known methods to the official micro level data, the extent of technical efficiency (TE) of individual firms in two major mass consumption good industries in India, viz., textile and leather. In fact, the study tries to measure as well as explain the extent of a temporal variation in TE across firms. Let us discuss this aspect in detail.

Economic performance of a unit is generally supposed to be reflected in its *productivity* which is measured by the *ratio* of its *outputs* to its *inputs*. This ratio is easy to compute in case of a single input turning out a single output. However, if the unit uses several inputs to produce a number of outputs, the inputs in the denominator (as also the outputs in the numerator) must be meaningfully aggregated so that productivity remains the ratio of the two scalars – an aggregate output quantity and an aggregate input quantity. Measured in this fashion, productivity may vary across units for a variety of reasons – owing to differences, say, in production processes, in the efficiency levels of the individual units, in the environment in which production takes place and so on. The challenging problem for the empiricists is to ascertain which of these factors provide satisfactory explanations for such variations in productivity.

Initial studies in the literature have all ignored any potential contribution of efficiency change to productivity change. In fact, the seminal contribution of Solow (1957) sought to attribute output growth only to input growth and technical change, without making any allowance for possible efficiency change. Now, productivity in

[5] See Mookherjee (1995) for discussions on some of these issues.

question is basically what is called *total factor productivity* (TFP), and its rate of change is usually measured by the *difference* between the rate of change of an *output* quantity index and the rate of change of an *input quantity* index.[6] However, such rate of change of TFP can be decomposed into four distinct components: a *scale* component, an *allocative inefficiency* component, a *technological change* component and a *technical efficiency* (TE) change component.[7] Thus, even when there are no allocative inefficiency and no scale component – the case assumed by Solow – the rate of change in TFP will not be the same as the rate of technological change, since the former will also be affected by whatever changes in TE take place. Thus measuring TE is as much important as measuring technical change. A second important reason for taking interest in measuring efficiency is that it is expected to throw up indicators of performance or success in terms of which production units may be evaluated and compared. In fact, once the sources of efficiency differentials across different units of an industry or even across different industries are identified, it will help private or even public authorities to design appropriate policies to improve performance of the relatively inefficient units.

In fact, issues of productivity and efficiency of firms have assumed added importance ever since the process of liberalisation of the Indian economy was initiated in the early 1990s. Improved performance of producing units is now being emphasised and achieving efficiency is now supposed to be a prerequisite for growth or mere survival. However, these issues can be analysed rigorously only when firm-level efficiency is properly estimated and factors likely to explain cross-sectional or even inter-temporal variation in such efficiency are empirically identified. The factors which are supposed to cause such variation include firm's size, its age, its regional location and so on.

To discuss the second point very briefly here, the size of a firm is supposed to affect its performance for a number of reasons.[8] A large firm generally has diverse capabilities and greater ability to exploit economies of scale, thereby performing much better relative to a smaller firm (Penrose, 1959, pp. 89 & 218-219). On the other hand, size is correlated with market power (Shepherd, 1986a) which increases possibility of

[6] Here we assume a single output – multi input case.
[7] This decomposition is shown in detail in the Appendix to this chapter.
[8] See Majumdar (1997) for some more discussion on the relationship of firm's performance with its size and age.

generating X-inefficiency in production, leading to relatively inferior performance (Leibenstein, 1976). Theory, therefore, is equivocal on the relationship between size of a firm and its performance. If one now considers the Indian economy he/she observes that not only it had an ambivalent attitude towards the role and existence of large firms, the articulation and administration of policy had also been at cross-proposes with each other (Jalan, 1991). In the key industrial sectors there was a preponderance of units possessing sub-optimal scale as a result of industrial policy resolution of 1956 and subsequent follow-up legislations which favoured small private firms, ignoring the issue of economies of scale (Little, Mazumdar and Page, 1987). On the other hand, implementation of policies was far off from what was desired. Private sector industrial houses were able to flaunt established norms and, consequently, attain both economic power and large sizes with the careful management of the political and administrative apparatus of the 'license Raj', and with the active co-operation of some bureaucrats and politicians (Rudolph and Rudolph, 1987, pp. 31-32). Therefore, no a priori relation can be argued between size and performance for the Indian industrial sector and it is to be assessed only empirically.

A second factor which is likely to affect a firm's performance is its age. One stream of thought suggests that older firms display superior performance since they are more experienced and may reap the benefits of prior learning (Stinchcombe, 1965). There is, however, the counter argument, namely that the older firms are prone to inertia and bureaucratic ossification and hence, may lack the required flexibility and eagerness to adapt rapidly to the changing economic circumstances, thereby loosing out in performance to younger and more agile firms (Marshall, 1920). Thus any relationship between age and performance of a firm cannot be postulated a priori but be assessed only empirically.

Given the large volume of work that is involved in processing micro level data and analysing them, the present study has selected two industries to investigate these features. The two industries chosen, as we have already mentioned, are textile and leather which are very important traditional industries in India and also relatively large in size. We shall talk about the structure of each industry in the relevant chapter. Here we only mention that the present study not only measures TE of textile and leather firms, but also tries to examine empirically the kind of effect a firm's size and age in each industry have on its TE. Some additional queries have also been made, namely whether there exist any significant variation in firm level efficiency across states, and across types of ownership and patterns of organisation of firms in each industry. These factors seem to be quite relevant since India is a vast country having a number of states and union territories with their distinct sociological, economic, political and infrastructural features. Not only access to natural resources and other infrastructural facilities which affect unit cost of output is not evenly distributed across regions, but the work culture of the people may not be the same everywhere (Das, Ray and Nag, 2009).

The *second aspect* of the industrial structure on which the present study tries to throw some light is regarding the nature of relation between market structure and profitability in industries. In particular, the issue to be investigated is whether concentration in an industry affects its profitability favourably. High concentration in an industry means that a few big firms account for a large share of the industry. In the Indian industries, large firms operate in the organised capital and labour markets and small firms operate mostly in the unorganised input markets. Consequently, large firms get access to capital at a lower price but may have to pay higher wages to labour than the small firms. The regulatory policies pursued in India combined with such capital market imperfections and the presence of sub-optimal contractual arrangements cause higher market transaction cost, which is argued to be a source of long run market power to large firms and entry barriers to small ones (Patibandla, 1998, pp. 420). The conventional market Structure-Conduct-Performance (S-C-P) paradigm has been enriched much with the pioneering work of Bain (1956) which relates profitability to the degree of seller concentration and the depth of entry barriers in the market. It has been an area of active research in many countries ever since Bain (1956) made his study. We would like to examine this issue for the industrial sector in India.

To summarise, one may say that the first aspect is examined for the two selected industries from a microeconomic point of view while the second aspect, being analysed for the industrial sector as a whole, seems to have an aggregative perspective. Let us state the plan of the present dissertation.

1.2 Plan of the Thesis

The dissertation is organised as follows. ***Chapter 2*** presents a review of the relevant literature in the two areas of industrial economics which the present study considers. This review is brief and also selective in many cases.

Chapter 3 is concerned with estimating as well as analysing level of TE of individual firms in the textile industry in India for a number of years. Parametric *stochastic frontier analysis* (SFA) method has been used to estimate firm-level TE. Standard empirical exercises have been carried out to ascertain the impact of firm-specific factors on the firm-level TE. The results suggest that the latter is related positively to its size, but inversely to its age as far as the Indian textile industry is concerned. Again, regional location of a firm as well as its ownership pattern affects its TE. Finally, there seems to have an increasing trend in the average firm level TE in the textile industry during the post-liberalisation period.

Chapter 4 analyses all the issues examined in chapter 3 in respect of the same industry (viz., textile), but using the mathematical programming-based *data envelopment analysis* (DEA) method. Interestingly, almost all the findings of chapter 3 are confirmed here. The chapter also investigates an additional issue, namely whether measures of TE differ if one allows for the possibility of existence of any technological heterogeneity across firms located in different states, ownership patterns and/or different organisational structures. Results show that there do exist substantial technological heterogeneity in firms due to these factors. Finally, average firm level TE seems to have risen, although not monotonically, over the years under study.

Since two alternative methodologies have been used to estimate as well as analyse firm level TE in textile industry, it may be interesting to compare the results through the two alternative techniques. The purpose of ***Chapter 5*** is to make such a comparison. It is observed that in general, the nature of results obtained through two alternative methods is broadly the same except the two cases. One is that the level of a firm's TE estimated through SFA is much higher than that calculated through DEA. The other difference is that the histograms showing percentage distribution of firms against TE levels is highly negatively skewed in the case of the SFA method but more or less bell-shaped in the case of the DEA method. These dissimilarities apart, these two sets of TE scores are found to be highly correlated, as scatter diagrams of these scores for different years readily reveal.

Chapter 6 takes up the Indian leather industry for analysis and investigates the same set of issues as has been done in case of the textile industry in the preceding two chapters. Results of both the parametric as well as mathematical programming methods are presented and analysed in this chapter and a comparison of the two sets of results is also made. The findings are by and large the same as obtained in the case of the Indian textile industry. And once again the scatter diagram SFA-TE scores against DEA-TE scores is observed to show a highly positive correlation for each year under study. Further, some significant variation in state-wise average TE is also observed in different years. Finally, the average firm level TE of the Indian leather firms is observed to have shown some increasing tendency over the years.

Chapter 7 examines some aspect of industrial organisation for the industrial sector of India, in particular the nature of relationship between the structure of an industry and some measure of its performance. A market structure basically specifies the ways in which a market departs from a perfectly competitive set up. In standard market models, such as 'models of monopoly and competition, market structure determines market conduct, the behavioural rules followed by buyers, sellers and potential entrants to choose the variables under their control. Market performance is assessed by comparing the results of market conduct to first best ideals such as perfect competition or feasible alternatives' (Schmalensee, 1989, pp. 954). Such conventional structure-conduct-performance (S-C-P) paradigm – popularised by the pioneering work of Bain (1956) – has been examined in this chapter for the Indian industrial sector. The results obtained suggest that the conventional S-C-P paradigm is valid for the Indian industries. Specifically, industrial concentration along with some entry barrier variables like minimum efficient size of a plant, advertisement and R&D intensity etc are all found to be important in affecting profitability of Indian industries.

Chapter 8 is the concluding chapter of the dissertation. This chapter summarises the main results obtained in the study, comments on a few policy implications and points out some limitation of the study.

Appendix 1.1

Consider the traditional production function which assumes that the level of output (*Y*) is the best practice or frontier output given by the following function

$$Y = f(X, t; \beta) \tag{A.1}$$

where X is the vector of quantities of various inputs, β the vector of the associated parameters and t is time standing for technology available in the period in question. Differentiating with respect to time *t*, denoting $\partial f / \partial t$ by f_t, $\partial f / \partial X_k$ by f_k, dz/dt by $\dot{z}$ and the rate of growth of *z* by $\hat{z}$, i.e., $\hat{z} = \dot{z} / z$ we get

$\dot{Y} = \dot{f} = f_t + \sum f_k \dot{X}_k$, or dividing by Y,

$$\frac{\dot{Y}}{Y} = \frac{\dot{f}}{f} = \frac{f_t}{f} + \sum \frac{f_k}{f} \dot{X}_k = \frac{f_t}{f} + \sum \frac{f_k X_k}{f} \frac{\dot{X}_k}{X_k} = \mathrm{TC} + \sum \varepsilon_k \hat{X}_k \tag{A.2}$$

where TC is the rate of technical change (= f_t / f) and ε_k $\{= (\partial f / \partial X_k)/(f / X_k)\}$ is the elasticity of output with respect to the k^{th} input.

Let us write w_k for the price of the k^{th} input, *E*, for the total expenditure on all inputs ($E = \Sigma w_k X_k$) and s_k, for the k^{th} input's share in this expenditure ($s_k = w_k X_k / E$). The rate of change in *total factor productivity* (**TFP**) is defined to be the difference between the rates of change of output (*Y*) and an input quantity index (*I*):

$$\hat{TFP} = \hat{Y} - \hat{I} = \hat{Y} - \sum s_k \hat{X}_k \qquad [\text{where } \hat{I} \equiv \sum s_k \hat{X}_k]$$

$$= \mathrm{TC} + \sum \varepsilon_k \hat{X}_k - \sum s_k \hat{X}_k, \qquad [\text{by (A.2)}]$$

$$= \mathrm{TC} + (\varepsilon - 1) \sum \frac{\varepsilon_k}{\varepsilon} \hat{X}_k + \sum \left(\frac{\varepsilon_k}{\varepsilon} - s_k\right) \hat{X}_k, \qquad [\varepsilon \equiv \sum \varepsilon_k] \tag{A.3}$$

Thus the rate of change in TFP can be *decomposed* into three terms: a *technological change* component (the first term on the RHS of the last expression), a *scale* component (the second term) and an *allocative inefficiency* component (the third term). Solow assumes (i) constant returns to scale ($\varepsilon \equiv \sum \varepsilon_k = 1$) and (ii) marginal productivity theory, i.e., the case in which each factor is paid the value of its marginal product ($\varepsilon_k / \varepsilon = s_k$).[9] However, assumptions (i) and (ii) imply that the second and the third terms are each zero so that the rate of change in TFP is the same as the rate of technical change:

$$\hat{TFP} \;=\; \text{TC} \tag{A.4}$$

However, this simple result is not valid when (**a**) assumptions (i) and/or (ii) are **violated,** as well as when (**b**) there is **inefficiency** of producing units. Consider case (b). The production frontier, i.e., the maximum possible output in a deterministic frontier approach is the relation already used, $f(X,t;\beta)$. However, an individual firm's observed output (*Y*) may lie on or below the frontier output:

$$Y = f(X,t;\beta)\, e^{-u}\;, \qquad (u \geq 0) \tag{A.5}$$

A measure of technical efficiency (TE) is given by the ratio of actual output to the frontier output, $TE = \dfrac{Y}{f(X,t;\beta)} = e^{-u}$, so that the rate of change of technical efficiency is: TEC $= \dfrac{\dot{TE}}{TE} \;=\; -\,\dot{u}$. Thus,

$$\frac{\dot{Y}}{Y} = \frac{\dot{f}}{f} - \dot{u} = \frac{f_t}{f} + \sum \frac{f_k X_k}{f}\frac{\dot{X}_k}{X_k} - \dot{u} = \text{TC} + \sum \varepsilon_k\, \hat{X}_k + \text{TEC} \tag{A.6}$$

Thus TFP change is now given by[10]

$$\begin{aligned} \hat{TFP} \;&=\; \text{TC} + \sum \varepsilon_k\, \hat{X}_k \;+ \text{TEC} \;-\sum s_k\, \hat{X}_k \\ &=\; \text{TC} + \text{TEC} + (\varepsilon - 1)\sum \frac{\varepsilon_k}{\varepsilon}\hat{X}_k \;+ \sum\left(\frac{\varepsilon_k}{\varepsilon} - s_k\right)\hat{X}_k \end{aligned} \tag{A.7}$$

Thus, even if constant returns to scale prevail (i.e., $\varepsilon = 1$) and factors are paid their marginal products (i.e., $\varepsilon_k / \varepsilon = s_k$), $\hat{TFP}$ is not just TC but equals the sum, TC + TEC.

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[9] $\varepsilon_k = f_k \dfrac{X_k}{Y} = \dfrac{w_k X_k}{pY}$ (if marginal productivity theory holds). Hence, $\varepsilon = \sum \varepsilon_k = \dfrac{\sum w_k X_k}{pY} = \dfrac{E}{pY}$, where p is the price of output. It then follows that $\varepsilon_k / \varepsilon = w_k X_k / E = s_k$.

[10] See Kumbhakar et al (2000), chapter 8, pp. 282-285 for detailed derivation of this decomposition.

Chapter 2

A Brief Review of the Literature

2.1 Introduction

During the early years of development of economic theory, the notion of efficiency was tacitly assumed in any analysis of production behaviour of firms. In fact, the concept of a production function presumes that firms attain maximum possible output, given their uses of inputs. The reasons for such a presumption are not difficult to guess. During the early period neither there was any proper economic theory to analyse lack of efficiency on the part of firms nor was any rigorous statistical or analytical method developed to measure such inefficiency. In addition, suitable micro-level data were also not available then which could have made possible any analysis of firm-level efficiency. Over time, however, improvement in methods of data collection made possible compilation of more and more precise micro-level data. When suitable alternative methodologies were also developed to analyse them, it became apparent that inefficiency on the part of a producing unit is what was to be expected in general rather than as an exception.

The immediate post-world war II witnessed a general interest in growth and productivity and the celebrated paper by Solow on these issues within a macro set-up appeared in 1957 (Solow, 1957). At the same year distinguishing work of Farrell (1957) laid the foundation for new approaches to efficiency and productivity studies at the micro level and presented new insights on two issues, viz., how to define efficiency and productivity of a unit, and how to obtain the benchmark technology against which efficiency of a unit is to be measured. Farrell’s seminal paper and subsequent discussions of different scholars on it were the basis of almost all approaches (to efficiency measurement) developed in the modern productivity literature. Anyway, the fundamental idea in Farrell’s seminal work was the possibility of inefficient operations of a producing unit if measured from a benchmark production function, popularly called a *frontier production function*, as opposed to what may be called *average production function* sought to be estimated in the relevant econometric literature up to that time.[1] In fact, it is Farrell (1957), who first explored the possibility of estimating the so-called *frontier* production functions. So far as the choice of a production function benchmark is concerned, Farrell adopted a very pragmatic approach, viewing the frontier as the observed best practice one. His contribution was to introduce a *piecewise linear* envelopment of the data as the frontier in the sense of the function being as close to the observations as possible, and then to show how the frontier could be estimated by solving a set of linear equations. His measures of efficiency were based on radial (uniform) contraction of inputs or expansion of outputs from an inefficient unit of observation up to the frontier.

Farrell's seminal work was followed by a large number of refinements and extensions, which may broadly be classified into three different schools of thought. As distinguished by Thompson and Thrall (1993), the first one is the *Afriat School* which is based on the parametric estimation approach of the econometricians, the second one is the *Charnes-Cooper School* which is based on the mathematical programming approach and the third one is the *Shephard School* which may be called as an axiomatic production theory approach. Since our study will be based on the first two approaches, we discuss below the literature which has grown relating to the *first two* Schools only.

The two schools referred to above are in fact, two competing paradigms on how to construct frontiers. One uses parametric techniques while the other employs mathematical programming techniques. The main advantage of the mathematical programming based approach is that it does not require any explicit functional form to be imposed on the data. However, the calculated frontier may be warped if the data are contaminated by statistical noise. In fact, critics are particularly vocal on this limitation of the programming approach, and argue that whatever efficiency measure is obtained relative to this frontier is just a calculated value (without any standard error) rather than an estimate. On the other hand, the econometric approach which accommodates statistical noise, does so only at the cost of imposing an explicit, and possibly overly restrictive,

[1] As Aigner, Lovell and Schmidt (1977, pp. 21) puts it, 'the theoretical definition of a production function expressing the maximum amount of output obtainable from given input bundles with fixed technology has been accepted for many decades. And for almost as long, econometricians have been estimating average production functions'.

functional form for technology. In addition, an explicit distribution for the inefficiency term has also to be imposed unless panel data are available. Ideally, one either knows the correct structure to impose a priori or else estimates a sufficiently flexible model so that several alternative restrictions can be incorporated and tested.

Productivity and efficiency constitute one aspect of empirical industrial economics. A somewhat related aspect is a firm's economic performance reflected say in its profitability. In other words, attempts may be made to examine whether there is any possible relation between industrial structure and industrial profitability – a relation that leads to the notion of Structure-Conduct-Performance (S-C-P) paradigm. Most economists agree that *Industrial Economics* (or, *Industrial Organisation*) as a distinct field of economics has emerged from out of the works of Edward Chamberlin and Edward Mason at Harvard in the early 1930s. The S-C-P paradigm has played an important role in research on industrial organisation since the pioneering work of Mason (1939). The research programme led by Mason sought to improve our knowledge about imperfectly competitive markets by way of induction on the basis of careful examination of particular examples. However, these studies made relatively little use of either formal economic theory or econometric techniques.

It was Joe Bain (1951, 1956) first who changed the focus of empirical research in industrial economics by showing how powerful and meaningful statistical studies of industry-level cross-sectional data could be undertaken to explain industry's profitability. Since we shall examine this issue empirically in the context of the Indian industrial sector, the literature which has grown since Bain (1951, 1956) will also be discussed in this chapter. The present chapter is thus organised as follows. Section 2.2 describes the parametric methodologies and their applications in estimating the level of TE of an individual firm. Section 2.3 contains a discussion on the development of mathematical programming tool and its empirical application to calculate unit-level TE within a sector. Finally, section 2.4 presents a summary of the literature on the S-C-P paradigm.

2.2 The Parametric Frontier School

The school, also known as the *Afriat School* has effectively begun with the discussion of Winsten (1957) on the original work of Farrell (1957). Conceptually it deviates from the traditional trend, at that time, of estimating an average production function from the observed data points following parametric method. Several alternative methodologies have gradually been developed to estimate productive efficiency of individual production units. The methodologies are discussed below along with a brief account of some important/initial empirical works using each methodology.

2.2.1 Deterministic Frontier Production Function (DFPF) Model

Let us suppose that cross-sectional data on the quantities of k inputs (denoted by vector X) and the quantity of a single output (denoted by Y) are available for each of N producers (indexed by i). A production frontier model may be written as:

$$Y_i = f(X_i;\, \beta)\, TE_i \tag{2.1}$$

where Y_i is the output of producer i, $f(X_i;\, \beta)$ is the production frontier, X_i is the vector of k inputs used by producer i and β is the vector of the corresponding technology parameters (which is to be estimated). Now, the (output-oriented) technical efficiency of producer i, TE_i, is defined to be the ratio of the observed output (Y_i) to the maximum output feasible at the input quantities used by the producer i, viz., $f(X_i, \beta)$. By definition then TE_i lies between 0 and 1. The literature[2] on such parametric estimation of a *frontier* from the observed data points started with the discussion of Winsten (1957) and became popular after the publication of the seminal work by Aigner and Chu (1968), who estimated a Cobb-Douglas production frontier following linear and quadratic programming techniques. Timmer (1971) developed this procedure further by introducing the probabilistic frontier production model. To illustrate the method, consider the work of Aigner et al (1968) in which the deterministic production frontier is assumed to be of the following log-linear Cobb-Douglas form

$$\ln f(X_i, \beta) = \beta_0 + \sum_{n=1}^{k} \beta_n \ln X_{ni} \tag{2.2}$$

so that the logarithm of the observed output is

[2] See Førsund, Lovell and Schmidt (1980), Schmidt (1986), Bauer (1990), Greene (1993), Coelli, Rao and Battese (1998), Kumbhakar and Lovell (2000) etc for a detailed survey of the literature concerning the estimation of parametric frontier production functions.

$$\ln Y_i = \beta_0 + \sum_{n=1}^{k} \beta_n \ln X_{ni} - u_i \tag{2.3}$$

where it is assumed that $u_i \geq 0$ for each i so as to ensure that $Y_i \leq f(X_i, \beta)$. In other words, the observed level of output of any firm is at most as large as that of the frontier level achievable at its input vector and hence, any deviation from this frontier would imply inefficiency on the part of the firm.

Equation (2.3) is a linear regression model with a non-positive disturbance. The objective is to obtain an estimate of the parameter vector β (which describes the structure of the production frontier), as well as an estimate of the disturbance term u_i, which yields an estimate of TE_i for each producer i (in view of the fact that $TE_i = \exp(-u_i)$).[3] Three alternative methodologies which have been proposed in the literature to estimate such a deterministic frontier model are briefly discussed below.

Corrected Ordinary Least Squares (COLS) Method

The idea of such a method originated from Winsten's (1957) discussion on Farrell's 1957 paper and ultimately the corrected ordinary least squares (COLS) method was developed by Gabrielsen (1975). The model (2.3) could be estimated following a two-step procedure. In the first step, the ordinary least squares (OLS) method is applied to obtain consistent and unbiased estimates of the slope parameters (say, $\hat{\beta}_n$'s) and consistent *but biased* estimate of the intercept parameter (say, $\hat{\beta}_0$). In the second step this (biased) intercept estimate is shifted up, i.e., *corrected* in the following manner so as to ensure that the estimated frontier bounds the data from above:

$$\hat{\beta}_0^* = \hat{\beta}_0 + \max_i \{\hat{u}_i\} \tag{2.4}$$

where $\hat{u}_i$'s are the OLS residuals and $\hat{\beta}_0^*$ is the COLS estimate of the intercept. It may be noted that the OLS residual $\hat{u}_i$ satisfies

[3] Note that an output-oriented technical efficiency of firm i (TE_i) is given by the ratio of the observed output to the frontier output achievable at its input vector: $TE_i = Y_i / f(X_i, \beta) = \exp(-u_i)$ [using (2.2) and (2.3)].

$$\widehat{\ln Y_i} = \hat{\beta}_0 + \sum_{n=1}^{k} \hat{\beta}_n \ln X_{ni} + \hat{u}_i$$

$$= \hat{\beta}_0 + \max_i \{\hat{u}_i\} + \sum_{n=1}^{k} \hat{\beta}_n \ln X_{ni} + \hat{u}_i - \max_i \{\hat{u}_i\}$$

$$= \hat{\beta}_0^* + \sum_{n=1}^{k} \hat{\beta}_n \ln X_{ni} + \hat{u}_i - \max_i \{\hat{u}_i\} \text{ [using the definition (2.4)]} \qquad (2.5)$$

Define now $\hat{u}_i^*$ as

$$\hat{u}_i^* = -\left[\, \widehat{\ln Y_i} - \hat{\beta}_0^* - \sum_{n=1}^{k} \hat{\beta}_n \ln X_{ni} \,\right]$$

$$= \max_i \{\hat{u}_i\} - \hat{u}_i \qquad \text{[by (2.5)]} \qquad (2.6)$$

which is non-negative for all i and zero for at least one i. The $\hat{u}_i^*$ is the COLS residual which may be used to obtain consistent estimate of individual firm's TE as shown below:

$$TE_i^* = \exp\left(-\hat{u}_i^*\right) \qquad (2.7)$$

To cite a few studies, Belbase and Grabowski (1985) used COLS method to estimate a deterministic Cobb-Douglas production frontier model so as to investigate efficiency in Nepalese agriculture. Again, Seaver and Triantis (1989) used this method to fit a Cobb-Douglas production frontier and to obtain plant and process level technical efficiency of the linerboard manufacturing facilities in the U. S.

However, one limitation of the procedure is that the COLS frontier does not necessarily bound the data from above as closely as possible, since it is required to be parallel to the estimated OLS regression equation. And this imposes undesirable restrictions on the production technology (see Kumbhakar et al, 2000, pp. 70-71, for details).

Goal Programming Approach

Aigner et al (1968) showed that the deterministic production frontier could be converted into either of a pair of mathematical programming models and that in each such model the goal would be to find a set of *optimal* values of the parameters $\beta_0, \beta_1, ..., \beta_k$ such that the observed output of no producer exceeds the maximum output feasible for its input vector.

$$\beta_0 + \sum_{n=1}^{k} \beta_n \ln X_{ni} \geq \ln Y_i, \qquad \text{for each} \quad i = 1,2,.........., N. \tag{2.8}$$

As (2.3) shows, for each firm i, u_i is the difference between its frontier output and observed output (both in logarithms) and hence, is non-negative, by (2.8). *Optimal* β's are obtained by minimising the sum of the u_i's (i.e., $\sum_i u_i$) in the case of the linear programming model, and the sum of the squares of the u_i's (i.e., $\sum_i u_i^2$) in the case of the quadratic programming problem, satisfying in each case the set of constraints (2.8). Once parameter values are calculated from either model, TE of each producer can be computed from the (optimal) slack in the corresponding constraint:

$$TE_i = \exp\left(-u_i^*\right) = \exp\left(\beta_0^* + \sum_{n=1}^{k} \beta_n^* \ln X_{ni} - \ln Y_i\right)\left(i = 1, 2, ..., N\right) \tag{2.9}$$

where an asterisk (*) corresponding to a variable (parameter) indicates the optimal value of the variable (parameter) in question. Levin (1974) employed Aigner et al (1968) parametric, non-stochastic linear programming model to account for technical inefficiency in educational production. Shapiro and Müller (1977) sought to measure technical efficiency through a deterministic Cobb-Douglas production frontier constructed using linear programming method. Van den Broek et al (1980) solved a non-linear programming problem to construct the frontier for the data on the general milk processing from twenty-eight individual dairy plants collected from the Swedish Dairy Federation for the period 1964-1973. Bjurek et al (1990) estimated Cobb-Douglas frontier by using both linear and quadratic programming techniques to analyse productive efficiency of about four hundred local social insurance offices in Sweden using data for the period 1974-1984 collected from the National Social Insurance Board.

However, a major drawback of this approach is that the optimal parameter values are *calculated* rather than *estimated* (such as the ones done in regression techniques) and hence statistical inference concerning the calculated parameter values becomes difficult.

Later development of the literature includes the work of Schmidt (1976) who pointed out that the models could be given a statistical interpretation, if a distributional assumption is imposed on the u_i. In fact, the calculated values can be shown to be the maximum likelihood estimates (MLE) of the parameters for the linear model if the $u_i \left(\geq 0\right)$ follow an exponential distribution and, for the quadratic model if the u_i follow a half-normal distribution.

Modified Ordinary Least Squares (MOLS) Method

Afriat (1972) and Richmond (1974) suggested that the parameters of the deterministic production frontier model (the one shown in (2.3)) as well as the estimates of firm level TE's could be obtained using a variant of the COLS method. The method, widely known as the MOLS method, is a two step method, performing OLS regression in the first step (as in the case of COLS method) and then modifying in the second step the OLS estimates of both intercept ($\hat{\beta}_0$) and residuals ($\hat{u}_i$'s) in the following way:

$$\hat{\beta}_0^{**} = \hat{\beta}_0 + E\left(\hat{u}_i\right) \tag{2.10}$$

and

$$\hat{u}_i^{**} = E\left(\hat{u}_i\right) - \hat{u}_i \tag{2.11}$$

The modification is done, using the *mean* of the estimates of a disturbance term, instead of its *maximum* value as is done in the case of the COLS method. Individual efficiency estimate could then be obtained as $TE_i^{**} = \exp\left(-\hat{u}_i^{**}\right)$. Rossi and Canay (2001) estimated a frontier model using this method and compared its results with those obtained through alternative methods of estimation. They used four different data sets consisting of information on gas distribution firms in Argentina, water companies in Asia and Pacific region, water companies in England and electricity distribution firms in South America.

The method is, however, flawed owing to an important limitation. Using the mean of $\hat{u}_i$'s to modify the intercept of the frontier equation in order to shift it upwards may not ensure that all the observed data points are bounded by the estimated production frontier from above (see Olson et al, 1980, for some detailed discussion on this).

2.2.2 Stochastic Frontier Production Function (SFPF) Model

The methods discussed above are all subject to a serious deficiency, namely that each measures TE relative to a deterministic production frontier, i.e., a frontier in which the maximum feasible output for a given vector of inputs is not affected by any random factors like weather, strike, luck etc. Aigner et al (1977) and Meeusen and van den Broeck (1977) independently proposed a model where an additional random error v is added to the non-negative random variable u to take care of effect of such unobserved random factors as well as measurement error (if any) on the frontier output. Their model is known as the Stochastic Frontier Production Function (SFPF) approach, since the proposed method takes the frontier itself be stochastic, being subject to random variations beyond the control of the producer.[4]

A stochastic frontier rather than a deterministic one is usually the preferred alternative, as the former accommodates random factors (affecting output) beyond a firm's control. Use of a stochastic frontier may also take care of errors arising out of possible misspecification owing to the omission of any relevant variables (uncorrelated with the included regressors) from the function to be fitted. However, the exercise of obtaining firm level estimates of efficiency is an involved one when a stochastic frontier is used. It may be noted that in the case of a deterministic frontier such estimates are readily obtained from the estimated values of the residuals. Alternative techniques have been used in the literature to obtain estimates of firm level efficiency under SFPF. These techniques differ depending on how the difference between an inefficiency error and a random error is captured, which functional forms are specified for the frontier, and what kind of distributional assumptions are made about the two disturbance terms. We summarise such discussions below assuming a flexible translog functional form (the one used most widely in the literature). In this case the SFPF model is given by

$$\ln Y_i = \beta_0 + \sum_{n=1}^{k} \beta_n \ln X_{ni} + \frac{1}{2} \sum_{m=1}^{k} \sum_{n=1}^{k} \beta_{mn} \left(\ln X_{mi}\right)\left(\ln X_{ni}\right) + v_i - u_i$$

[4] Maximum Likelihood Estimation method for such frontier model with composed error has also been discussed in Battese and Corra (1977) with an empirical illustration for the Pastoral Zone of Eastern Australia using the data on sheep production from a survey of the Australian Grazing Industry.

$$= \left\{ \beta_0 + \sum_{n=1}^{k} \beta_n \ln X_{ni} + \frac{1}{2} \sum_{m=1}^{k} \sum_{n=1}^{k} \beta_{mn} (\ln X_{mi})(\ln X_{ni}) + v_i \right\} - u_i \qquad (2.12)$$

where the expression within the second brackets represents (the logarithmic value of) frontier output and the coefficients β_{mn}'s are assumed to be symmetric, i.e., $\beta_{mn} = \beta_{nm} \;\; \forall \; m$ and n. Note that the frontier itself is stochastic in nature since it contains a random error term, v_i which is generally assumed to follow a normal distribution with zero mean and constant variance.[5] The estimation of the equation (2.12) also requires specific distributional assumption for the one-sided inefficiency error component, u_i. A number of alternative distributions have been used for the u_i in the literature. These include (a little bit inflexible) half-normal distribution (proposed in the original Aigner et al (1977) model) and an exponential distribution (proposed in the Meeusen et al (1977) model), both sharing a common feature, namely that the density of the disturbance is concentrated most near zero. In contrast, Stevenson (1980) suggested shifting the half-normal distribution so as to yield a non-zero mode, producing thereby a general truncated normal distribution. He also proposed a restricted version of Gamma model in his paper.[6] Greene (1990) had proposed a two-parameter Gamma distribution where a COLS estimator, obtained by using the method of moments estimation, had also been presented. Parameters of these alternative models could easily be estimated following a Maximum Likelihood Estimation (MLE) method.[7] All these studies assumed v_i and u_i to be distributed independently of each other.[8]

However, estimation of observation specific TE had remained a difficult task up to the early eighties. Waldman (1982) showed that the likelihood function might not behave properly if a truncated normal distribution were assumed for the inefficiency

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[5] Kopp and Mullahy (1990) uses a generalised method of moments estimation technique in the case of a non-normal statistical noise term.
[6] To be specific, Greene (1980) has proposed the Gamma model in the context of the deterministic frontier model.
[7] Tests of the appropriateness of these various distributions can be conducted using Lagrange multiplier techniques proposed by Lee (1983) and Schmidt and Lin (1984).
[8] Pal and Sengupta (1999), however, relaxes this restrictive assumption as well as provides some justification for such relaxation, particularly in the case of agricultural production behaviour. They also provide an empirical application of their theoretical model using the various data on agricultural production in India.

term u_i. An additional limitation of this truncated normal distribution model is that it would fail to identify u_i and v_i separately at the firm level. Jondrow, Lovell, Materov and Schmidt (1982) were the first to develop a method of segregating the inefficiency term u_i from the statistical noise term v_i, using the distribution of the u_i conditional on the estimate of the composite error term ε_i $(\equiv v_i - u_i)$ for each individual unit i. An empirical application of this method for the case of 111 privately owned steam electric generating plants in the U. S. was also presented in their paper.[9] To get some idea about this issue, we discuss below estimation strategies along with the corresponding likelihood functions and analytical expressions for the observation specific estimates of TE under a few alternative distributional assumptions.

As far as the conventional random term (v_i) in case of SFPF is concerned, it is usually assumed to be a normal variable, identically and independently distributed with zero mean and constant variance, i.e., $v_i \sim iid\ N\left(0, \sigma_v^2\right)$ (for all i), irrespective of the assumptions made about the distribution of the inefficiency variable, u_i. Coming now to the inefficiency variable (u_i), let us first consider the case where u_i follows an *exponential distribution*, being identically and independently distributed with variance, σ_u^2. The log likelihood function for a sample of N producers may then be written as[10]

$$\ln L = -N \ln \sigma_u + N\left(\frac{\sigma_v^2}{2\sigma_u^2}\right) + \sum_{i=1}^{N} \ln \Phi\left(A_i\right) + \sum_{i=1}^{N}\left(\frac{\varepsilon_i}{\sigma_u}\right) \tag{2.13}$$

where $A_i = \tilde{\mu}_i / \sigma_v$, $\tilde{\mu}_i = -\varepsilon_i - \left(\sigma_v^2 / \sigma_u\right)$ (for all i) and $\Phi(\bullet)$ is the distribution function of a standard normal variate (i.e., normal variable with zero mean and unit variance). Again, conditional density of the u_i, given the value of ε_i, i.e., $f\left(u_i \middle| \varepsilon_i\right)$ can be shown to be the density of a normally distributed variable but truncated below at zero, with

[9] Such a model with an empirical illustration may also be found in Kalirajan and Flinn (1983). Battese and Coelli (1988) and Kumbhakar (1988) have extended the method to the case of panel data.

[10] See Kumbhakar et al (2000, Ch. 3) and the references cited therein for detailed discussions on this topic and the derivation of various results given in this section.

(prior to truncation) mean $\tilde{\mu}_i$ and variance σ_v^2. A firm specific estimate of TE can then be obtained using the expression given below.

$$TE_i = E\left[\exp(-u_i)\middle|\varepsilon_i\right] = \frac{\left[1-\Phi\left(\sigma_v - \frac{\tilde{\mu}_i}{\sigma_v}\right)\right]}{\left[1-\Phi\left(-\frac{\tilde{\mu}_i}{\sigma_v}\right)\right]} \exp\left(-\tilde{\mu}_i + \frac{\sigma_v^2}{2}\right) \tag{2.14}$$

To cite a few applications, Van den Broek et al (1980) estimated the composed error model for the Swedish dairy industry, assuming an exponentially distributed inefficiency variable. In a later study Cummins and Zi (1998) assume exponential distribution for the inefficiency disturbance term to estimate a cost frontier and then measure cost efficiency of the U. S. life insurance industry using a variety of econometric and mathematical programming techniques.

Consider now the *general* truncated normal model which assumes that for all i, $u_i \sim iid\ N^+\left(\mu,\ \sigma_u^2\right)$. The log likelihood function for a sample of N producers in this case can be written as follows:[11]

$$\ln L = \text{constant} - \frac{\sum_{i=1}^{N}(\mu+\varepsilon_i)^2}{2\left(\sigma_u^2+\sigma_v^2\right)} + \sum_{i=1}^{N}\ln\left\{\Phi\left(\frac{\mu_i^*}{\sigma_*}\right)\right\} - \frac{1}{2}\ln\left(\sigma_u^2+\sigma_v^2\right) - N\ln\left\{\Phi\left(\frac{\mu}{\sigma_u}\right)\right\} \tag{2.15}$$

where $\mu_i^* = \dfrac{\mu\sigma_v^2 - \varepsilon_i\sigma_u^2}{\sigma_u^2+\sigma_v^2}$ and $\sigma_*^2 = \dfrac{\sigma_u^2\sigma_v^2}{\sigma_u^2+\sigma_v^2}$. Firm level estimates of TE is given by

$$TE_i = E\left[\exp(-u_i)\middle|\varepsilon_i\right] = \frac{\left[1-\Phi\left(\sigma_* - \frac{\mu_i^*}{\sigma_*}\right)\right]}{\left[1-\Phi\left(-\frac{\mu_i^*}{\sigma_*}\right)\right]} \exp\left(-\mu_i^* + \frac{\sigma_*^2}{2}\right) \tag{2.16}$$

To cite a few applications, such frontier model with composite disturbance structure (as proposed by Aigner et al (1977)) had been fitted for earning functions in

[11] Note that half-normal distribution is a special case of the general truncated normal distribution, obtained by setting μ to be zero. It is also simpler, since only one parameter is to be estimated. Ritter and Simar (1997), however, point to some difficulties associated with two-parameter distributions such as truncated normal and gamma.

labour markets by Herzog et al (1985), Hofler and Polachek (1985) and later by Robinson and Wunnava (1989). Assuming a half-normal distribution for the one-sided inefficiency variable Ali and Flinn (1989) measured efficiency among Basmati rice producers of Pakistan Punjab relative to an estimated normalised profit frontier. Using two alternative methods viz., OLS and MLE Hunt-McCool and Warren (1993) estimated semi-loglinear earning frontiers, both deterministic as well as stochastic, to find labour market efficiency. They assumed the one-sided inefficiency variable to follow a gamma distribution in the case of the deterministic frontier, but a half-normal distribution in the case of the stochastic frontier model. Recently, Fuwa et al (2007) also used this model to estimate individual-level technical efficiency of rice farms of Chhotanagpur Plateau in eastern India. Cavalluzzo and Baldwin (1993) estimated stochastic frontier models to obtain productivity differences across union and non-union projects in office building construction, assuming both a half-normal as well as an exponential distribution for the inefficiency variable, u_i.

Obviously, the task should not end in only estimating TE's of individual producing units. Attempts should be made to explain inter-unit differences in the level of TE's in terms of economic factors. Some early exercises on this include Kalirajan (1981) and Pitt and Lee (1981) who followed a two-stage method to identify the factors responsible for the inter-firm differences in TE within an industry. They estimated a stochastic frontier production function and estimated firm specific TE at the first stage. At the second stage, these estimated levels of inefficiency were regressed on a number of firm specific factors like size, age, ownership pattern, level of education, managerial experience of a firm and so on which are likely to affect its TE. Since these firm specific factors (say, z_i for firm i) used to explain technical inefficiency of a firm varies across firms, u_i, the inefficiency error component for the i^{th} firm, should be assumed to be distributed independently *but not* identically across i. Here we assume that the distribution of u_i differs only in its mean, i.e., $u_i \sim iid\, N^+\left(\mu_i, \sigma_u^2\right)$, but its variance remains constant across firms, as was assumed in the cases discussed earlier.[12] However,

[12] Interested reader may look at Kumbhakar et al (2000, Ch. 3) for detailed discussion on heteroscedastic disturbances.

it immediately became apparent that such a two-stage procedure suffered from serious inconsistency problem, as the model estimated at the first stage was misspecified. The results obtained would therefore be biased.[13] The solution to this bias problem, as proposed in the literature, is a one-step procedure based on a correctly specified model for the distribution of Y_i, given the input vector X_i and the vector of firm specific factors affecting its TE. Such a one-step procedure has been proposed by Kumbhakar, Ghosh and McGuckin (1991) and Reifschneider and Stevenson (1991). They specify stochastic frontier models in which the inefficiency effects are defined to be an explicit function of the z_i. The associated parameters along with those of the frontier production function are then estimated through a single-stage maximum likelihood estimation method. Such a model can be represented by adding the following relation to the equation (2.12):

$$\mu_i = z_i \delta \qquad (2.17)$$

where δ is the vector of parameters associated with the firm specific factors, z_i. The non-neutral model proposed by Huang and Liu (1994) is applicable to the case when some of the input variables of the model appear in the z_i. The alternative models which have been developed in the literature may be seen as alternative ways of specifying the z_i. For example, if the first element of z_i is unity with non-zero associated parameter while remaining parameters in δ are all zero, the general truncated normal distribution for the u_i proposed by Stevenson (1980) and Battese et al (1988) would be obtained. The half-normal distribution originally proposed by Aigner et al (1977) would be obtained, if each of the elements of δ is zero.[14] Obviously, Y_i should not be included in

[13] Although it is widely recognised that two-stage procedures are biased, there seems to be little evidence on the severity of this bias. Caudill and Ford (1993) provide evidence on the bias of the estimated technological parameters, but not on the efficiency level themselves or their relationship to the firm specific factors. More recently, Wang and Schmidt (2002) provide extensive Monte Carlo evidence on the bias at each of the two stages. They also introduce some new theoretical insights into the issue by providing some arguments in favour of models which have *scaling property*, namely that, conditional on z_i, the one sided error term can be written as a function of z_i, times a one-sided error distributed independently of z_i. They also explain the convenience and intuitive plausibility of this property for a one-step model discussed later in this section.

[14] A number of extensions have also been made following this method. Mention may be made of Battese and Coelli (1995), Battese and Broca (1997), Wang and Schmidt (2002).

the z_i. For example, if one variable in z_i is a measure of firm size, it may be defined in terms of some variable (say, the amount of an input used) but not in terms of output (see Wang and Schmidt, 2002, pp-130).

With the relation (2.17) added to the equation (2.12), the log likelihood function and estimates of the firm specific TE are as follows:

$$\ln L = \text{constant} - \frac{\sum_{i=1}^{N}(z_i\delta + \varepsilon_i)^2}{2(\sigma_u^2 + \sigma_v^2)} + \sum_{i=1}^{N} \ln\left\{\Phi\left(\frac{\mu_i^{**}}{\sigma_*}\right)\right\} - \frac{1}{2}\ln(\sigma_u^2 + \sigma_v^2) - \sum_{i=1}^{N}\ln\left\{\Phi\left(\frac{z_i\delta}{\sigma_u}\right)\right\} \tag{2.18}$$

where $\mu_i^{**} = \dfrac{z_i\delta\sigma_v^2 - \varepsilon_i\sigma_u^2}{\sigma_u^2 + \sigma_v^2}$ and

$$TE_i = E[\exp(-u_i)|\varepsilon_i] = \frac{\left[1 - \Phi\left(\sigma_* - \frac{\mu_i^{**}}{\sigma_*}\right)\right]}{\left[1 - \Phi\left(-\frac{\mu_i^{**}}{\sigma_*}\right)\right]} \exp\left(-\mu_i^{**} + \frac{\sigma_*^2}{2}\right) \tag{2.19}$$

The similarity among the equations given in (2.14), (2.16) and (2.19) for the estimates of firm-level TEs and between (2.15) and (2.18) for the likelihood functions may be noted. This model has been applied widely in the recent past in a number of economic activities, e.g., agriculture (Battese and Broca, 1997; Coelli and Battese, 1996; Wilson et al, 2001), marine fishing (Sharma and Leung, 1998), industry (Hjalmarsson et al, 1996; Lundvall and Battese, 2000; Bhandari and Maiti, 2007), electricity distribution (Hattori, 2002)[15], transport (Coelli et al, 1999) and so on. Several other studies have also used this model. Mention may be made of by Nourzad (2002) to find out the effects of real money balance on production efficiency for ten developed and ten developing countries.

In this connection we may briefly review the studies which have been done to estimate levels of technical efficiency (TE) prevailing in the various industries in India. Some of the studies are based on the data collected through surveys specifically designed for this purpose (e.g., Little, Mazumdar and Page, 1987; Page, 1984). Many of

[15] A distance function approach has been followed in this paper in the context of measuring and compare technical efficiency of electricity distribution in Japan and in the U. S.

the studies are concerned with estimating and explaining variations in TE in only the small-scale industrial units by fitting either a deterministic or a stochastic production frontier (e.g., Bhavani, 1991; Goldar, 1985; Neogi and Ghosh, 1994; Nikaido, 2004; Ramaswamy, 1994). A review of some other studies in this area may be found in Goldar (1988).

All the studies mentioned above, however, use data relating to years prior to the beginning of economic reforms. For instance, Bhavani (1991) uses the data collected under the first Census of Small Scale Industrial Units, 1973 to estimate TE of firms at the four 4-digit level industries of metal product groups by fitting a (deterministic) translog production frontier. Similarly, on the basis of the data thrown up by the Second All India Census of Small scale Industrial Units, 1987-88, Nikaido (2004) fits a single stochastic production frontier, considering firms under all the (two-digit) industry-groups and using intercept dummies to distinguish different industry groups. Neogi et al (1994) examines the inter-temporal movement of TE using panel kind of industry-level summary data for the years 1974-75 to 1987-88. The studies by Goldar, Renganathan and Banga (2004) and Lall and Rodrigo (2001), however, relate to the post-reform era. Using the panel data for 63 firms in the engineering industry for ten years from 1990-91 to 1999-2000 drawn from the Prowess data base 2001 version of the Centre for Monitoring Indian Economy (CMIE), Goldar et al (2004) fit a translog stochastic production frontier to estimate firm-level TE scores in each year. At the second stage they attempt to explain variation in TE in terms of some economic variables like export and import intensity, degree of vertical integration etc. Lall et al (2001) examines TE variation across four industrial sectors in India during the year 1994 along with examining TE in relation to scale, location, extent of infrastructure investment and some other determinants.

Modeling Technical as well as Allocative Inefficiency

In addition to the notion of technical inefficiency there is another concept of inefficiency, viz., allocative inefficiency of a firm. A firm is known to be allocatively inefficient if its choice of input mix deviates from their optimal proportion, given the market prices. Literature dealing with such allocative inefficiency of production units has also been well developed. However, as we do not consider allocative inefficiency in the present work (due to non-availability of price data), we do not discuss the topic any further in this dissertation. One may see Kumbhakar (1987, 1989), Kumbhakar et al (1991), and others for some detailed discussion on this issue.

2.2.3 Frontier Models with Heterogeneous Technologies

A limitation of the conventional stochastic frontier approach is sometimes pointed out, namely that the frontier in question takes coefficient of a given input to be the same across all firms and that inefficiency is measured by allowing for random changes in the intercept term only. In other words, all firms are assumed to have access to exactly the same production possibilities and differ only with respect to their degree of inefficiency caused by a host of factors including, for example, differences in the quality of managerial input. However, the assumption of an identical technology being followed by each practitioner may result in incorrect measurement of inefficiency, as it fails to distinguish between poor performance arising out of technological differences and that arising out of technology-specific inefficiency. Specifically, an inability to produce efficiently, given the amounts of inputs used, may also be due to the use of different (and possibly inferior) technology and one needs to take account of this possibility. In fact, adoption of a new technology is costly and if this cost is very high for a firm it may be reluctant to do so, being constrained by availability of funds. In any case, firms adopt new technology only with considerable lags. As a result, the old technology used by a firm will result in a fewer quantity and/or poorer quality of output produced at a given level of inputs compared to that obtained by those who become able to adopt the latest and improved version of technology. Under the assumption of a common technology this firm will then turn out to be more inefficient, whereas the underlying reason is the use of an inferior technology. Indeed, this firm might even turn out to be more efficient than a firm using the latest (improved) technology if, somehow, one were able to separate out the two different factors affecting its output namely technological inferiority and technical inefficiency.

It is thus reasonable to hold that there may be diversity in individual firms' methods of input application so that the (marginal) productivity of an input (at the same uses of input quantities) may vary across firms. Swamy (1970, 1971) introduced random coefficient regression model (RCRM) of Hildreth and Houck (1968) to the econometric literature to address this problem. Kalirajan and Obwona (1994) sought to popularise this model by bringing in cross-sectional heterogeneity in both slopes and intercepts. To discuss it briefly, let y_i and x_{ni} be respectively the (logarithmic values of) the output produced and the n^{th} input used by the i^{th} firm. Consider a simple log linear production function they postulate that

$$y_i = \sum_{n=1}^{k} \beta_{ni} x_{ni} + \eta_i = x_i' \beta_i + \eta_i \qquad (i = 1,2,\ldots.., N), \tag{2.20}$$

where $\beta_i = (\beta_{ni})$ and $x_i = (x_{ni})$ are each a *k*-component column vector and η_i is a disturbance term. Next, each firm's parameter vector β_i is assumed to vary from the mean vector $\overline{\beta}$ by a vector of random errors, $\psi_i : \beta_i = \overline{\beta} + \psi_i$. With suitable assumptions and methods, stable estimates of $\overline{\beta}$ and variance-covariance matrix of the ψ_i's can be obtained (see Griffiths, 1972 and Swamy and Mehta, 1975 for details). Kalirajan et al (1994) considered the vector $\beta^* = (\beta_n^*)$ as estimates of the parameters of the frontier production function where for each n, $\beta_n^* = \max_i \{\beta_{ni}\}, (n = 1, 2, \ldots.., k)$ and defined the (logarithmic value of the) frontier output of the i^{th} firm as $y_i^* = \sum_{n=1}^{k} \beta_n^* x_{ni}$. The TE of the i^{th} firm is then estimated to be the ratio of $\exp(y_i)$ to $\exp(y_i^*)$. Kalirajan et al (1994) and recently Bhandari and Maiti (2007)[16] have empirically estimated the model but there are also other studies along this line.

However, critics argue that what Kalirajan et al (1994) have specified is a random coefficient average production function model which measures inefficiency from a frontier constructed by using maximum (across firms) response coefficients. As Tsionas (2002) has rightly pointed out, their motivation for using a random coefficient model was not to incorporate the case of heterogeneous firm technologies but to relax

[16] Their estimation results are given in the Appendix to Chapter 3 of this dissertation.

the assumption that the frontier was a *neutral* shift of the conventional production function. Although their contribution is important, inefficiency measure proposed by them is not free from the limitation mentioned earlier, namely that it includes the effects of both technological differences and firm technical efficiency differences. In addition, they could derive only relative, but not absolute, inefficiency measures. Tsionas (2002) proposed a random coefficient stochastic frontier model in a panel data framework where (absolute) firm specific efficiency could be separated from technological differentials across firms. Along with an empirical illustration using the famous electric utility data of Christensen and Greene (1976) he provided exact finite sample estimates of the parameters. Some more studies have been done by Orea and Kumbhakar (2004) and Huang (2004). The latter proposes a very *flexible* stochastic frontier model with random coefficients to measure firm specific technical (in)efficiency, while allowing for the possibility of heterogeneous technologies being adopted by different firms.

2.3 The Mathematical Programming School

The mathematical programming tool – widely known as the Data Envelopment Analysis (DEA) – is also used extensively to measure TE of producing unit. The intellectual origin[17] of the DEA in economics can be traced back to the early 1950s when Koopmans (1951) recognised the commonality between the problem of existence of non-negative prices and quantities in a Walras-Cassel economy and the mathematical programming problem of optimising an objective function subject to a set of linear inequality constraints. He defined a point in the commodity space as efficient whenever an increase in the net output of one good required a decrease in that of some other good. In view of its obvious similarity with the notion of Pareto optimality, this definition is known as the Pareto-Koopmans condition for TE. In the same year Debreu (1951) introduced the concept of *coefficient of resource utilisation* as a measure of TE for the economy as a whole (from the point of view of cost of resources), and interpreted any deviation of this measure from unity as a deadweight loss for the society on account of inefficient

[17] See Seiford and Thrall (1990), Coelli et al (1998), Førsund and Sarafoglou (2002) and Ray (2004) for a detailed history of the DEA literature.

utilisation of resources. The measures of efficiency developed by Farrell (1957)[18] have, however, a close link with the notion (in axiomatic production theory) of radial contraction of inputs/expansion of outputs from an observed point to the frontier, i.e., the concept of *distance function* developed independently by Malmquist (1953)[19] and Shephard (1953).

In his pioneering work of 1957 Farrell assumed constant returns to scale (CRS) technology in production. Hoffman (1957) pointed out that the dual simplex method, an algorithm to solve a linear programming (LP) problem, could be applied to obtain Farrell's measure of efficiency. This turned out to be an important pragmatic suggestion, and was adopted by Farrell himself in his later work with Fieldhouse (1962) where the case of increasing returns to scale was also incorporated.[20]

One of the earliest attempts to measure efficiency using Farrell's non-parametric methodology in the context of the Indian data was by Bharadwaj and Bharadwaj (1965). Using aggregated Farm Management Survey data for Bombay pertaining to the year 1955-56 they observed a U-shaped relationship between efficiency and size class of farmers, thereby implying that both large and small farmers seemed to be more efficient than those in the intermediate size classes.

Despite a few early attempts to measure firm-specific TE using appropriately constructed LP problems, DEA became popular only after Rhodes' (1978) dissertation topic on evaluation of program follow-through in U. S. education. The first published paper describing the methodology and labeling the approach as DEA was by Charnes, Cooper and Rhodes (1978) which is widely known as the CCR model. Later, they wrote

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[18] Farrell himself mentions Debreu (1951) as an inspiration for developing his measure of TE. In fact, this has led some scholars to call it the "Debreu-Farrell measures of efficiency" (Färe and Lovell, 1978; Färe, Grosskopf and Lovell, 1985; Russell, 1998). In this connection, it may be noted that Färe et al (1978) were the first to formulate some axioms which an ideal efficiency measure should satisfy (Russell, 1998). Extensive accounts of such axiomatic approach can be found in Färe et al (1985) and Färe, Grosskopf, Lindgren and Roos (1994).

[19] The work of Malmquist (1953) inspired Caves, Christensen and Diewert (1982) to introduce the *Malmquist productivity index* based on ratios of Farrell efficiency indices.

[20] Farrell's approach was further refined by a group of agricultural economists at the University of California, Berkeley. The group comprising Boles, Bressler, Brown, Seitz, and Sitorus used explicit LP modeling developed by Boles (1967) and their papers were published in a symposium volume of Western Farm Economic Association in 1967. Unfortunately, the works of Berkeley economists have been largely ignored by the subsequent contributors (Kumbhakar and Lovell, 2000, pp. 7).

two more papers in 1979 and 1981 in which a generalised DEA in a multiple-output – multiple-input framework was also discussed.[21]

The imposition of a CRS structure for the production technology implicitly assumes that producing units operate on optimal scales. Such a presumption may not, however, be always tenable, as different firms operate under different types of market power, financial constraints, and externalities. Subsequently DEA theory advanced considerably relaxing, in particular, the relatively stronger CRS property. In fact, a variable returns to scale (VRS) model was developed by Banker, Charnes and Cooper (1984). This is known as the BCC model which distinguishes between *technical inefficiency* and *scale inefficiency*[22] by defining and estimating the former at a given scale of operation under the assumption of a unique optimum (Maindiratta, 1990). We present this model below.

Apart from considering a VRS structure the model assumes the following fairly general axioms[23] for the production technology of firms: (a**)** all the observed input-output bundles are feasible; (b) the production possibility set is *convex* implying that given a set of *N* feasible input-output bundles, *any* weighted average of these *N* input bundles can produce the same weighted average of the corresponding *N* output bundles and (c) any input or output is *freely disposable.* These assumptions enable one to construct, following the DEA method, a production possibility frontier on the basis of the observed inputs-output bundles of a given set of producing units. The *frontier,* basically a piece-wise linear surface over the data points, is constructed by the solution of a sequence of linear programming problems – each one for each individual unit in the sample. It then yields, as a by-product, the extent of technical inefficiency of a unit in terms of the distance between the observed data point corresponding to the unit and the frontier so constructed. We briefly describe the method below.

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[21] Charnes, Cooper, Lewin and Seiford (1994) spelled out briefly primal and dual specifications along with a number of extensions of the basic CCR model.

[22] Byrnes, Färe and Grosskopf (1984) independently developed a non-parametric model allowing for scale inefficiency.

[23] For economic implications and interpretations of these axioms, see Ray (2004; pp. 27).

Let the firm i be observed to produce Y_i, an *r*-component (column) vector[24] of quantities of outputs, by using the input bundle X_i, a *k*-component (column) vector of quantities of inputs, the j^{th} element of X_i (Y_i) is taken to be zero, if the i^{th} firm does not use (produce) the j^{th} input (j^{th} output). The DEA method seeks to construct a frontier on the basis of the observations on inputs and outputs of the *N* firms, by solving a set of *N* linear programmes, one for each firm. The problem for the firm *s* is to find a scalar φ and an *N*-component vector $\lambda_s = (\lambda_{si})$ which solve the following linear programme:

$\left(P_s^M\right)$ *Maximise* φ

subject to (i) $\sum_{i=1}^{N} Y_i \lambda_{si} \geq \varphi Y_s$, (ii) $\sum_{i=1}^{N} X_i \lambda_{si} \leq X_s$, (iii) $\sum_{i=1}^{N} \lambda_{si} = 1$ and (iv) $\lambda_s \geq 0$.

Let (P_s^M) have an optimal solution, say [φ_s^M, $\lambda_s^M = (\lambda_{si}^M)$]. The optimal value, φ_s^M, then indicates the *maximum* possible *proportional increase*[25] in the output vector that could be achieved by the s^{th} firm, with their input quantities being held constant at X_s. This *proportion* may then used to get a measure of (an *output-oriented*) technical efficiency of the s^{th} firm relative to the frontier (TE_s^M) as defined below:

$$TE_s^M = 1/\varphi_s^M$$

One may also define and measure an *input-oriented* technical efficiency of a firm. The problem for the firm *s* is then to find a scalar θ and an *N*-component vector $\alpha_s = (\alpha_{si})$ which

(P_s^I) minimise θ

subject to (i) $\sum_{i=1}^{N} \alpha_{si} Y_i \geq Y_s$, (ii) $\sum_{i=1}^{N} \alpha_{si} X_i \leq \theta X_s$, (iii) $\sum_{i=1}^{N} \alpha_{si} = 1$ and (iii) $\alpha_s \geq 0$.

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[24] Note that Y_i will be a scalar in case all firms produce a single and the same good.

[25] Note that a feasible solution to the above problem is given by $\varphi = 1$ and λ_s = a unit vector (the s^{th} component being unity). Hence, the optimal value, φ_s^{M*}, will be greater than or equal to one.

Let the problem (P_s^I) have an optimal solution, say [θ_s^I, $\alpha_s^I = (\alpha_{si}^I)$]. The optimal value, θ_s^I, then gives the maximum possible *proportional decrease*[26] in the input vector that could be achieved by the s^{th} firm, while retaining its production unchanged at Y_s. An (input-oriented) *technical efficiency* of the firm *s* is then given by θ_s^I.

The models (P_s^M) and (P_s^I) describe the basic DEA framework. Several extensions have been proposed/made in the literature to incorporate some specific features of different (possible) economic and operations research modeling.[27] The basic DEA framework as well as its several extensions have been applied to estimate efficiency of producing units in a large number of economic activities like hospitals[28] (Bedard, 1985), post offices (Deprins et al, 1984), electric utilities (Färe and Grosskopf, 1983), banking (Gold, 1982), mass transit system (Kusbiantoro, 1985), courts (Lewin, Morey and Cook, 1982), agriculture (Färe, Grabowski and Grosskopf, 1985), maintenance (Bowlin, 1984), mining (Byrnes et al, 1984), pharmacies (Capettini, Dittman and Morey, 1985) etc. Links between DEA and basic production theory (Byrnes et al, 1984) and comparisons between DEA and regression methods (Bowlin, Charnes, Cooper and Sherman, 1985) have also been discussed in the literature. The studies by Färe, Grosskopf, Norris and Zhang (1994), Ray and Desli (1997), Førsund and Kittelsen (1998), Banker, Chang et al (2002) and others have enriched the DEA literature on measurement of productivity change. Researchers have also begun to investigate into the statistical as well as the stochastic properties[29] of DEA methodology (e.g., Banker, 1993; Banker and Natarajan, 2004; Sengupta, 1982).

In this connection we may briefly mention the non-parametric empirical studies done in the recent past using the Indian economic data. These studies have been done for a number of sectors. For example, Ray and Bhadra (1993) studied the productivity of the

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[26] Note that a feasible solution to the above problem is given by θ = 1 and α_s = a unit vector (the s^{th} component being unity). Hence, the optimal value, θ_s^{I*}, will be less than or equal to one.
[27] A detailed discussion on such extensions can be found in Ray (2004).
[28] See Seiford (1996) for more details.
[29] See Grosskopf (1996) for a selective survey of various stochastic approaches to DEA.

Indian agricultural and allied activities. Ali and Bhargava (1998) examined efficiency of the Indian dairy co-operatives. Jha, Chitkara and Gupta (2000), Ahuja and Majumdar (1998) and Majumdar (1999) studied performance of the Indian state-owned enterprises. Studies on performance of Indian manufacturing enterprises include Ferrantino, Ferrier and Linvill (1995), Majumdar (1996), Ray (1997), Mukherjee and Ray (2004), and others. Both technical and scale efficiency of the Indian state tax jurisdiction have been measured by Thirtle et al (2000) for fifteen Indian states while operational inefficiencies of the Indian power generating units have been studied by Chitkara (1999). A number of studies have been carried out for the Indian banking sector as well, e.g., Bhattacharyya, Lovell and Sahay (1997), Saha and Ravisankar (2000), Das, Ray and Nag (2009, forthcoming), and others.

2.4 On Structure-Conduct-Performance (S-C-P) Paradigm

It is widely believed as well as discussed in the literature that an industry's structure (for instance, the degree of concentration) determines the behaviour of its constituent firms and the latter, in turn, determines its performance (reflected, say, in profit). Thus, the theory predicts that market structure determines the conduct (or strategy) of firms which, in turn, determines industry performance. Empirical research during the past few decades has provided useful insights into such a relationship between profitability (a measure of performance) and various structural characteristics of industry.

A measure of market performance determines the extent to which the market becomes beneficial to the consumers. Such a measure regards perfectly competitive framework as the benchmark in which case it is taken to assume the minimum possible value. The measure then seeks to determine how close is the performance of an industry to that of the benchmark and a higher value of the measure is taken to indicate a lower degree of performance. Three alternative measures of market performance have been proposed in the literature viz., rate of return, price-cost margin and Tobin's *q* (Tobin, 1969, 1980). The literature relating the conventional S-C-P paradigm may, therefore, be classified into three different groups corresponding to the three alternative measures of market performance. In what follows we present a brief survey[30] of empirical studies on the relationship between industry structure and its performance where the latter is measured by one of the three alternative indices mentioned above. In the present study we shall use rate of return as the indicator of an industry's profitability. Therefore we discuss here the other two measures only very briefly.

Studies Considering Rate of Return as a Measure of Performance

The pioneering work of Bain (1951) is the first empirical study relating rate of return to concentration in an industry. He examined 335 U. S. firms belonging to 42 industries for the period 1936-40. The results confirm his hypothesis that profit rates of firms in industries with high degrees of concentration should, on an average, be high. In his later work Bain (1956) argued that not only concentration but also entry barriers in an industry would enable it to earn profits above the competitive level. His sample contained 20 U. S. manufacturing industries (for the period 1947-51) with high levels of concentration (the latter being measured by the 4-firm concentration ratio).

Bain (1956) found that the large firms in industries with very high entry barriers generally earned relatively higher rate of return compared to those with moderate barriers. Mann (1966) re-examined the relationship between profit and his own (subjective) estimates of entry barriers. His sample consisted of 30 U. S. industries during 1950-60 and his results confirmed Bain's hypothesis. Moreover, he hypothesised that the impact of entry barriers on profitability was independent and additive to that of concentration. Comanor and Wilson (1967) employed a sample of 41 Internal Revenue Service minor consumer good industries to analyse the simultaneous impact of advertising, market concentration, economies of scale, and other factors on industry profitability. Their results generally showed advertising intensity to be more important determinant of profitability than market concentration. However, using as an explanatory variable the product of 4-firm concentration ratio and a high barrier-to-entry dummy variable, they found the effect of concentration to be significantly positive which is consistent with Bain's argument that the impact of concentration and entry

[30] See Weiss (1974), Bresnahan and Schmalensee (1987), Caves (1989), Schmalensee (1989), Scherer and Ross (1990), Chakravarty (1995) and Martin (2002) for more detailed surveys on the topic.

conditions is interactive.[31] Using the Canadian data for 1964-67, the studies by Orr (1974, 1974a) also confirmed Bain's hypothesis. The other studies examining Bain's hypothesis using rate of return as a measure of performance include George (1968), Rhoades (1970, 1972), Caves, Porter and Spence (1980), Salinger (1984), Mueller and Raunig (1999).

While the above studies have been done at the industry-level there are some studies at the firm-level as well. Early industry-level studies have emphasised the characteristics of market, viz., concentration and entry conditions, as determinants of differences in economic profitability across industries. However, firm-level data are required to examine the impact of firm characteristics on profitability. One of the earliest efforts in this direction is due to Shepherd (1972). His results are typical of many studies conducted later in which both market share and concentration appear as variables explaining profitability. The results of his study tend to show a negative effect of greater firm size on rate of return, which is interpreted as an evidence of inefficiency of large-scale firms. In addition, positive and significant effects of advertising-sales ratio as well as entry-barrier dummy variables obtained in his study suggest that, other thing remaining unchanged, firms in high-barrier industries are more profitable compared to those in low-barrier industries. Firm-level studies conducted later include the studies by Berger (1995) and Mendes and Rebelo (2003).

Studies Considering Price-Cost Margin as a Measure of Performance

A number of empirical studies in the area of industrial organisation have considered price-cost margin as a measure of performance. One such study is that of Collins and Preston (1969) in which the basic hypothesis was that there would be a positive relationship between market concentration and price-cost margins. Using a sample of 417 (4-digit standard industrial classification (S.I.C)) U. S. manufacturing industries in 1963 they found the hypothesis to be valid for the consumer good industries with significant impact of concentration on price-cost margins but relatively less significant for the producer good industries. Using the U. S. data over the period 1958-81,

[31] It is also known to be Bain's interactive hypothesis.

Domowitz et al (1986) observes the relationship between price-cost margins and concentration to be an unstable one, and at best a weak one for only the later years. Domowitz et al (1986a) addresses the issue of inter-temporal stability of the concentration-margins relationship empirically for the first time in the literature. Ornstein (1975) analyses IRS source book data (which roughly correspond to the 3-digit S.I.C.) for 116 industries in 1963 and data for 4-digit S.I.C. industries taken from the census time profile tapes covering 1958-68. His results suggest that there is no consistent association between concentration and the price-cost margin. Most of the studies of the U. K., like those of Hart and Morgan (1977), Hart and Clarke (1980), Clarke (1984) etc., have failed to find any positive linear relation between concentration and profitability. There are some relatively recent studies on the topic. Mention may be made of the studies by Sawhney and Sawhney (1973), Beng and Yen (1977), Kwoka (1979, 1981), Geroski (1982), Chou (1986), Domowitz et al (1987), Conyon and Machin (1991), Bhattacharya and Bloch (1997), Vlachvei and Oustapassidis (1998) and Bhuyan (2002).

Studies Considering Tobin's *q* as a Measure of Performance

Several empirical studies on structure-performance use *Tobin's q* as a measure of a firm's performance. It is defined as the ratio of the market value of a firm (i.e., the market value of its outstanding stock and debt) to the replacement cost of its assets.[32] Lindenberg and Ross (1981) observe that *q* coefficients are low for the competitive industries, i.e., the industries with relatively lower degree of market power. Using U. S. data of 1976, Salinger (1984) tests Bain's interactive hypothesis but does not find strong support for it. Smirlock et al (1984) examines relationship between Tobin's *q* and the market structure variables like concentration and market share and observes little evidence to support the contention that concentration induces collusion and generates monopoly rents in any industry except possibly a few most concentrated ones. Other

[32] The measure *q* will take on the minimum value 1 when the firm earns competitive rate of return and exceed 1 if it earns excess profit whence it is valued at more than what it would cost to rebuild it. Calculation of a firm's *q* may pose difficulty in view of the difficulty in obtaining/estimating the replacement cost of its assets.

studies employing Tobin's *q* as a measure of market performance include those by Shepherd (1986), Stevens (1990), Agarwal (1991) and Hirsch and Seaks (1993).[33]

[33] Thomadakis (1977) examines the S-C-P relationship utilising both market share and concentration in the same regression equation to explain the monopoly rent. Thomadakis' rent measure is quite similar to Tobin's *q*. He finds both the market structure variables to be significant.

Chapter 3*

Efficiency of the Indian Textile Industry: A Stochastic Frontier Analysis

3.1 Introduction

The major objective of the present chapter is to examine some aspects of productivity of the Indian industry at the micro level through the stochastic frontier analysis. The development of the Indian industrial sector has not been a smooth one, at least up to the early 1980's, with its performance experiencing several ups and downs. As we have mentioned in Chapter 1, during this period the domestic industrial sector was protected from competition from foreign modern technology-based industries by various restrictive laws and regulations. However, the shocks that the economy experienced in the early 1990's and the economic reforms which have been initiated intensively thereafter have changed this scenario. Improved performance of industrial firms is now being called for and efficiency of a unit is now supposed to be a prerequisite for growth or even mere survival. In fact, government policies, particularly after 1991, have been gradually turning out to be less friendly to inefficient firms, even if they are in the public sector.

This change in the economic scenario and policy has raised some interesting questions. Apart from the issue of estimating firm-level efficiency, there is the question of explaining variation in efficiency level across firms. Additional issues may also be investigated, namely whether there is any significant variation in firm-level efficiency across states or across private and public ownership of firms. These issues are all very pertinent in the changed scenario in India and have not really been examined in detail at least for the large organised industrial sector of India. We propose to do that in the present exercise. An additional feature of our study is that it is based on the official firm-level data collected under the Annual Survey of Industries (ASI) in India and made available in soft version. These data, which are quite rich in coverage and yet have

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* The results of this chapter are published in Bhandari and Maiti (2007).

remained largely unused, are not only costly to procure, but demand substantial processing time as well. We have, therefore, confined our analysis in this chapter to one particular industry, namely, the *textile industry*. We have taken up textile industry on the ground that it is one of the largest industries in India. In fact, it accounted for about 20 percent of India's total industrial output and about a third of her total industrial employment in 1970-71. Although these figures have come down gradually (e.g., to respectively 9 and 16 percent in 1999-2000), these are still substantial. And, in the present century till 2007-08 they have remained almost stagnant around 8 to 10 per cent and 15 to 16 per cent, respectively. An additional reason for the selection of the textile industry is that it is a major export earning industry. In fact, share of this industry in India's total merchandise export was around 25% upto 2000-01 and fell gradually thereafter, but was 12% in 2007-08. However, for a long time such exports have been guided by the Multi-Fibre Arrangement of 1974, which has handed country-wise quota for exports of textiles. This act has, however, been dismantled since 2005. It may, therefore, be interesting to examine whether textile firms had already acquired high efficiency (by and large) within this period. However, a limitation of our data set is that these correspond to textile firms which are in the organised sector only, i.e., the sector covered by the ASI. Since data on the economic activities of the textile firms in the so-called unorganised sector are not available regularly, we have to leave out firms in this sector, although quantitatively the size of this sector would be quite large, may even be larger than that of the organised sector.

The chapter is organised as follows. In Section 3.2 we review some important aspects of government's industrial policies – both general policies as well as policies specific to the textile industry. This section also points to some general features of the Indian textile industry. Section 3.3 outlines very briefly the existing theory of stochastic production frontier model and also discusses our dataset and the definitions of the variables considered for our empirical analysis. Section 3.4 presents the empirical results, and Section 3.5 makes concluding observations. A few additional algebraic derivations as well as empirical results are presented in a couple of Appendices to this chapter.

3.2 Government Industrial Policies and Indian Textile Industry

Efficiency and productivity of the Indian manufacturing sector were supposed to have been inhibited by some earlier official policies, e.g., reservation of production of a large number of items for the small scale sector, high customs tariffs distorting resource allocation and inhibiting the Indian firms’ ability to compete in global markets, some rigid laws acting as impediments to a firm’s attaining an efficient size, frictions faced in establishing and closing down of firms in response to normal competitive market dynamics and various other distortions created by the structure of domestic trade, taxes and excise duties. Fortunately, the policy makers have realised the shortcomings of the earlier strategies as well as the urgency on the part of the Indian industries to become efficient (Government of India, 2000-01, pp. 149). Over the years several measures have been taken by the government to help domestic industries achieve efficiency. These include both financial measures such as rationalisation of excise duties, liberalisation of tax laws and rates, reduction in interest rates and so on, as well as such physical measures as those meant to remove infrastructural constraints in the form of say inadequate availability of power and poor transport and telecommunication services.

So far as the structure of the textile industry is concerned, it continues to be predominantly cotton-based with about 65 per cent of raw materials consumed being cotton. It has three sub-sectors – mills, powerlooms and handlooms. The latter two are jointly considered under the heading ‘decentralised sector’. Over the years the government has granted many concessions and incentives to the decentralised sector, resulting in a phenomenal increase in the share of latter. For example, while the percentage share of the mill sector in total fabric production was 76 in 1950-51, it fell to 38 in 1980-81 and further to just 4 in 2001-02. The share of the decentralised sector rose correspondingly. In the decentralised sector, it is the powerlooms sub-sector that has grown at a faster pace, producing nearly 80 per cent of the total fabric output of this industry in 2001-02.

The factors that have contributed to the fast development of the powerloom sub-sector include government’s favourable policies on synthetic fabric industry as well as the ability of this sub-sector to introduce flexibility in the product mix in line with the market situation. In the mid-1980's, a new textile policy was announced to enable the industry to increase the supply of good quality cloth at reasonable prices for both domestic consumption and export. In addition, a Textile Modernisation Fund of INR 7.5 billion was created to meet the modernisation requirements of this industry. In the early 1990's textile industry was delicensed thereby abolishing the requirement of prior government approval to set up textile units including powerlooms. A Technology Upgradation Fund Scheme (TUFS) was also launched in 1999 to enable the textile units to take up modernisation projects, by providing an interest subsidy on borrowings.

So far as trading on global markets is concerned, the textile and clothing industry has long been governed by Multi-Fibre Arrangement (MFA) of 1974, which handed country-wise quota for exports of textile. India has bilateral arrangements under MFA with the developed countries like USA, Canada, countries of the European Union etc. Almost 70 per cent of India's clothing exports have gone to the quota countries of USA and the European communities. However, the Agreement on Textiles and Clothing (ATC), 1995 of WTO envisages the dismantling of the MFA over a ten-year period. Thus, after three decades textile industry has really been open to free competition at the international level from 1st January 2005. The Indian textiles industry is now at the crossroads with the phasing out of quota regime and the full integration of the textiles sector in the WTO. Most of the studies undertaken to estimate the impact of ATC expiry on textile trade share the finding that some Asian countries are most likely to benefit from the dismantling of the quotas. They predict a substantial increase in market shares for China and India (see Government of India, 2004-05, pp. 144, for some discussion on this issue).

India has a natural competitive advantage in terms of a strong and large multi-fibre base and abundant cheap skilled labour. However, with prices being expected to fall in the post-quota regime presumably owing to increased international trade and competition, such an advantage may not be enough. Enhanced efficiency and productivity are a must to meet this emerging challenge of global competition. It is against this background that the performance of the Indian textile firms needs to be examined rigorously. And that is the major objective of the present chapter.

3.3 A Brief Description of the Analytical Model, Variables and Data Used

In this chapter we shall estimate technical efficiency of Indian textile firms using stochastic frontier analysis (SFA). We have described the method at length in Chapter 2. To summarise this discussion, a stochastic production frontier, $f(X_i;\beta)\exp(v_i)$, represents the *maximum* possible output producible with the input vector used by the i^{th} firm (X_i) given the vector of the corresponding technology parameters (β) and a random variable (v_i) seeking to capture all random factors outside the firm's control which are likely to affect its maximum possible output. However, the i^{th} firm's observed output, Y_i, may fall short of the frontier output for a variety of reasons, e.g., workers not putting the required level of effort and/or having lower ability, owner(s)/supervisor(s) having lower managerial capability of monitoring efforts of subordinates etc. Such shortfalls are then attributed to the presence of technical inefficiency in the firm. Since the actual output can be no more than the frontier output, we introduce an additional random term u_i which is restricted to be nonnegative and write:

$$Y_i = f(X_i\,;\beta)\;\exp(v_i)\exp(-u_i), \qquad [u_i \geq 0 \text{ and hence, } \exp(-u_i) \leq 1] \tag{3.1}$$

An output-oriented Farrell measure of the TE of the i^{th} firm, TE_i, is then given by the ratio of the actual output to the frontier output:

$$TE_i = \frac{Y_i}{f(X_i\,;\beta)\exp(v_i)} = \exp(-\,u_i), \tag{3.2}$$

Since $\exp(-u_i) \cong 1-u_i$, the TE_i varies inversely with u_i and lies between 0 and 1 (the *maximum* (attainable) value is 1 when there is *no inefficiency*, i.e., u_i = 0). Alternatively, u_i may be taken as an index of inefficiency. It is assumed that the usual error term v_i is $\mathrm{iid}\,\mathrm{N}\left(0,\,\sigma_v^2\right)$ while the inefficiency term u_i is $\mathrm{id}\,\mathrm{N}^{+}\left(\mu_i,\,\sigma_u^2\right)$, where μ_i is the mean before truncation.[1] Further, these two random terms are assumed to be independent of each other as well as of the regressors. We follow the approach developed by Battese et al (1993) (and later used by Lundvall et al (2000)), which seeks to estimate as well as explain firms' efficiency at a single stage. This approach consists of adding the following relation explaining the *inefficiency* of the i^{th} firm in terms of a vector of firm-specific variables, z_i, and estimate the vector of its parameters, δ, along with the parameters of frontier production function through a single-stage maximum likelihood method:

$$\mu_i = \delta' z_i \tag{3.3}$$

where δ' is the transpose of δ. Note that this assumption is consistent with the assumption that the u_i is a non-negative truncation of N ($\delta' z_i$, σ_u^2). Further, for this type of specification, the density function of u_i conditional on $\varepsilon_i (= v_i - u_i)$ as well as the expected value of TE_i for a given value of ε_i, i.e., $\mathrm{E}\left[\exp(-u_i) | \varepsilon_i\right]$, can easily be obtained (for details, see Battese and Coelli, 1988, 1993).

We use micro-level data for our study, i.e., data on a number of variables for different individual industrial units collected by the Central Statistical Organisation (CSO) of the Government of India through its ASI. Our data, a subset of the ASI dataset, are not available in a published form, but are to be obtained electronically from the CSO. To fit the stochastic frontier function, we have considered data for each of the five selected years, 1985-86, 1990-91, 1996-97, 1998-99 and 2001- 02, for the firms in the entire textile industry which covers units related to the production of cotton, woolen, silk, terrycotton, and other natural fibers like jute, coir, mesta etc.

We use *five* variables in our empirical analyses. These variables along with the corresponding notations are mentioned below.[2] It would have been very useful if we had the panel data. However, the lack of sufficient information did not allow one to construct panel firm-level data over the years.

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[1] It may, however, be mentioned that the distribution of the estimated inefficiency error, i.e., $\hat{u}_i$ may not be identical to that assumed for the population (Wang and Schmidt, 2009). This point is discussed in detail in Appendix 3.2 to this chapter.

[2] The definitions of the various concepts like ex-factory value, fixed asset, manday etc are as used by the CSO.

***Output**:* the total ex-factory value of products and by-products produced by the firm during the year in question (to be denoted by Y).

***Intermediate Inputs*:** the nominal value of inputs (both indigenous and imported ones, including power, fuels etc.) used by the firm during the year (to be denoted alternatively by X_1 and I).

***Capital*:** the net value of fixed assets of the firm at the beginning of a year (to be denoted alternatively by X_2 and FA).

***Labour**:* the total number of mandays worked during the year (to be denoted alternatively by X_3 and L).

***Age*:** the difference between the current year and the firm's initial production year.

The stochastic frontier production function used for the econometric analysis is taken to be of the following *translog* form owing to its flexible nature:

$$\ln Y_i = \left\{ \beta_0 + \sum_{j=1}^{3} \beta_j x_{ji} + \sum_{j \le k=1}^{3} \sum^{3} \beta_{jk} x_{ji} x_{ki} \right\} + (v_i - u_i) \tag{3.4}$$

Here, the subscript i refers to the i^{th} firm ($i = 1, 2, ..., N$; N being the number of firms in the industry), X_{ji} is the amount of the j^{th} input used by the i^{th} firm and x_{ji} is the natural logarithm of X_{ji} ($j = 1, 2, 3$). So far as the inefficiency equation (3.3) is concerned, the mean of the u_i is postulated to be determined by

$$\mu_i = \delta_0 + \delta_1 \ln(I_i) + \delta_2 \ln(Age_i) + \delta_{11} \{\ln(I_i)\}^2 + \delta_{22} \{\ln(Age_i)\}^2 + \delta_{12} \{\ln(I_i)\}\{\ln(Age_i)\} + \delta_{01} D_1 + \delta_{02} D_2 \tag{3.5}$$

where D_1 and D_2 are the two (intercept) dummy variables used to distinguish firms located in two groups of Indian states and under two different ownership patterns, respectively. These dummies will be explained in detail when we shall discuss the empirical results.

Going to describe the remaining variables, the amount of intermediate inputs (I_i) is used as a proxy for the size of a firm as in Lundvall et al (2000). Further, this variable is used *both* as an input in the frontier production function and also as one seeking to explain deviations from the same frontier owing to technical inefficiency. Such a practice of using the same variable in the production function and the inefficiency model is not uncommon in the efficiency literature (see Battese and Broca, 1997; Hunag and Liu, 1994; and Lundvall et al, 2000). As shown in Battese et al (1997), for the distributional assumption made here about the random term u_i, the elasticity of TE with respect to a given explanatory variable, say X_i, is given by

$$\left\{\frac{1}{\sigma_u}\left[\frac{\varphi((\mu_i/\sigma_u)-\sigma_u)}{\Phi((\mu_i/\sigma_u)-\sigma_u)}-\frac{\varphi(\mu_i/\sigma_u)}{\Phi(\mu_i/\sigma_u)}\right]-1\right\}\left(\frac{\partial\mu_i}{\partial\ln X_i}\right), \qquad (3.6)$$

where $\varphi(\bullet)$ and $\Phi(\bullet)$ are, respectively, density and distribution functions of a standard normal variable and X_i is either I_i (size) or Age_i and $\partial\mu_i/\partial\ln X_i$ is to be computed from the estimated relation (3.5).

3.4 Empirical Findings

The maximum-likelihood estimates of the parameters of the frontier model defined by equations (3.4) and (3.5) are obtained for each of the five years, using the computer program **FRONTIER 4.1** available in Coelli (1994). We first obtain the parameter estimates without using any dummy variable in the equations (3.4) and (3.5) and estimate the level of TE of each firm in each sample year. We observe that these estimates vary not too marginally across firms.

India is a vast country with a number of states and union territories with their distinctive sociological, economic, political and infrastructural features. Hence, one might be interested to know whether TE's of firms vary significantly across these different geographical regions. We had, therefore, tried to examine this issue by considering a number of alternative grouping of states and using intercept dummy variables to distinguish the different groups. Carrying out these exercises we observed that one intercept dummy would be all right. As a result we have considered one state dummy, D_1 which takes the value 1, if the i^{th} firm is located in any one of the states of Gujrat, Maharashtra, Karnataka and Kerala and 0, otherwise.[3]

[3] Let us first describe the procedure we have followed in this regard. To start with, we chose a dummy for each of about ten major textile producing states and fit frontier function. Since a large number of state dummies (with some non-significant coefficients) can hardly be meaningfully interpreted, we have tried to reduce this number by classifying the states into a few groups, verifying that the dummy coefficients for the

Another factor, which might cause variation in TE across firms is the difference in the ownership structures of the different firms. Indian economy is of the mixed-type, having both government owned firms as well as privately owned firms in almost all the important sectors of the economy, and the textile industry is not an exception. For instance, about 12 per cent of the textile firms in the year 1985-86 were in the public sector producing more than one fifth of the total output of this industry. Fitting the stochastic frontier model defined by the equations (3.4)-(3.5) to the given data and estimating TE of each textile firm, we observe that the estimated TE's of public sector firms are in general lower than the corresponding ones of the private sector firms. (The detailed result is not shown here). This has prompted us to introduce a dummy variable, D_2 which takes the value 1, if the i^{th} firm is in the public sector and zero, otherwise.

Using these two sets of dummies for the equation (3.5), the model was re-estimated and the corresponding regression results are given in Table 3.1. It may be noted that the equation (3.5) explains μ_i, the mean of the inefficiency variable, u_i. Hence, a higher μ_i indicates a lower expected value of TE. We find from Table 3.1 that the state dummy is negative for some years, particularly before 1991, but positive for later years. This might indicate that the group of states which had fared better earlier have now lagged behind, in general. Of course, a clear picture can emerge only after one tries with all kinds of alternative grouping of states for each year – an exercise we have not done here. So our result is tentative in this regard. From Table 3.1 we also find that the ownership dummy D_2 is positive for all years and significant for almost all years, implying thereby that other things remaining unchanged, a private sector firm is relatively more efficient than a public sector firm.

From Table 3.1 one notes that some individual parameter estimates are not statistically significant. However, the decision of reducing the number of variables (and

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states/group of states merged were of the same signs and of roughly similar magnitudes. In this way we have tried to reduce the number of groups of states successively. At each stage we have also tried to test whether such a process of merging of states affects regression results significantly, by conducting likelihood ratio tests for the null hypotheses that the dummy coefficients (at the preceding stage) for the states/groups of states merged were equal. If such a hypothesis were not rejected, we proceeded to merge so as to get a smaller number of groups at the next stage. We have carried out this exercise for one year and finally arrived at two groups of states, the group including the four states (mentioned above) and the group containing the rest of the states. We admit that this is not a very rigorous procedure and that there may be scope for improving this exercise. But that is how we have arrived at the two groups.

the corresponding parameters) should be based on tests of hypotheses regarding inclusion or exclusion of explanatory variables. Results of such tests are presented in Table 3.2 that gives the values of the generalised likelihood-ratio (LR) statistic under different null hypotheses for the various parameters. The first row of the Table shows that given the assumption of a translog production frontier, the LR test rejects the Cobb-Douglas function. Thus the input elasticities are likely to depend on the estimated values of the parameters as well as the levels of the explanatory variables. Since we have fitted a translog function one has to check whether the fitted function is well behaved. This is usually done by checking two things: monotonicity (non-negative input elasticities for each input) and quasi-concavity (negative semi-definite bordered Hessian of first and second derivatives) for a majority of observations. We have computed these quantities (reported in Table 3.3 and Table 3.4) and found these two regularity conditions to be satisfied at the *sample mean* as well as at majority of the observations for each year. However, for 1998-99 the percentage of firms satisfying quasi-concavity is relatively low. Hence, our results for this year may not be robust.

The second row of Table 3.2 shows rejection of the null hypothesis of no technical inefficiency among firms for each year. Thus, given that the technology can be described by a translog stochastic frontier, firms can not be supposed to be technically efficient. The parameter γ, i.e., $\sigma_u^2 / \left(\sigma_u^2 + \sigma_v^2\right)$, measures the proportion of the total variability of output (across firms with the same values of inputs) which is due to variation in TE. With the estimated values of γ varying between 0.91 and 0.995 (Table 3.1), almost the entire variability in output in each year may be supposed to be due to variation in technical inefficiency in production.

The next three tests reported in Table 3.2 are concerned with hypotheses involving restrictions on the size and age parameters in the inefficiency model. The null hypotheses of no size effect or of no age effect are rejected – in fact, almost all are rejected at even the 0.5 per cent level. The last three tests seek to ascertain whether the firm-level TE varies significantly across different groups of states and/or different ownership patterns. As reported earlier, we consider only intercept dummies to investigate these issues and find from the Table that the null hypotheses of no state-wise or ownership-wise variations either separately or jointly are all rejected except one.

For each year TE value of each firm is computed and an (arithmetic) average of these values across firms is then calculated (last row of Table 3.1). We observe that the average TE of firms to range from 0.68 to 0.84 over the years. Histograms of TE's of individual firms (not shown here) are observed to be negatively skewed.

Firm Size, Firm Age and Technical Efficiency

An important aspect of our enquiry is to ascertain how a firm's size and age affect its TE. To examine the first relationship we, first of all, use expression (3.6) to compute elasticity of TE with respect to size for each firm for each year. (As that expression clearly indicates, values of such elasticities depend on the firm-level values of the various variables). For each year we then average these values across firms to find mean elasticity and also compute its standard error. Such mean elasticities for different years, given in Table 3.7, are found to be all positive and significant. Such elasticities can be interpreted as follows: Consider the estimated value of this elasticity for 1985-86, viz., 0.12. This means that a firm with a TE score 0.50 would have experienced an increase of its TE (by 12 per cent) to 0.56, if it could have increased its size by 1 per cent.

We also try to examine the relationship between firm size and TE in an alternative way. Each year individual firms are arranged in *ascending* order of size (measured by values of intermediate inputs used by them) and then the firms are classified into different decile groups like the lowest ten per cent, next ten per cent and so on up to the highest ten per cent. The mean TE of each decile group is then computed. The results of this exercise are given in Table 3.5. We observe that every year, except for one or two decile groups, TE increases uniformly with firm size, thereby pointing to a positive relationship between the two. Finally, we consider scatter diagrams of firms' TE and size for different years (Figure 3.1). Although the nature of these scatters differ, the positive association between the two is obvious.

So far as the relationship between firm's age and its TE is concerned, we first of all consider a classification of firms in terms of three age groups, namely, *Very Old, Old* and *Young*, according as firms were established before twenty years, between ten to twenty years and within the last ten years. For each year the mean TE of firms in each age group has been computed and is presented in Table 3.6 which shows that, by and large, mean TE rises from very old to the young group. This is also confirmed by values of mean elasticities of TE with respect to firm's age for each year (Table 3.7) which are seen to be all negative and sgnificant. Thus we find that, broadly speaking, TE tends to be lower for an older firm. However, we do not present the scatters of firms' TE score against their ages as no clear picture emerges from these scatters.

3.5 Concluding Observations

The unit-level data on industrial firms in India collected and compiled officially under the Annual Survey of Industries (ASI) are quite rich in coverage and content, but have remained largely unexploited till date. The purpose of the present study is to find some microeconomic features of the Indian industries on the basis of these data for some selected years. We have considered textile industry in the present chapter as it is one of the largest industries in India. One kind of issues that may be investigated is more or less descriptive in nature. How does performance, or what is our prime concern, technical efficiency (TE), varies across firms in this industry? Further one may like to know whether there is any variation in firm level efficiency across different regions or states. One may also ask whether firms under private ownership are more efficient than their counterparts under public sector. These issues, particularly the last two, have certain policy implications to the extent that the officials are now very much concerned with reducing regional disparity as well as improving performance of the public sector undertakings. Our empirical exercises have come up with affirmative answers to the above questions.

We have next turned to some analytical questions. Our methodology – fitting a translog production frontier – permits us to explore how observed variation in TE's may be explained in terms of firm-specific factors. For instance, one might argue that efficiency has got something to do with size, that a large firm may have an easier access to cheaper or superior quality of inputs and/or get some other benefits from operating on a bigger scale and hence may be able to obtain a larger value of output incurring the same costs on inputs compared to a smaller size firm. All this will be reflected in our present framework in a higher TE for larger firms. Our empirical results do support this contention. Similarly, age of a firm might affect its TE. There may be some positive effects of age. It may be argued that an older firm is a successful survivor in an environment in which it has succeeded to have easy access to finance and smoothly-functioning buyer-supplier linkages and is more experienced and hence is run more efficiently. However, there may be counter arguments as well. Young firm may have assets/plants of later generations, have younger, more recently educated workers etc and hence may have higher efficiency (see Lall et al, 2001). Our empirical results, however, point to an inverse relationship between a firm's age and its TE for each year implying that the younger firms tend to be more efficient than the older ones.

A question that has been kept postponed is: has the process of economic reform initiated in the early nineties made any perceptible impact on the efficiency levels of textile firms? An answer to this question is not easy to obtain from the data we have and the type of exercises that can be, and have been, carried out with these data. For instance, in order to investigate this issue one needs panel data set, i.e., data on a number of relevant variables corresponding to a *given set* of firms for several years; one may then examine how the extent of efficiency of a given firm or a group of firms has undergone changes. Unfortunately, we do not have any panel data on Indian firms collected and made available by CSO or any other government agency. It is then quite likely that the firms that we are examining at different years may be different or that the firms that we observe in a year are the relatively better firms, the inefficient firms having failed to survive through.

Under these circumstances one may estimate average TE of firms existing at a year and try to examine whether such efficiency has any time trend. Carrying out this exercise we observe that there is no distinct trend in the average TE of textile firms over the years. It has only fluctuated. However, one point seems to be borne out by our exercises, namely that the average TE has shown some improvement if we take the post-reform years only. It is estimated to be 0.68 in 1996-97 which has gone up to 0.76 in 1998-99 and further to 0.80 in 2001-02.

Table 3.1: Estimated Regression Results (with State and Ownership Dummy Variables)

Regressor	Associated Parameter	*Estimated Values of the Parameters* 1985-86	1990-91	1996-97	1998-99	2001-02
Constant	β_0	9.57(19.83)	5.92(28.61)	9.67(13.15)	11.23(14.09)	2.97(6.15)
$\ln I$	β_1	- 0.78(- 11.13)	- 0.095(- 2.94)	- 0.537(- 6.06)	- 0.82(- 7.65)	0.63(8.3)
$\ln FA$	β_2	0.23(8.97)	0.12(6.71)	0.337(7.80)	0.23(3.45)	- 0.08(- 1.76)
$\ln L$	β_3	0.72(19.01)	0.56(22.38)	0.349(4.64)	0.72(6.96)	0.314(4.46)
$(\ln I)^2$	β_{11}	0.09(33.32)	0.06(35.08)	0.066(15.65)	0.08(16.95)	0.015(3.38)
$(\ln FA)^2$	β_{22}	0.012(8.37)	0.007(7.34)	0.011(6.64)	0.003(1.26)	0.0007(0.55)
$(\ln L)^2$	β_{33}	0.025(6.44)	0.029(11.45)	0.02(3.95)	0.02(3.93)	0.017(3.25)
$\ln I \times \ln FA$	β_{12}	- 0.034 (- 12.75)	- 0.016 (- 9.43)	- 0.0315 (- 6.95)	- 0.03 (- 3.8)	0.0045 (0.92)
$\ln FA \times \ln L$	β_{23}	0.0004 (0.11)	- 0.0018 (- 0.78)	- 0.006 (- 1.37)	0.02 (2.48)	- 0.0002 (- 0.04)
$\ln I \times \ln L$	β_{13}	- 0.072 (- 15.13)	- 0.062 (- 20.11)	- 0.036 (- 4.68)	- 0.08 (- 8.95)	- 0.033 (- 3.92)
Constant	δ_0	9.85(16.24)	11.33(13.18)	46.62(5.02)	5.93(4.6)	- 25.85(- 3.99)
$\ln I$	δ_1	- 0.87 (- 12.47)	- 1.365 (- 9.79)	- 4.77 (- 4.40)	- 0.24 (- 1.43)	2.63 (3.99)
$\ln Age$	δ_2	- 0.556 (- 3.04)	- 0.40 (- 3.92)	- 2.80 (- 2.65)	0.007 (0.03)	1.87 (2.99)
$(\ln I)^2$	δ_{11}	0.004 (1.73)	0.027 (5.63)	0.077 (2.66)	- 0.02 (- 4.13)	- 0.08 (- 4.93)
$(\ln Age)^2$	δ_{22}	0.09(5.02)	0.16(11.01)	0.92(5.84)	0.18(6.08)	0.16(3.29)
$\ln I \times \ln Age$	δ_{12}	0.0156 (1.06)	- 0.015 (- 1.73)	- 0.085 (- 1.72)	- 0.036 (- 2.27)	- 0.138 (- 4.17)
D_1	δ_{01}	- 0.20(- 4.11)	- 0.255(- 8.21)	0.101(2.63)	0.977(8.44)	0.625(7.32)
D_2	δ_{02}	0.929(12.41)	1.78(12.13)	1.23(1.27)	1.57(12.56)	1.86(11.95)
	$\sigma^2\left(=\sigma_u^2+\sigma_v^2\right)$	0.66(24.28)	0.60(17.5)	10.16(12.63)	1.21(11.88)	1.27(11.82)
	$\gamma\left(=\dfrac{\sigma_u^2}{\sigma^2}\right)$	0.91(201.55)	0.96(435.67)	0.995(2351.5)	0.96(214.23)	0.98(432.3)
Log-Likelihood Value		- 2502.49	178.27	- 2917.25	- 678.92	- 254.1
No. Of observations		5546	4750	3598	1423	1748
Mean TE		0.73	0.84	0.68	0.76	0.80

Figures in the parentheses are the corresponding t-ratios.

Table 3.2: Generalised Likelihood-Ratio Tests of Null Hypothesis for Parameters Values in the Estimated Stochastic Frontier Production Function

Null Hypothesis	*Estimated value of generalised likelihood ratio statistic* [a]					*Critical value(at 1% level)*
	1985-86	1990-91	1996-97	1998-99	2001-02	
$\beta_{jk} = 0, j,k = 1,2,3$. (Cobb-Douglas function)	2437.4	2175.9	542.36	190.48	54.42	16.81
$\gamma = \delta_0 = \delta_1 = \delta_2 = \delta_{11} = \delta_{22} = \delta_{12} = \delta_{01} = \delta_{02} = 0$ (no inefficiency effect)	1818.96	2135.84	3958.78	449.22	501.66	20.97 [b]
$\delta_1 = \delta_{11} = \delta_{12} = 0$ (no size effect)	1963.84	634.8	3974.64	178.78	50.9	11.34
$\delta_2 = \delta_{22} = \delta_{12} = 0$ (no age effect)	11.68+	23.48	24.28	29.7	7.3**	11.34
$\delta_1 = \delta_2 = \delta_{11} = \delta_{22} = \delta_{12} = 0$ (no size and age effect)	1980.54	645.04	3976.46	155.46	51.4	15.09
$\delta_{01} = 0$ (no state wise variation)	6.8+	5.76*	3.94*	23.76	5.34*	6.64
$\delta_{02} = 0$ (no ownership wise variation)	100.24	169.58	5.48*	39.3	27.6	6.64
$\delta_{01} = \delta_{02} = 0$ (neither state wise nor ownership wise variation)	114.1	172.42	0.30	65.02	36.0	9.21

a The values marked with a plus (+), an asterisk (*) and two asterisks (**) are significant at 1 % level,5 % level and 10 % level respectively. All other values are significant even at 0.5 % level except the last one for the year 1996-97 which is insignificant.

b Critical value for the test involving γ is taken from Table 1 of Kodde and Palm, 1986, pp. 1246.

Table 3.3: Percentage of Firms Having Non-Negative Input Elasticities

Input	*Percentage of Firms*				
	1985-86	1990-91	1996-97	1998-99	2001-02
Intermediate Input	100	100	100	99.93	100
Fixed Asset	87	97	95	68	96
Mandays	95	95	90	83	99

Table 3.4: Percentage of Firms Satisfying Various Regularity Conditions

Regularity Condition	*Percentage of Firms*				
	1985-86	1990-91	1996-97	1998-99	2001-02
Monotonicity	86	93	86	68	94
Quasi-Concavity	68	80	58	33	87
Both of them	68	80	58	33	87

Table 3.5: Distribution of Mean Technical Efficiency by Size Group of Firms

Size Group (in deciles)	*Mean Technical Efficiency*				
	1985-86	1990-91	1996-97	1998-99	2001-02
Lowest 10 %	0.33	0.64	0.44	0.49	0.76
10 –20 %	0.51	0.74	0.60	0.68	0.76
20 – 30 %	0.64	0.80	0.61	0.71	0.75
30 – 40 %	0.73	0.84	0.64	0.71	0.76
40 – 50 %	0.80	0.87	0.69	0.75	0.79
50 – 60 %	0.83	0.89	0.72	0.83	0.80
60 – 70 %	0.85	0.90	0.75	0.84	0.83
70 – 80 %	0.87	0.91	0.76	0.86	0.85
80 – 90 %	0.885	0.91	0.78	0.86	0.86
Highest 10 %	0.887	0.90	0.75	0.87	0.87
All Firms	*0.73*	*0.84*	*0.68*	*0.76*	*0.80*

Table 3.6: Distribution of Mean Technical Efficiency by Age Group of Firms

Age Group	*Mean Technical Efficiency*									
	1985-86		1990-91		1996-97		1998-99		2001-02	
	% of Firms	Mean TE	% of Firms	Mean TE	% of Firms	Mean TE	% of Firms	Mean TE	% of Firms	Mean TE
Very Old	30.9	0.74	30.3	0.83	26.3	0.67	35.7	0.73	31.2	0.78
Old	27.3	0.73	28.5	0.84	28.3	0.68	29.3	0.76	32.3	0.81
Young	41.8	0.74	41.3	0.85	45.4	0.68	35.0	0.78	36.5	0.82
All Firms	*100*	*0.73*	*100*	*0.84*	*100*	*0.68*	*100*	*0.76*	*100*	*0.80*

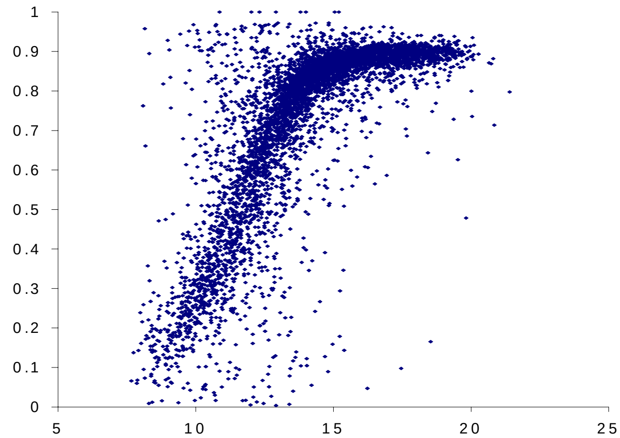
Table 3.7: Mean Elasticity of Technical Efficiency with respect to Size and Age

Inefficiency Variable	*Mean Elasticity of Technical Efficiency*				
	1985-86	1990-91	1996-97	1998-99	2001-02
Size	0.1203 (0.002)	0.0457 (0.001)	0.0589 (0.001)	0.0665 (0.002)	0.0216 (0.0005)
Age	- 0.0085 (0.0006)	- 0.0155 (0.0007)	- 0.0051 (0.001)	- 0.0344 (0.0026)	- 0.0183 (0.0009)

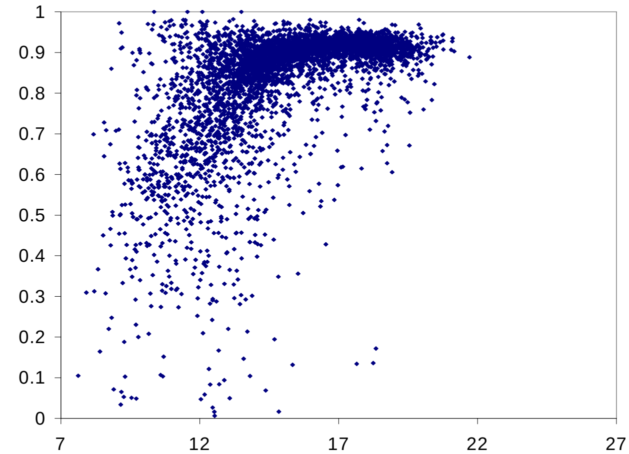
Figures in the parentheses are the corresponding standard errors.

Figure 3.1: Scatter Diagrams of Sizes (Horizontal Axis) and TE Scores (Vertical Axis) of Textile Firms

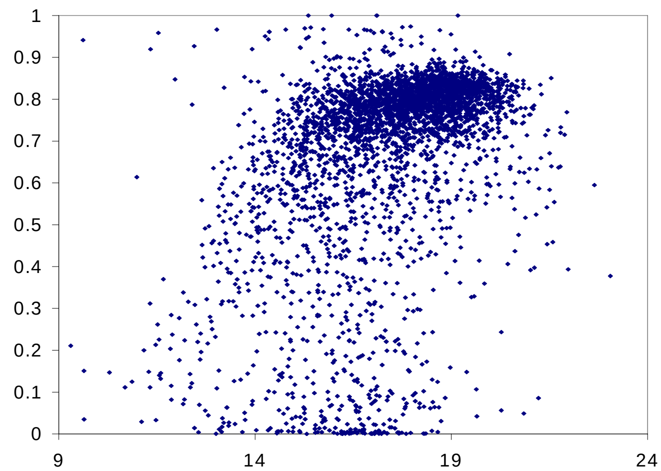
1985-86



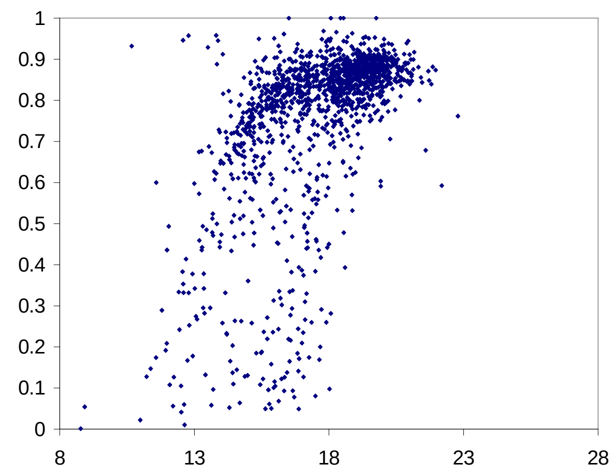
1990-91



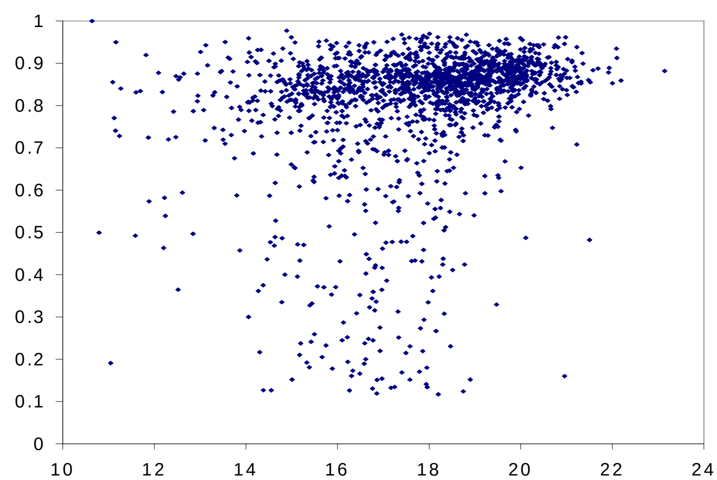
1996-97



1998-99



2001-02



Appendix 3.1

The random coefficient regression model discussed at length in Chapter 2 is not very widely used in the production frontier literature. The additional problem on our part was that the software we could access can handle only about 220 observations (and that too with a few explanatory variables), while in any year the number of firms in our sample far exceeded 1400. To illustrate the point we, therefore, consider the data for a single year, namely the latest year 2001-02. To get a representative sample, we initially arrange all firms in ascending order of their size and then classify them in 100 fractile groups – lowest one per cent, next one per cent and so on, up to the top one per cent. From each group we then select two firms from the middle of the group so that the number of firms comes out to be 206. We have then fitted Cobb-Douglas frontier by both the RCRM and stochastic frontier model (SFM) to this sampled data set. The results are given in the Table 3A.1 below. We find that although the mean TE of firms under RCRM is much lower than that under the SFM, there is hardly any difference in the estimated (corresponding) frontier coefficients under the two models. Computing firm level TE, we also observe a high positive correlation between estimates of individual TE's obtained under the two methods. We have not tried to verify whether this result would carry through, if the RCRM were applied to the entire data set rather than a selected part of it.

Table 3A.1

Frontier Coefficients Estimated for 2001-02by Alternative Methods

	RCRM	SFM
Intercept	0.71	1.02 (6.09)
Inputs	0.97	0.916 (46.79)
Fixed Assets	0.01	0.019 (1.29)
Mandays	0.04	0.06 (3.01)
$\sigma^2\left(=\sigma_u^2+\sigma_v^2\right)$	----	0.24 (8.08)
$\gamma\left(=\sigma_u^2/\sigma^2\right)$	----	0.91 (36.1)
Log Likelihood	----	- 42.02
Breush-Pagan χ^2 value (with dfs. = 3)	104.56	----
Mean TE (%)	51	74
Figures in the parentheses are the corresponding t-ratios.		

Appendix 3.2

Here we show the distribution of the estimated inefficiency error for the case we have assumed but in the light of Wang and Schmidt (2009). They show that it may not be identical to the one assumed for the population distribution of the inefficiency error term. We assume that $u_i \sim idN^{+}\left(\mu_i = z_i\delta, \sigma_u^2\right)$ and $v_i \sim iidN\left(0, \sigma_v^2\right)$. Let probability density function of any random variable θ be denoted by f_θ and joint density function of any two random variables θ and ϑ be denoted by $f_{\theta,\vartheta}$. We will use two standard results: (a) if $m = m(p)$ where p is a random variable, and thus, m is also a random variable, then $f_m = f_p \left|\frac{\partial p}{\partial m}\right|$; and (b) if $q = q(x, y)$ and $r = r(x, y)$, then $f_{q,r} = f_{x,y}\left|\frac{\partial(x, y)}{\partial(q, r)}\right|$. The second term of the right hand side expression of both (a) and (b) are known as the Jacobian of transformation. Observe that the term within '| |' in (a) is a scalar but that in (b) is a matrix. So, $\left|\frac{\partial p}{\partial m}\right|$ refers to the absolute value of $\frac{\partial p}{\partial m}$ and $\left|\frac{\partial(x, y)}{\partial(q, r)}\right|$ refers to the determinant of $\frac{\partial(x, y)}{\partial(q, r)}\left(\equiv\left[\begin{array}{cc}\frac{\partial x}{\partial q} & \frac{\partial x}{\partial r}\\ \frac{\partial y}{\partial q} & \frac{\partial y}{\partial r}\end{array}\right]\right)$.

Considering the simple transformations $z_1 = g(u, v) = u$ and $z_2 = h(u, v) = \varepsilon = v - u$, we get $u = z_1$ and $v = z_2 + z_1$. Hence, using above result (b) we get,

$$f_{z_1,z_2} = f_{u,v}\left|\frac{\partial(u, v)}{\partial(z_1, z_2)}\right| \quad \text{where} \quad \left|\frac{\partial(u, v)}{\partial(z_1, z_2)}\right| = \det\left[\begin{array}{cc}\frac{\partial u}{\partial z_1} & \frac{\partial u}{\partial z_2}\\ \frac{\partial v}{\partial z_1} & \frac{\partial v}{\partial z_2}\end{array}\right] = \det\left[\begin{array}{cc}1 & 0\\ 1 & 1\end{array}\right] = 1 - 0 = 1.$$

Hence, $f_{u,\varepsilon}(u_i, \varepsilon_i) = f_{u,v}\left(u_i, v_i(u_i, \varepsilon_i)\right)$.

In order to simplify expressions we shall use the following notations and simplifications.

(i) Note that for the distribution function of a standard normal variable, $\Phi(\bullet)$,

$$\left\{1-\Phi\left(-\frac{z_i\,\delta}{\sigma_u}\right)\right\}=\Phi\left(\frac{z_i\,\delta}{\sigma_u}\right)$$

(ii) The following notations have been used in the text:

$$\mu_i^* = \frac{z_i\delta\sigma_v^2 - \varepsilon_i\sigma_u^2}{\sigma_u^2+\sigma_v^2}\;;\; \sigma_*^2 = \frac{\sigma_u^2\sigma_v^2}{\sigma_u^2+\sigma_v^2}.$$

(iii) Note that

$$\left(\frac{z_i\delta}{\sigma_u}\right)^2+\left(\frac{\varepsilon_i}{\sigma_v}\right)^2-\left(\frac{\mu_i^*}{\sigma_*}\right)^2$$

$$=\left(\frac{z_i\delta}{\sigma_u}\right)^2+\left(\frac{\varepsilon_i}{\sigma_v}\right)^2-\left(\frac{z_i\delta\sigma_v^2-\varepsilon_i\sigma_u^2}{\sigma_u\sigma_v\sqrt{\sigma_u^2+\sigma_v^2}}\right)^2 \qquad \text{[using (ii)]}$$

$$=\frac{z_i^2\delta^2}{\sigma_u^2}+\frac{\varepsilon_i^2}{\sigma_v^2}-\left(\frac{z_i^2\delta^2\sigma_v^2}{\sigma_u^2\left(\sigma_u^2+\sigma_v^2\right)}+\frac{\varepsilon_i^2\sigma_u^2}{\sigma_v^2\left(\sigma_u^2+\sigma_v^2\right)}-2\frac{z_i\delta\,\varepsilon_i}{\left(\sigma_u^2+\sigma_v^2\right)}\right)$$

$$=\frac{z_i^2\delta^2}{\sigma_u^2\left(\sigma_u^2+\sigma_v^2\right)}\left[\left(\sigma_u^2+\sigma_v^2\right)-\sigma_v^2\right]+\frac{\varepsilon_i^2}{\sigma_v^2\left(\sigma_u^2+\sigma_v^2\right)}\left[\left(\sigma_u^2+\sigma_v^2\right)-\sigma_u^2\right]+2\frac{z_i\delta\,\varepsilon_i}{\left(\sigma_u^2+\sigma_v^2\right)}$$

$$=\frac{z_i^2\delta^2}{\left(\sigma_u^2+\sigma_v^2\right)}+\frac{\varepsilon_i^2}{\left(\sigma_u^2+\sigma_v^2\right)}+2\frac{z_i\delta\,\varepsilon_i}{\left(\sigma_u^2+\sigma_v^2\right)}$$

$$=\left[\frac{z_i\delta+\varepsilon_i}{\sqrt{\sigma_u^2+\sigma_v^2}}\right]^2$$

(iv) Note that

$$\left(\frac{u_i-z_i\delta}{\sigma_u}\right)^2+\left(\frac{\varepsilon_i+u_i}{\sigma_v}\right)^2=\frac{u_i^2-2u_iz_i\delta+z_i^2\delta^2}{\sigma_u^2}+\frac{\varepsilon_i^2+2\varepsilon_iu_i+u_i^2}{\sigma_v^2}$$

$$=\left(\frac{z_i\delta}{\sigma_u}\right)^2+\left(\frac{\varepsilon_i}{\sigma_v}\right)^2+\frac{u_i^2\left(\sigma_u^2+\sigma_v^2\right)}{\sigma_u^2\sigma_v^2}-2\frac{u_i\left(z_i\delta\sigma_v^2-\varepsilon_i\sigma_u^2\right)}{\sigma_u^2\sigma_v^2}$$

$$=\left(\frac{z_i\delta}{\sigma_u}\right)^2+\left(\frac{\varepsilon_i}{\sigma_v}\right)^2-\left(\frac{\mu_i^*}{\sigma_*}\right)^2+\left(\frac{\mu_i^*}{\sigma_*}\right)^2+\left\{\frac{u_i\sqrt{\sigma_u^2+\sigma_v^2}}{\sigma_u\sigma_v}\right\}^2$$

$$-2\left(\frac{u_i\sqrt{\sigma_u^2+\sigma_v^2}}{\sigma_u\sigma_v}\right)\left(\frac{z_i\delta\sigma_v^2-\varepsilon_i\sigma_u^2}{\sigma_u\sigma_v\sqrt{\sigma_u^2+\sigma_v^2}}\right)$$

$$=\left(\frac{z_i\delta}{\sigma_u}\right)^2+\left(\frac{\varepsilon_i}{\sigma_v}\right)^2-\left(\frac{\mu_i^*}{\sigma_*}\right)^2+\left(\frac{\mu_i^*}{\sigma_*}\right)^2+\left(\frac{u_i}{\sigma_*}\right)^2-2\left(\frac{u_i}{\sigma_*}\right)\left(\frac{\mu_i^*}{\sigma_*}\right)$$

$$=\left[\frac{z_i\delta+\varepsilon_i}{\sqrt{\sigma_u^2+\sigma_v^2}}\right]^2+\left(\frac{u_i-\mu_i^*}{\sigma_*}\right)^2 \qquad \text{[using (iii)]}$$

Using (i) – (iv), the joint density function of (u_i,ε_i) may be rewritten as

$$f_{u,\varepsilon}(u_i,\varepsilon_i)=\frac{1}{\sigma_u\sigma_v(2\Pi)\Phi\left(\frac{z_i\delta}{\sigma_u}\right)}\exp\left[-\frac{1}{2}\left\{\left(\frac{u_i-z_i\delta}{\sigma_u}\right)^2+\left(\frac{\varepsilon_i+u_i}{\sigma_v}\right)^2\right\}\right]$$

$$=\frac{1}{\sigma_u\sigma_v(2\Pi)\Phi\left(\frac{z_i\delta}{\sigma_u}\right)}\exp\left[-\frac{1}{2}\left\{\left(\frac{z_i\delta+\varepsilon_i}{\sqrt{\sigma_u^2+\sigma_v^2}}\right)^2+\left(\frac{u_i-\mu_i^*}{\sigma_*}\right)^2\right\}\right] \qquad \text{[using (iv)]}$$

Therefore, marginal density of ε is given by

$$f_\varepsilon(\varepsilon_i)=\int_0^\infty f_{u,\varepsilon}(u_i,\varepsilon_i)\,du_i=\frac{1}{\sigma_u\sigma_v(2\Pi)\Phi\left(\frac{z_i\delta}{\sigma_u}\right)}\exp\left[-\frac{1}{2}\left\{\left(\frac{z_i\delta+\varepsilon_i}{\sqrt{\sigma_u^2+\sigma_v^2}}\right)^2\right\}\right]$$

$$\times\int_0^\infty \exp\left[-\frac{1}{2}\left\{\left(\frac{u_i-\mu_i^*}{\sigma_*}\right)^2\right\}\right]du_i$$

$$= \quad =\frac{\exp\left[-\frac{1}{2}\left\{\left(\frac{z_i\delta+\varepsilon_i}{\sqrt{\sigma_u^2+\sigma_v^2}}\right)^2\right\}\right]}{\sigma_u\sigma_v\sqrt{2\Pi}\,\Phi\left(\frac{z_i\delta}{\sigma_u}\right)}\sigma_*\int_{-\frac{\mu_i^*}{\sigma_*}}^{\infty}\frac{1}{\sqrt{2\Pi}}\exp\left\{-\frac{1}{2}(t_i)^2\right\}dt_i$$

(using the transformation $t_i=\dfrac{u_i-\mu_i^*}{\sigma_*}$ so that $du_i=\sigma_*\ dt_i$ and t_i ranges from $\left(-\dfrac{\mu_i^*}{\sigma_*}\right)$ to infinity)

$$=\left(\exp\left[-\frac{1}{2}\left\{\left(\frac{z_i\delta+\varepsilon_i}{\sqrt{\sigma_u^2+\sigma_v^2}}\right)^2\right\}\right]\Big/\sqrt{2\Pi\left(\sigma_u^2+\sigma_v^2\right)}\right)\frac{\Phi\left(\frac{\mu_i^*}{\sigma_*}\right)}{\Phi\left(\frac{z_i\delta}{\sigma_u}\right)}$$ and, therefore,

$$f_u\left(u_i\left|\varepsilon_i\right.\right)=\frac{f_{u,\varepsilon}\left(u_i,\varepsilon_i\right)}{f_\varepsilon\left(\varepsilon_i\right)}=\frac{\exp\left[-\frac{1}{2}\left(\frac{u_i-\mu_i^*}{\sigma_*}\right)^2\right]}{\sigma_*\sqrt{2\Pi}\,\Phi\left(\frac{\mu_i^*}{\sigma_*}\right)}$$

Hence, $\hat{u}_i=\mathrm{E}\left(u_i\left|\varepsilon_i\right.\right)=\int_0^\infty u_i\,f_u\left(u_i\left|\varepsilon_i\right.\right)du_i=\int_0^\infty u_i\,\frac{\exp\left[-\frac{1}{2}\left(\frac{u_i-\mu_i^*}{\sigma_*}\right)^2\right]}{\sigma_*\sqrt{2\Pi}\,\Phi\left(\frac{\mu_i^*}{\sigma_*}\right)}du_i$

$$=\frac{1}{\sigma_*\sqrt{2\Pi}}\cdot\frac{1}{\Phi\left(\frac{\mu_i^*}{\sigma_*}\right)}\int_{-\frac{\mu_i^*}{\sigma_*}}^{\infty}\left(\mu_i^*+\sigma_*\,t_i\right)\exp\left(-\frac{t_i^2}{2}\right)\sigma_*\,dt_i \qquad \text{(using } t_i \text{ as before)}$$

$$=\frac{1}{\sigma_*\sqrt{2\Pi}}\cdot\frac{1}{\Phi\left(\frac{\mu_i^*}{\sigma_*}\right)}\left[\int_{-\frac{\mu_i^*}{\sigma_*}}^{\infty}\mu_i^*\sigma_*\exp\left(-\frac{t_i^2}{2}\right)dt_i+\int_{-\frac{\mu_i^*}{\sigma_*}}^{\infty}\sigma_*^2\,t_i\exp\left(-\frac{t_i^2}{2}\right)dt_i\right]$$

$$=\frac{\mu_i^*}{\Phi\left(\frac{\mu_i^*}{\sigma_*}\right)}\int_{-\frac{\mu_i^*}{\sigma_*}}^{\infty}\frac{1}{\sqrt{2\Pi}}\exp\left(-\frac{t_i^2}{2}\right)dt_i+\frac{\sigma_*}{\Phi\left(\frac{\mu_i^*}{\sigma_*}\right)\sqrt{2\Pi}}\int_{-\frac{\mu_i^*}{\sigma_*}}^{\infty}t_i\exp\left(-\frac{t_i^2}{2}\right)dt_i$$

$$=\frac{\mu_i^*}{\Phi\left(\frac{\mu_i^*}{\sigma_*}\right)}.\Phi\left(\frac{\mu_i^*}{\sigma_*}\right)+\frac{\sigma_*}{\Phi\left(\frac{\mu_i^*}{\sigma_*}\right)\sqrt{2\Pi}}\left[-\exp\left(-\frac{t_i^2}{2}\right)\right]_{-\frac{\mu_i^*}{\sigma_*}}^{\infty} \qquad \text{[using (i)]}$$

$$=\mu_i^*+\frac{\sigma_*}{\Phi\left(\frac{\mu_i^*}{\sigma_*}\right)\sqrt{2\Pi}}\exp\left\{-\frac{1}{2}\left(\frac{\mu_i^*}{\sigma_*}\right)^2\right\}$$

$$=\mu_i^*+\sigma_*\frac{\varphi\left(-\frac{\mu_i^*}{\sigma_*}\right)}{\left[1-\Phi\left(-\frac{\mu_i^*}{\sigma_*}\right)\right]} \qquad \text{[since } \varphi(\bullet) \text{ is symmetric]}$$

$= g\left(\varepsilon_i\right)(say)\Rightarrow \varepsilon_i = g^{-1}\left(\hat{u}_i\right)$

Now, $\hat{u}_i = g(\varepsilon_i) = \mu_i^* + \sigma_* \dfrac{\varphi\left(-\dfrac{\mu_i^*}{\sigma_*}\right)}{\left[1-\Phi\left(-\dfrac{\mu_i^*}{\sigma_*}\right)\right]} = \mu_i^* + \sigma_* \lambda\left(-\dfrac{\mu_i^*}{\sigma_*}\right)$ where $\lambda(\bullet) = \dfrac{\varphi(\bullet)}{\left[1-\Phi(\bullet)\right]}$.

So, $\dfrac{\partial \hat{u}_i}{\partial \varepsilon_i} = -\dfrac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2} + \sigma_* \times \lambda'\left(-\dfrac{\mu_i^*}{\sigma_*}\right) \times \dfrac{\partial}{\partial \varepsilon_i}\left(-\dfrac{\mu_i^*}{\sigma_*}\right) = \gamma\left[\lambda'\left(-\dfrac{\mu_i^*}{\sigma_*}\right) - 1\right]$ where, as in the text, $\gamma = \dfrac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2}$ and $\lambda'(s) = -s\lambda(s) + \lambda^2(s)$. Since $\hat{u}_i = g\left(\varepsilon_i\right)$, using above result (a) we get, $f_{\hat{u}}\left(\hat{u}_i\right) = f_\varepsilon\left(\varepsilon_i\right) \times \left|\dfrac{\partial \varepsilon_i}{\partial \hat{u}_i}\right| = f_\varepsilon\left(\varepsilon_i\right) \times \left| 1 \Big/ \dfrac{\partial \hat{u}_i}{\partial \varepsilon_i}\right|$

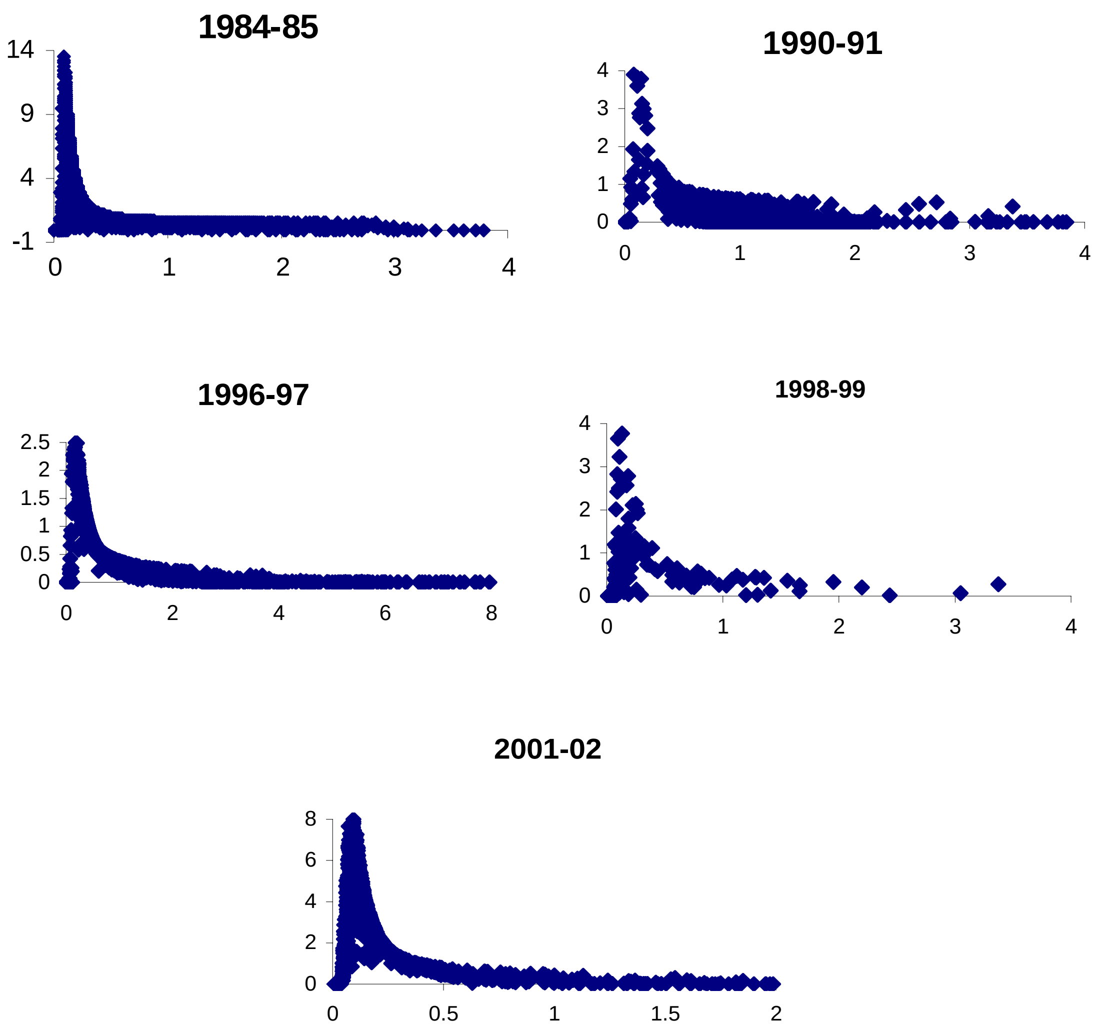
$$= \frac{\exp\left[-\frac{1}{2}\left(\frac{z_i\delta + \varepsilon_i}{\sqrt{\sigma_u^2 + \sigma_v^2}}\right)^2\right]}{\sqrt{2\Pi\left(\sigma_u^2 + \sigma_v^2\right)}} \times \frac{\left[1-\Phi\left(-\frac{\mu_i^*}{\sigma_*}\right)\right]}{\left[1-\Phi\left(-\frac{z_i\delta}{\sigma_u}\right)\right]} \times \left|\frac{1}{\gamma\left[\lambda'\left(-\frac{\mu_i^*}{\sigma_*}\right) - 1\right]}\right|$$

$$= \frac{\exp\left[-\frac{1}{2}\left(\frac{z_i\delta + \varepsilon_i}{\sqrt{\sigma_u^2 + \sigma_v^2}}\right)^2\right]}{\sqrt{2\Pi\left(\sigma_u^2 + \sigma_v^2\right)}} \times \frac{\Phi\left(\frac{\mu_i^*}{\sigma_*}\right)}{\Phi\left(\frac{z_i\delta}{\sigma_u}\right)} \times \left|\frac{1}{\gamma\left[\lambda'\left(-\frac{\mu_i^*}{\sigma_*}\right) - 1\right]}\right|$$

$$= \frac{\exp\left[-\frac{1}{2}\left(\frac{z_i\delta + \varepsilon_i}{\sqrt{\sigma_u^2 + \sigma_v^2}}\right)^2\right]}{\sqrt{2\Pi\left(\sigma_u^2 + \sigma_v^2\right)}} \times \frac{\Phi\left(\frac{\mu_i^*}{\sigma_*}\right)}{\Phi\left(\frac{z_i\delta}{\sigma_u}\right)} \times \left|\frac{1}{\gamma\left[\left(\frac{\mu_i^*}{\sigma_*}\right)\left\{\varphi\left(\frac{\mu_i^*}{\sigma_*}\right) \Big/ \Phi\left(\frac{\mu_i^*}{\sigma_*}\right)\right\} + \left\{\varphi\left(\frac{\mu_i^*}{\sigma_*}\right) \Big/ \Phi\left(\frac{\mu_i^*}{\sigma_*}\right)\right\}^2 - 1\right]}\right|$$

In the diagram below we plot this probability density function of $\hat{u}$ against $\hat{u}$ for each of the sample years we have considered.

Figure 3A.1: Scatter Diagram of Probability Density of $\hat{u}$ (Vertical Axis) against $\hat{u}$ (Horizontal Axis) for each Sample Year



Chapter 4[*]

Efficiency of the Indian Textile Industry: A Data Envelopment Analysis

4.1 Introduction

We have discussed the importance and the structure of the Indian textile industry in detail in the preceding chapter and presented estimates of average technical efficiency of groups of textile firms in selected years where such estimates have been obtained through stochastic frontier analysis (SFA). The objective of the present chapter is to obtain measures of technical efficiency (TE) of the same set of textile firms as analysed in Chapter 3, but using an alternative methodology, namely the DEA. The theoretical structure of the DEA method has already been outlined in Chapter 2. Using the DEA estimates we now try to investigate the same set of issues as discussed in Chapter 3.

However, we propose to do an additional exercise in this chapter. This exercise uses the concept of a *meta-frontier* (or *grand frontier*[1]) production function introduced by Hayami (1969) and Hayami and Ruttan (1970, 1971) in the literature as well as the concept of what may be called a group-specific frontier; the purpose is to examine how measures of technical efficiency would differ if technological possibilities available to different groups of producing units were different (groups being formed on the basis of one or more distinguishing factors). Battese and Rao (2002) and Battese, Rao and O'Donnell (2004) provided frameworks for such comparisons in case of efficiency measurements using parametric stochastic frontier models. Rao, O'Donnell and Battese (2003) developed similar frameworks in the context of both the non-parametric DEA and parametric SFA. They also made an empirical application of their methodology using FAO agricultural data on 97 countries. Very recently Das, Ray and Nag (2009) have used the concept of a *meta-frontier* as a national or grand frontier in order to

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[*] These results are based mainly on a working paper written jointly with Subhash C. Ray (Bhandari and Ray, 2007).

[1] We shall use the two terms, *meta-frontier* and *grand frontier* interchangeably, without any confusion.

analyse, through nonparametric methodology, branch level labour-use efficiency of a major public sector bank in India.

Studies on productivity and efficiency done so far for the Indian manufacturing sector, either at an aggregate level (e.g., Ray (1997, 2002), Mitra et al (2002), Krishna (2004), Ray and Mukherjee (2005)) or at an industry specific level (e.g., Hashim (2004), Trivedi (2004)), used mostly state-level data. Although Ram Mohan (2005) uses firm level data to compare the performance of public and private sector firms, his are data which have been constructed from the financial statements of the companies, rather than observed directly. The present chapter intends to add to the small number of studies that utilise input-output data at the establishment level. We would like to evaluate the levels of TE of individual firms measured through the DEA method.

The chapter is organised as follows. Section 4.2 describes the non-parametric methodology of DEA and explains the concept of a *meta-frontier* as distinct from that of a group frontier. We also mention here some justification why such a distinction is likely to be relevant for the Indian industrial sector. Section 4.3 briefly mentions the data used and the variables considered in this chapter. This section also presents our empirical findings. Concluding observations are included in Section 4.4.

4.2 The DEA Models

We have already discussed this method in Section 2.3 of Chapter 2. Since we shall try to measure only (output-oriented) technical efficiency (TE) of firms in this dissertation, we restate this method very briefly here, before we present our empirical findings. As already noted in Chapter 2, using a sample of actually observed input-output data and a number of fairly weak assumptions about production technology, the non-parametric method of DEA obtains the frontier output vector for each producing unit or firm in the sample by solving a relevant linear programming problem and then finds how much proportional increase of its output vector were feasible, given its observed use of various inputs. This *proportion* is then used to get a measure of (an *output-oriented*) TE of the firm. We summarise the approach below for the case of single-output firms (say, N in number), although the method is a general one applicable to the case of multi-product firms as well.

Let us, first of all, describe the method of obtaining a meta-frontier that is based on observations of all the firms in the industry. Let the firm i be observed to produce Y_i quantity of the good in question by using the input bundle X_i, a *k*-component (column) vector of inputs (the j^{th} element of X_i is taken to be zero, if the i^{th} firm does not use the j^{th} input). The DEA method seeks to construct a frontier – or what will be referred to as grand or *meta-frontier* in our later analysis – on the basis of the observations on inputs and outputs of all the *N* firms, by solving a set of *N* linear programmes, one for each firm. The problem for the firm *s* is to find a scalar φ and *N* number of λ_{si} 's which solve the following linear programme:

$\left(P_s^M\right)$ $\qquad$ *Maximise* φ

subject to (i) $\sum_{i=1}^{N} Y_i \lambda_{si} \geq \varphi Y_s$, (ii) $\sum_{i=1}^{N} X_i \lambda_{si} \leq X_s$, (iii) $\sum_{i=1}^{N} \lambda_{si} = 1$, and

(iv) $\lambda_{si} \geq 0$ for all $i = 1, ..., N$.

Let (P_s^M) have an optimal solution, say [φ_s^M , (λ_{s1}^M , ..., λ_{sN}^M)]. The optimal value, φ_s^M , then indicates the maximum possible *proportional increase* in output that could be achieved by the s^{th} firm, using the same input bundle as X_s.[2] Thus the technical efficiency of the s^{th} firm relative to the meta-frontier (TE_s^M) is given by:

$$TE_s^M = 1 / \varphi_s^M .$$

Meta-frontier and Group Frontiers

In order to carry out some further analysis in the context of DEA we would follow Battese, Rao and O'Donell (2004) and distinguish between a meta-frontier and a regional (in our case, group) frontier. To introduce the idea, note that the analysis in the preceding paragraph presumes that all the observed units have identical technology. This may not always be tenable, as different units may have access to different production technologies. A variety of geographical,

[2] As pointed out in footnote 25 in Chapter 2, by construction, the optimal value, φ_s^M , will be greater than or equal to one. In case of multi-product firms, Y_i and Y_s in the first inequality will each be a vector (of appropriate dimension), and *not* a *scalar* as is being assumed here. The meaning of the term '*proportional increase* in output' (vector) will be quite clear then.

institutional or other factors may give rise to such a situation. Construction of a general frontier for all the units might then result in an under-estimation of efficiency of a unit, since the inputs-output bundle used as the benchmark to compare the performance of this unit might turn out to lie outside the production possibility set relevant for it. A way to address this problem of non-availability of all techniques to all firms is to construct separate production possibility sets (and hence separate production frontiers) for separate groups of firms, each such set being defined on the basis of observations on inputs and outputs of the firms belonging to the group in question, and then to measure a firm's *within-group* technical efficiency. Thus for each firm one may compute two separate indices for its technical efficiency – one measured from what may be called its *own group* frontier (i.e., the one constructed on the basis of observations on the particular group of firms to which it belongs) and the other measured from the grand or *meta-frontier* (i.e., the one constructed on the basis of observations on all firms in the industry, i.e., the one outlined in the preceding couple of paragraphs). For later uses, we shall refer to these two different indices for a firm as its (own) group TE and its meta-frontier or grand TE, respectively. One may then compare two indices for each firm. We discuss the approach below in detail.

Suppose the observed N firms can be classified, according to some criterion, into G number of mutually exclusive and collectively exhaustive groups. Let a particular group, say g, contain N_g number of firms ($N = \sum_{g=1}^{G} N_g$) and let the symbol g also denote the set of indices corresponding to these N_g firms. Consider a given firm s. Suppose, it belongs to the group g. To measure its TE with reference to the technology of its *own* group, the DEA begins with finding a scalar φ and an N_g number of λ_{si}'s which will solve the linear programme – to be denoted by $\left(P_s^O\right)$ – that takes the same form as (P_s^M) except that the index i, used in constraints (i) – (iv), does not now run from 1 to N, but runs over only those indices that belong to the group g instead of running from 1 to N.[3]

[3] While the objective function remains unchanged, the set of constraints will now read as follows: (i) $\sum_{i \in g} Y_i \lambda_{si} \geq \varphi Y_s$, (ii) $\sum_{i \in g} X_i \lambda_{si} \leq X_s$, (iii) $\sum_{i \in g} \lambda_{si} = 1$, and (iv) $\lambda_{si} \geq 0$ for all $i \in g$.

Let the problem (P_s^O), which is solved for each firm *s* in the g^{th} group, have an optimal solution, $[\varphi_s^O; \{(\lambda_{si}^O), i \in g\}]$. Then the TE score of the s^{th} firm measured from its *own* frontier (i.e., the one constructed on the basis of the data on its *own* group of firms only), TE_s^O, is given by $TE_s^O = 1/\varphi_s^O$. This score cannot, however, fall short of its meta-frontier TE score, since the meta-frontier is the *outer-envelope* of all the group frontiers and hence[4] $TE_s^O \geq TE_s^M$. In other words, firms *cannot* be technically *more* efficient when assessed against the meta-frontier than against their own group frontier.

Technology Closeness Ratio (*TCR*)

One may be interested to know how close is the technology used by a given group of firms to that used by the other firms in the industry. An answer may be obtained by considering a few additional indices which are described below. When the TE of a firm *s* measured from its (*own*) *group frontier* (TE_s^O) is close to its TE measured from the *meta-frontier* (TE_s^M), this means that corresponding to the input bundle X_s, the point on the group frontier is close to that on the meta-frontier. However, in stead of evaluating the proximity of the *group frontier* to the *meta-frontier* at the input bundle of each individual firm, it may be useful to know how close is the frontier of the group as a whole to the meta-frontier. To illustrate the procedure let us consider a given group of firms, say *g*. One may first define an average TE of these firms relative to their own *group frontier* (to be denoted by $TE^O(g)$), by taking a geometric mean of TE_s^O's over all *s*'s in the group. Similarly, the average TE of these firms relative to the meta-frontier (to be denoted by $TE^M(g)$) may also be defined. For the group g these two indices are given by

$$TE^O(g) = \prod_{s \in g} (TE_s^O)^{1/N_g} \quad ; \qquad TE^M(g) = \prod_{s \in g} (TE_s^M)^{1/N_g}$$

[4] Note that the set of feasible solutions to (P_s^o) is a subset of the set of feasible solutions of (P_s^M). Suppose $[\tilde{\varphi}, \{(\tilde{\lambda}_{si}), i \in g\}]\}$ is a feasible solution to (P_s^o). Then a feasible solution to (P_s^M) is given by $[\tilde{\varphi}, \{(\lambda_{si}), s = 1,..., N, \text{ where } \lambda_{si} = \tilde{\lambda}_{si}, \ for\ i \in g \text{ and zero, otherwise}\}]$. Hence, the optimal value of (P_s^o) can be no greater than that of the firm's meta-frontier problem (P_s^M), implying that. $\varphi_s^o \leq \varphi_s^M$.

The *technology closeness ratio*[5] of group *g* – to be denoted by *TCR (g)* – gives an overall measure of proximity of its *group frontier* to the *meta-frontier* and is defined as follows:

$$TCR(g) = \frac{TE^{M}(g)}{TE^{O}(g)}$$

In view of the definitions of the two group averages and the result that $TE_s^O \geq TE_s^M$, $TCR(g)$ lies between 0 and 1 and higher is this value, closer is the technology of group *g* to that of the meta-frontier. We shall analyse these ratios when we discuss the TE scores of firms obtained through the DEA methodology.[6]

A Diagrammatic Illustration

We illustrate these concepts in Figure 4.1 for the case of a single input – single output and two groups of firms – group *p* and group *q*. Let the points P_1 through P_4 show the input-output bundles of four firms from group *p and* Q_1 through Q_4 be the input-output bundles of another four firms from group *q*. The group frontiers are shown by the broken line $AP_1P_3P_4C$ for group *p* and by the broken line $BQ_1Q_2Q_3D$ for group *q*. However, the grand frontier is the broken line $AP_1P_3\,Q_2Q_3D$ which is the outer envelope of the two group frontiers. Note that the points within the triangle P_3EQ_2 lie above both the group frontiers, but (by virtue of convexity) fall within the *meta-frontier*. Measured from their own group frontier the TE of each of the points Q_1, Q_2, and Q_3 equals unity while that of Q_4 is JQ_4/JK. However, measured from the *meta-frontier*, TE of each of the points, Q_2 and Q_3, remains unity, that of Q_1 equals BQ_1/BN which is below unity while that of the (inefficient) point Q_4 is the same as that measured from its group frontier (viz., JQ_4/JK). Thus the average TE of group *q* is, $TE^{O}(q) = (JQ_4/JK)^{1/4}$, if measured from its *own group frontier* and, $TE^{M}(q) = ((BQ_1/BN)(JQ_4/JK))^{1/4}$, if measured from the *meta-frontier*. (The latter is obviously smaller than the former). The ratio of the two measures the technology closeness ratio (TCR) of this group.

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[5] Battese et al (2004) calls it *technology gap ratio*. Note that such a ratio may also be defined separately for each firm *s* as the ratio of TE_s^M to TE_s^o.

[6] As shown in Battese and Rao (2002) and Battese et al (2004), a similar exercise can also be done in the context of SFA to find *TCR*'s of firms. We have not, however, done that exercise in the present study.

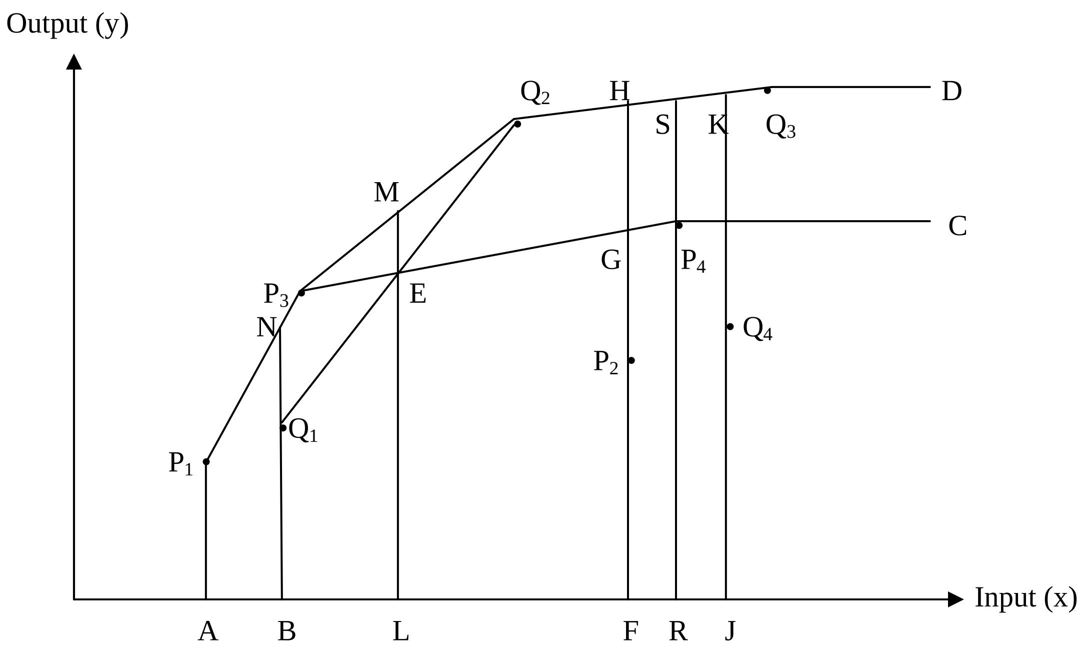


Figure 4.1: Group Frontiers and Meta-Frontier

Justification for Distinguishing between a Meta-Frontier and a Group Frontier in the Context of the Indian Industries

India is a vast country with a number of states and union territories with their distinct sociological, economic, political and infrastructural features. Easy access to natural resources and other infrastructural facilities (which help in achieving lower cost per unit of output) is not evenly distributed all over the country. States differ widely in respect of stability of government formed by political parties, the nature of the overall political environment, the level of militancy of labour unions, political and economic agenda of various governments and so on. Work culture of the people of some states is supposed to be more conducive to productive efficiency than what one finds in some other states (Das et al, 2009, pp. 415). All these factors are important determinants of the level of TE being attained by a firm located in a particular region. In fact, one may argue that even if the core production functions for the different regions were not different, these region-specific factors might cause their accessible production possibility sets to be different from one another and hence, from the grand production possibility set. It, therefore, makes sense to treat the production technology itself to differ across the different regions.

While geographical factors are likely to play the most important role in creating differences in production possibility sets across groups of firms, such differences may also arise due to differences in types of ownership and structures of organisations of firms. For instance, a firm in the public sector may perform differently from a firm, otherwise identical and located in the same state, but run under private ownership. Among the public sector firms again, those owned by the central government might have different types of working norms and managerial and administrative efficiency than those owned by a local government. Even within the private sector also, a firm owned and operated by a public limited company might perform differently from that operated by a private limited company or a partnership.

In our empirical analysis, we try to examine whether TE's of firms differs, owing to differences in their geographical locations, ownership types and organisational patterns. We also try to access whether the production frontier itself differs across groups due to variation in the factors mentioned above, by comparing their TCR's.

4.3 Empirical Findings

We have used the same data set as used in Chapter 3, viz. those on individual units – called here firms – in textile industry for the years 1985-86, 1990-91, 1996-97, 1998-99 and 2001-02. The units relate to the production of cotton, woolen, silk, synthetic (e.g., terry cotton), and other natural fibers (like jute, coir, and mesta). Further, as in Chapter 3 here also we consider a single output – three inputs technology. To repeat, the output is measured by the total ex-factory value of products and by-products turned out by the firm during each year under study. The inputs are labour (measured by the total number of man-days worked), capital (measured by the net value of fixed assets of the firm at the beginning of a year) and intermediate inputs (measured by the nominal value of material inputs (both indigenous and imported) inclusive of energy (power, fuels etc). We now present our empirical findings.

In order to carry out *meta-frontier* analysis for studying the effects of difference in location on productive efficiency, we single out six major textile-producing states namely *Gujarat*, *Maharashtra*, *Punjab*, *Rajasthan*, *Tamil Nadu* and *West Bengal*. Observations on textile firms located in the rest of the country are taken into account for constructing *meta-frontier* but are not considered as a separate group for measuring TCR. Similarly, we consider two types of ownership patterns: those firms owned entirely privately, called *private* and the rest of the firms, called *public*. For any year almost 90 per cent of firms were under private ownership. In addition, we consider six types of organisations: *individual proprietorship (IP), partnership (Part), public limited company (PULC), private limited company (PRLC), co-operative society (COOPS)*, the remaining types being clubbed together to form a residual category called *others*.

Table 4.1 gives, for each sample year, measures of average grand or meta-frontier TE as well as measures of group (i.e., state-specific) TE of firms for each of the six states mentioned above. Values of TCR for different states are also shown. In general West Bengal, with relatively smaller number of firms, seemed to have highest levels of average *meta-frontier* TE in most of the cases. However, level of its grand (i.e., *meta-frontier*) TE is not found to be very high except in the last year of our sample. Hence firms in West Bengal, although better than their counterparts elsewhere, are nevertheless quite inefficient. Further, for each state the average grand TE is observed to have improved over time.

So far as measures of average (own) group TE are concerned, firms in West Bengal and Punjab (with relatively smaller number of firms) seemed to have performed better compared to firms in other states. In addition, they have also displayed relatively smaller within group variations in their meta-frontier TE's (as reflected in figures of CV given in this table). In contrast, states having relatively larger number of textile firms like Gujarat, Maharashtra and Tamil Nadu had displayed relatively lower values of average group TE of firms and larger within group variation in their meta-frontier TE values.

A high level of TCR *does not* imply that firms in a specific state are, on an average, more efficient. As explained in an earlier section, the TCR of any group is an index of the extent of proximity of the *group* frontier to the *grand* or *meta-frontier* over the relevant range of variations in input bundles. A high value of TCR for any state implies that the maximum output producible from an input bundle by an average firm located within the state in question would be almost as high as what it could have produced were it located elsewhere in the country. This, in turn, reflects the absence of any significant physical, legal, cultural and other infrastructural constraints on production that hinder productivity in that state relative to the other states. The point may be illustrated by taking the case of Gujarat and West Bengal. In 1996-97 the TCR value of textile firms in Gujarat was as high as 91 per cent implying that the *group* frontier for the state was quite close to the *grand* frontier in that year. However, relative to either frontier, the average TE of firms in Gujarat was low, about 10 per cent in each case. Thus, even though the state faced no particular disadvantage relative to the other states, the firms therein performed poorly. A somewhat different story is revealed by textile firms in West Bengal for 1985-86. Their average TE was 66 per cent, if measured from their own group frontier, but was only 15 per cent, if measured from the grand frontier of that year. The corresponding TCR value of 0.23 shows that an average firm in West Bengal could produce only 23 per cent of what a firm somewhere else in India could produce, using the same input bundle as that used by the former. The West Bengal firms were doing reasonably well relative to a *state benchmark*, but not so relative to an *all-India benchmark*, presumably owing to the existence of various infrastructural constraints.

Another point to note is that the TCR value for each of the six states considered here appears to have improved over time, although not monotonically. This improvement is noticeable particularly after the initiation of the economic reforms in the early 1990s. During these years market forces could have been at work to remove the hurdles faced by all, bringing the state frontiers closer to each other and hence to the grand frontier.

Table 4.2 shows the results when firms are classified according to the ownership type only – public and private. We find that that except for the year 1985-86 average meta-frontier TE of the private sector firms either equals or exceeds that of the public sector firms. Moreover, the grand frontier is primarily constructed on the basis of observations on the firms from the private sector. This is evident from the high values of TCR for the group of private sector firms only. Interestingly, average TCR of the public sector is found to have increased during this period. This suggests that, as a group, public sector firms have also improved their productive *potential* in the recent years.

Coming to the results in respect of types of organisation (presented also in Table 4.2), public limited companies (denoted by PULC) have higher (grand) average TE as well as superior technology (as shown by TCR values) relative to firms belonging to the other types of organisatios. This is broadly consistent with the widely held belief that accountability of corporate management to its shareholders contributes to its better performance.

It is evident from Tables 4.1-4.2 that there are significant differences across groups when firms are classified by only a single criterion (either region or ownership type or organisation type). However, an exclusive focus on a single criterion to classify firms may not be enough. To take an example, it is not obvious from Table 4.1 that the superior performance of West Bengal firms is due to their location only. There might have worked other factors as well. For instance, these firms might have mostly come from an organisation/ownership type which usually has higher efficiency. These partial effects on TE arising out of differences in each category can be accurately captured, if one builds up a multiple regression model incorporating all the relevant variables which are likely to affect TE of a firm.

Table 4.3 reports the estimated regression equations for each sample year using the cross section data of the year. The dependent variable is the computed value of *meta-frontier* TE of a firm in that year. Six state dummy variables are considered – *Gujarat D* through *West Bengal D*. The remaining states are treated as the reference group. In the ownership classification, *Public D* is the dummy variable for public sector firms with firms under private ownership constituting the reference category. In the organisation type category, the dummy variables considered are those for firms under individual proprietorship (*IP D*), partnership (*Partnership D),* public limited companies (*PULC D*), private limited companies (*PRLC D*) and cooperatives (*Coops D*), the rest of the firms constituting the reference group. (It may be noted that for a firm the value of the dummy variable corresponding to a given category will assume a value one, if the firm falls in that category, and zero otherwise.)

In addition to these dummy variables, two more regressors are included, namely the size of a firm and the age of a firm. Size is measured by the value of the intermediate inputs used by a firm while age is measured in years. Since the data set does not reveal individual identities of firms, it was not possible to estimate a panel regression. In stead, annual cross section data were used to fit regressions equation separately for each year. Out of the 36 coefficients associated with the state dummy variables (6 dummies for each year *times* 6 years), 20 are found to be significant at the 5% (or lower) levels. In general, their signs and magnitudes are consistent with what one could deduce from the differences in means for the individual states given in Table 4.1. So far as other (non-categorical) explanatory variables are concerned, the estimated coefficient of size (*I*) is uniformly positive and highly significant. This implies that efficiency increases with firm size. In contrast, the coefficient of age is found to be significantly positive in the first two years but turns out to be non significant thereafter.

The main findings of our empirical analysis can be summarised as follows.

- Firms from the state of West Bengal performed at higher average levels of technical efficiency with respect to both their state frontier as well as the grand frontier (constructed on the basis of observations on all firms from all states).
- There seemed to have existed significant technological differences across states. However, firms from states with relatively more productive technologies might end up performing at low levels of efficiency (Gujarat in 1990-91 is a case in point).
- There is some evidence that states with less productive technologies are gradually catching up with the national benchmark, as their TCR values have improved particularly in the later years of our study period.
- Private sector firms are found to be more efficient as well as technologically superior compared to firms under the public sector.
- Firms organised as public limited companies are found to have performed better than those belonging to the other organisational types.
- Technical efficiency tends to increase with firm size.
- In spite of some evidence of positive impact in the initial years, the age of a firm does not seem to have significantly influenced TE.

4.4 Concluding Observations

The purpose of the present chapter was to analyse technical efficiency (TE) of the same textile firms as examined in Chapter 3 (through SFA); but through an alternative methodology, namely data envelopment analysis (DEA). We postpone to the next chapter a comparison of the results obtained through these two alternative methods. However, the main focus in the present chapter was to measure as well as distinguish between a firm's (*own*) *group* frontier TE and *meta-frontier* or *grand frontier* TE, in order to find technological differences, if any, across groups of firms. Low levels of meta-frontier or even group frontier TE's of firms observed in different states suggest considerable room for increasing their outputs without requiring any additional inputs. Thus whatever level of allocative inefficiency those firms experience owing to the use of any inappropriate input mix, the average cost of production of these firms could still be lowered significantly – often by 40 per cent or more. This would go a long way to improve the competitive position of Indian firms in the world market. Superior performance of public limited companies in the private sector – both higher efficiency as well as technological superiority – suggests that this should be encouraged as a preferred organisational form. Also, consolidation of smaller firms into larger entities is likely to enhance efficiency as our regression exercises suggest.

Table 4.1: Average Technical Efficiency (TE) and Technology Closeness Ratio (TCR) of Firms in Each of Major Textile Producing States

Item	*State*	Year				
		1985-86	1990-91	1996-97	1998-99	2001-02
Percentage of Firms	Gujarat	16.73	16.55	16.26	10.42	12.30
	Maharashtra	17.94	14.29	8.56	9.71	9.94
	Punjab	8.64	7.73	6.81	5.85	4.66
	Rajasthan	7.14	8.48	8.78	10.35	7.53
	Tamil Nadu	18.10	18.40	22.10	25.98	28.62
	West Bengal	3.30	3.05	3.00	5.21	4.77
	All -India	100	100	100	100	100
Average TE Measured from Meta-Frontier	Gujarat	0.10	0.35	0.09	0.15	0.44
	Maharashtra	0.09	0.33	0.11	0.14	0.46
	Punjab	0.10	0.37	0.21	0.14	0.49
	Rajasthan	0.09	0.35	0.14	0.15	0.48
	Tamil Nadu	0.08	0.31	0.13	0.13	0.47
	West Bengal	0.15	0.40	0.13	0.20	0.60
	All- India (GM)*	0.09	0.33	0.13	0.15	0.47
	All- India (AM)*	0.15	0.38	0.22	0.20	0.52
Average TE Measured from Own Group Frontier	Gujarat	0.28	0.50	0.10	0.52	0.60
	Maharashtra	0.33	0.50	0.36	0.30	0.63
	Punjab	0.47	0.70	0.63	0.81	0.80
	Rajasthan	0.13	0.50	0.42	058	0.60
	Tamil Nadu	0.40	0.57	0.32	0.18	0.57
	West Bengal	0.66	0.77	0.53	0.69	0.84
CV** (in percentage)	Gujarat	88.20	40.76	253.42	45.15	40.35
	Maharashtra	72.09	51.61	83.04	98.45	36.14
	Punjab	50.38	24.43	29.91	23.58	23.92
	Rajasthan	214.02	48.64	64.36	39.71	41.11
	Tamil Nadu	68.79	34.51	77.31	111.37	32.03
	West Bengal	33.18	26.28	58.20	31.36	18.46
TCR	Gujarat	0.35	0.70	0.91	0.29	0.74
	Maharashtra	0.28	0.66	0.31	0.48	0.73
	Punjab	0.22	0.53	0.33	0.18	0.61
	Rajasthan	0.68	0.70	0.34	0.26	0.80
	Tamil Nadu	0.20	0.54	0.40	0.76	0.82
	West Bengal	0.23	0.51	0.24	0.29	0.72

**Average TE, which is computed and reported in this chapter, is obtained by taking geometric mean (GM) of TE scores of the constituent firms. We also report arithmetic mean (AM) of TE scores of these firms. In these two rows we have taken all textile firms.*
***CV refers to Coefficient of Variation in meta-frontier TE scores of firms within a group.*

Table 4.2: Average Technical Efficiency (TE) and Technology Closeness Ratio (TCR) of Firms Classified by Ownership Type[1] as well as Organisation Type[2]

Item	*Group of Firms*	Year				
		1985-86	1990-91	1996-97	1998-99	2001-02
Percentage of Firms	Private	88.33	87.81	88.74	83.80	89.07
	Public	11.67	12.19	11.26	16.20	10.93
	IP	14.84	15.35	10.89	7.14	5.11
	Part	31.72	34.91	24.57	17.13	13.45
	PULC	10.85	14.17	26.15	41.40	39.66
	PRLC	12.75	16.59	23.71	18.63	29.71
	COOPS	6.85	6.59	5.00	6.14	5.11
	Others	22.99	12.38	9.67	9.56	6.95
Average TE Measured from Meta-Frontier	Private	0.09	0.33	0.1417	0.1550	0.485
	Public	0.11	0.33	0.09	0.11	0.39
	IP	0.06	0.26	0.18	0.15	0.47
	Part	0.08	0.31	0.15	0.13	0.47
	PULC	0.24	0.50	0.17	0.18	0.52
	PRLC	0.14	0.38	0.10	0.13	0.45
	COOPS	0.06	0.26	0.13	0.13	0.42
	Others	0.08	0.32	0.09	0.09	0.37
Average TE Measured from Own Group Frontier	Private	0.11	0.36	0.1427	0.1556	0.486
	Public	0.18	0.46	0.42	0.36	0.58
	IP	0.28	0.40	0.30	0.52	0.76
	Part	0.11	0.49	0.24	0.25	0.49
	PULC	0.49	0.54	0.18	0.25	0.57
	PRLC	0.37	0.56	0.27	0.16	0.57
	COOPS	0.24	0.59	0.49	0.65	0.74
	Others	0.13	0.43	0.36	0.53	0.58
CV (in percentage)	Private	176.55	49.65	141.30	118.95	38.35
	Public	133.76	62.48	70.04	69.18	39.34
	IP	93.50	64.35	98.06	40.34	24.26
	Part	183.57	30.34	104.27	105.34	39.21
	PULC	44.41	35.33	110.45	85.75	31.52
	PRLC	55.98	33.79	90.94	142.50	37.06
	COOPS	111.49	37.24	55.12	36.19	24.00
	Others	152.07	63.42	82.79	51.95	42.65
TCR	Private	0.79	0.921	0.993	0.996	0.998
	Public	0.62	0.72	0.21	0.29	0.67
	IP	0.20	0.65	0.60	0.28	0.63
	Part	0.69	0.63	0.63	0.53	0.96
	PULC	0.48	0.94	0.96	0.72	0.90
	PRLC	0.39	0.68	0.35	0.82	0.79
	COOPS	0.26	0.44	0.26	0.20	0.57
	Others	0.62	0.73	0.24	0.18	0.64

[1] *Two types of ownership are considered, viz., private and public.*
[2] *Six types of organisation are considered, viz., IP, Part, PULC, PRLC, COOPS and Others.*

Table 4.3: Estimated Regression Equations for Explaining Meta-Frontier (DEA) TE Scores of Firms (using State, Ownership and Organisation Dummies) for Selected Years

Regressor	*Estimated Coefficient*				
	1985-86	1990-91	1996-97	1998-99	2001-02
Gujarat D	0.011 (2.14)	0.022 (3.08)	- 0.051 (- 5.40)	- 0.002 (- 0.12)	- 0.035 (- 2.48)
Maharashtra D	0.008 (1.56)	0.018 (2.47)	- 0.058 (- 4.94)	- 0.017 (- 1.11)	- 0.012 (- 0.79)
Punjab D	0.015 (2.24)	0.045 (4.81)	0.015 (1.18)	- 0.051 (- 2.72)	- 0.017 (- 0.85)
Rajasthan D	0.020 (2.76)	0.032 (3.58)	- 0.042 (- 3.57)	- 0.013 (- 0.87)	0.001 (0.04)
Tamil Nadu D	- 0.002 (- 0.32)	- 0.011 (- 1.65)	- 0.072 (- 8.60)	- 0.033 (- 3.03)	- 0.022 (- 2.01)
West Bengal D	0.022 (2.22)	0.016 (1.13)	- 0.024 (- 1.25)	0.050 (2.43)	0.102 (4.76)
Public D	0.035 (5.51)	0.015 (1.68)	- 0.069 (- 4.97)	- 0.046 (- 2.74)	- 0.071 (- 3.97)
IP D	- 0.033 (- 5.68)	- 0.039 (- 3.97)	0.058 (3.61)	0.076 (3.06)	0.057 (2.08)
Partnership D	- 0.007 (- 1.35)	- 0.007 (- 0.84)	0.033 (2.25)	0.036 (1.66)	0.047 (2.03)
PULC D	0.103 (15.22)	0.091 (9.09)	- 0.029 (- 2.06)	0.006 (0.33)	0.043 (2.11)
PRLC D	0.059 (9.69)	0.047 (4.88)	- 0.056 (- 3.82)	0.014 (0.64)	0.025 (1.16)
Coops D	- 0.039 (- 4.92)	- 0.059 (- 5.23)	0.010 (0.61)	0.008 (0.38)	0.028 (1.14)
$\left(I/10^8\right)$	0.152 (47.19)	0.071 (26.91)	0.019 (18.58)	0.022 (18.87)	0.014 (14.33)
$\left(Age/10^2\right)$	0.058 (5.82)	0.082 (6.21)	0.007 (0.39)	0.008 (0.43)	0.015 (0.72)
Constant	0.094 (18.74)	0.320 (36.26)	0.238 (16.79)	0.155 (7.63)	0.465 (21.23)
$\overline{R}^2$ *(in percentage)*	46.75	29.97	14.95	24.46	16.55

Figure in the parenthesis is the corresponding t-ratio.
For a firm the value of the dummy variable of a given category is taken to be 1, if the firm belongs to that category and 0, otherwise.

Chapter 5

Efficiency of the Indian Textile Industry: A Comparison of Results Obtained through the SFA and the DEA

5.1 Introduction

In the preceding two chapters we have examined Indian textile industry with a view to estimating technical efficiency (TE) levels of individual firms in this industry and also analysing a few other related issues. The analysis was carried out in Chapter 3 by using the stochastic frontier analysis (SFA) and in Chapter 4 by using the data envelopment analysis (DEA). The issues we had sought to analyse therein include the overall scenario about the TE levels of individual firms in this industry in selected years and the question whether a firm's TE is related to some of its important characteristics like size and age. In addition, we had also tried to examine whether there was any systematic variation in the firm's efficiency across location, ownership or organisational patterns. The objective of the present chapter is to attempt a comparison of the main results obtained in the preceding two chapters through the two alternative methods. This is discussed in the following section.

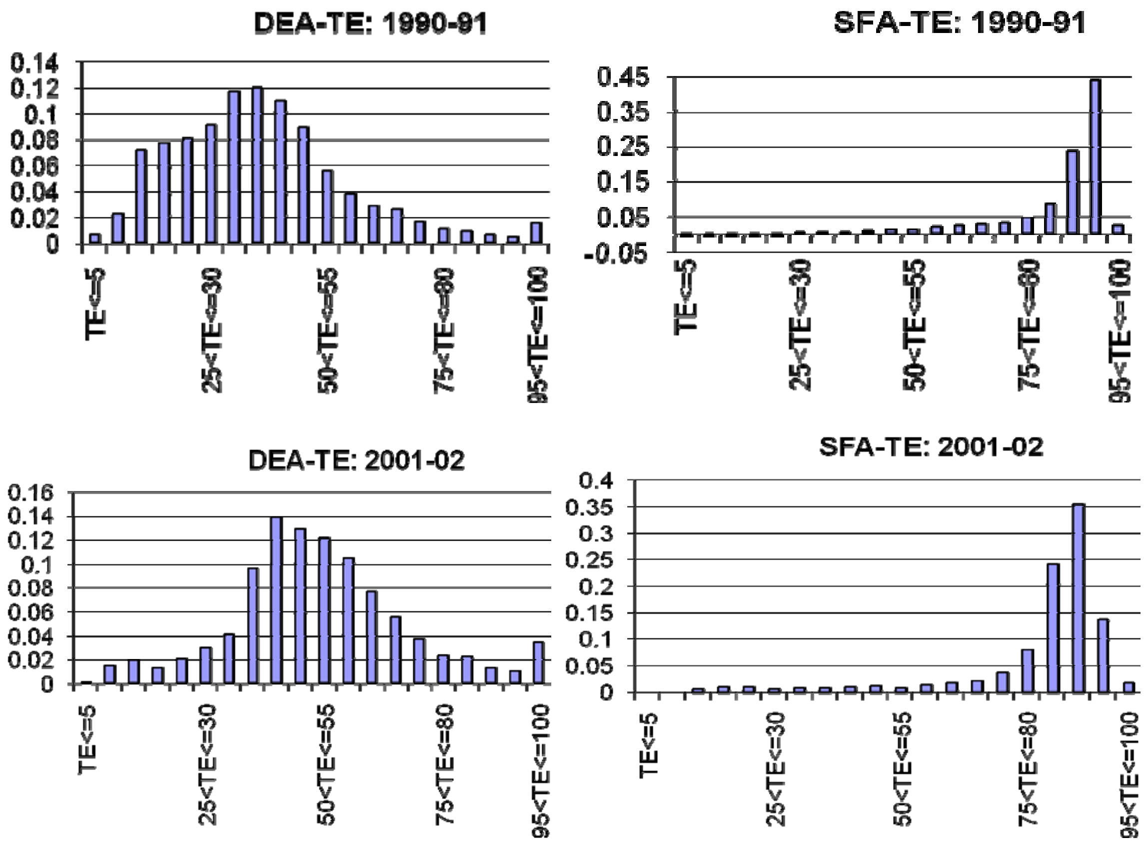
5.2 Some Major Findings Obtained using the Two Methods

For each of the sample years we have computed two alternative series of TE values of textile firms – one obtained through SFA (to be called SFA-TE) and analysed in Chapter 3 and the other containing values of meta-frontier DEA[1] (to be called DEA-TE) and discussed in Chapter 4. With a few exceptions, the patterns displayed by these two sets of TE's are more or less similar. We first point out cases of dissimilarities.

[1] We have also computed in Chapter 4 levels of TE's of individual textile firms from their respective (own) group frontiers, where the groups were obtained by a number of alternative criteria. We are not considering such group frontier TE's in this chapter.

One case where the results differ is in the nature of the frequency distribution of firms by level of TE. If one constructs histograms taking say twenty class intervals of TE values (viz., 0 – 0.05, 0.05 – 0.1, 0.1 – 0.15, ….., up to 0.95 – 1.0), one finds that, in general, histogram of SFA-TE’s is negatively skewed (with a long left tail) while that of DEA-TE’s is more or less bell-shaped. As an illustration we present such histograms for a couple of years, viz., 1990-91 and 2001-02 in Figure 5.1.

Figure 5.1: Histograms Showing Percentage of Firms (*Vertical Axis*) in Different Classes of TE Scores (in percentage) (*Horizontal Axis*): Selected Years



One may, however, argue whether such a direct comparison is valid, since TE scores obtained through SFA come from a model which has already accounted for inefficiency effects (equation (3.5)) due to some firm-specific factors like size, age, location etc. whereas the DEA scores come from the frontier constructed just on the basis of the observed output and input variables. The question is: how these two sets of TE scores could be made comparable, as far as possible? For this purpose, we have followed a *three-step* procedure. In the *first step* we have computed the *negative* of the logarithmic values[2] of the DEA-TE scores. In the *second step*, we have sought to explain these scores by estimating the same equation as the equation (3.5), but through OLS and then compute its *explained part only* (i.e., the part without the estimated error term). Let it be denoted by $\hat{E}_i$ for observation i. At the *final step*, we get the modified TE of each observation i, say $\mathrm{TE}_i^{\mathrm{mod}}$, by computing $\mathrm{TE}_i^{\mathrm{mod}} = \exp(-\hat{E}_i)$ and compare it with its TE score obtained through SFA.[3] We have done this exercise for the two selected years namely 1990-91 and 2001-02. Figure 5.2 below presents the histograms of $\mathrm{TE}_i^{\mathrm{mod}}$ along with those of SFA-TE's. We observe that the distribution of (modified) DEA-TE score is not much different from that of the original DEA-TE score except that the left tail of the former becomes relatively shorter. Even the overall mean level of TE has remained almost the same.

Again, the relation between age of a firm and its TE appears to be negative in case of SFA-TE (negative elasticity as shown by Table 3.7), but no such clear relation is revealed by DEA-TE series (Table 4.3).

There are, however, many other cases where the two TE series display identical nature of results. Both TE series show a positive association between firm size and its efficiency in each year. This is displayed by statistically significant positive elasticity of SFA-TE with respect to size (row 1, Table 3.7). The result is also confirmed by the variation of average TE value across different size classes of firms (Table 3.5 in case of SFA), while in case of DEA this is confirmed by the statistically significant coefficient of firm size in explaining variation in DEA-TE (along with some other variables) (row 13, Table 4.3). (These Tables are reproduced below.)

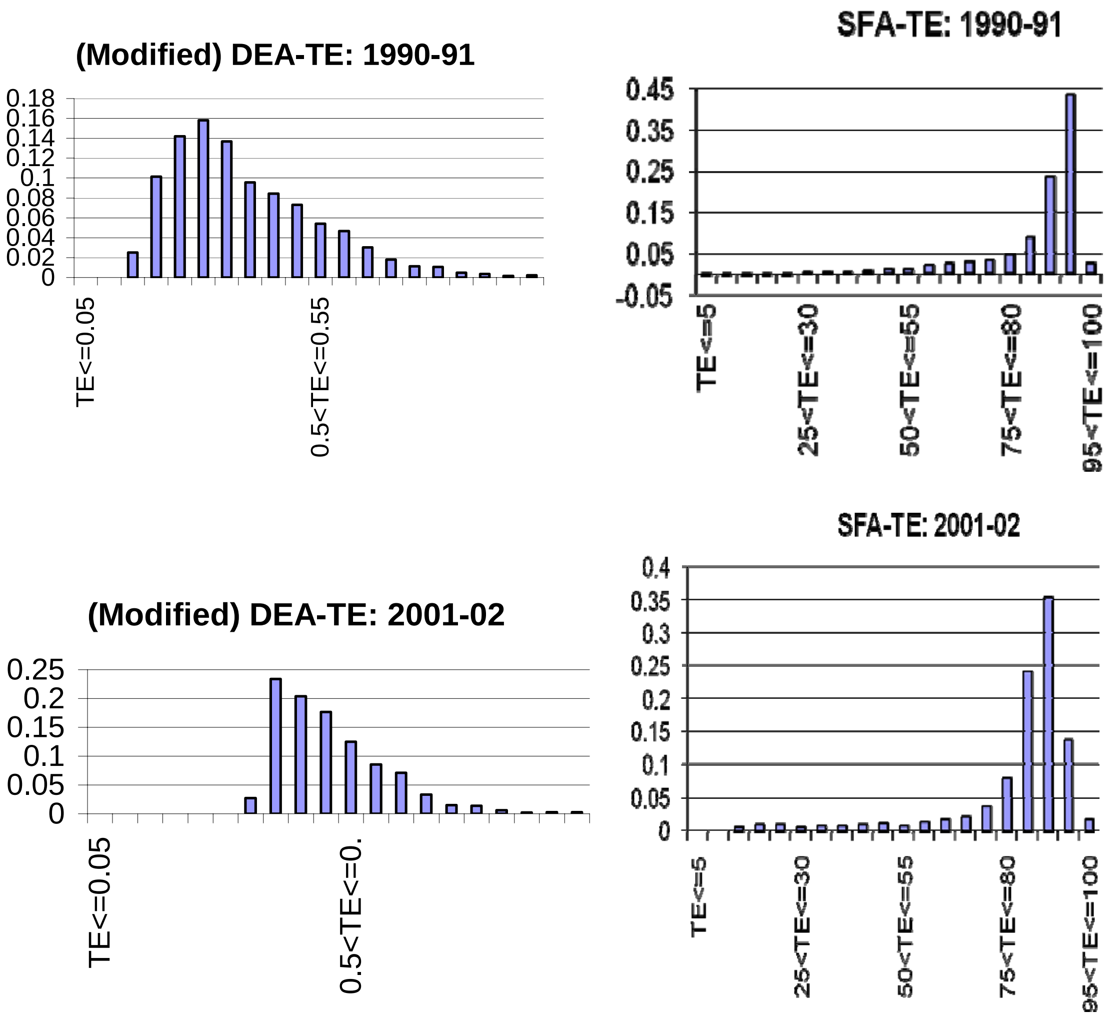
Further, although in any year the arithmetic mean of DEA-TE's of firms is lower than that of SFA-TE's of firms (see the row corresponding to all India meta-frontier TE in Table 4.1 and the last row of Table 3.1), both series of means show a similar movement – a dip during the middle of the 1990s and a rising tendency thereafter. To continue this discussion, we note that for the years considered here, average SFA-TE of

[2] In our specified SFA model, $\mathrm{TE}_i = \exp(-u_i)$ so that $u_i = -\ln \mathrm{TE}_i$

[3] After modifying TE scores in this way we find $\mathrm{TE}_i^{\mathrm{mod}}$ of a few firms to be larger than 1. We, therefore, fix their TE scores at unity.

firms varied between 68 to 84 per cent while average DEA-TE varied between 15 to 52 per cent. Thus both sets of measures reveal that the Indian textile firms have substantial room to improve their productive efficiency even if they operate with their existing technology and use no additional quantities of inputs.

Figure 5.2: Histograms Showing Percentage of Firms (*Vertical Axis*) in Different Classes of (Modified) TE Scores (in percentage) (*Horizontal Axis*): Selected Years



It is widely believed that the firms in the private sector are more efficient than their counterparts in the public sector, presumably owing to the absence of any accountability in the latter set of firms. This is also confirmed for the Indian textile in our exercise in the case of each.

Location (as indicated by different states of India) of a firm may play an important role in determining its TE. India is a vast country with a number of states and union territories with their distinct sociological, economic, political, cultural and other infrastructural features. All these factors are important determinants of the level of TE being attained by a firm located in a particular region. We do find some such evidence of varying TE scores of firms across different states as revealed by each of the two alternative methods of analysis.

Internal organisational structure may be argued to be another factor causing productive efficiency to differ across firms as revealed by our DEA analysis. In fact, firms belonging to public limited company type are seen to have performed relatively better than others. We did not, however, attempt this exercise in our SFA study due mainly to an inadequate number of firms under many such categories.

Table 3.5: Distribution of Mean Technical Efficiency by Size Group of Firms

Size Group (in deciles)	*Mean Technical Efficiency*				
	1985-86	1990-91	1996-97	1998-99	2001-02
Lowest 10 %	0.33	0.64	0.44	0.49	0.76
10 –20 %	0.51	0.74	0.60	0.68	0.76
20 – 30 %	0.64	0.80	0.61	0.71	0.75
30 – 40 %	0.73	0.84	0.64	0.71	0.76
40 – 50 %	0.80	0.87	0.69	0.75	0.79
50 – 60 %	0.83	0.89	0.72	0.83	0.80
60 – 70 %	0.85	0.90	0.75	0.84	0.83
70 – 80 %	0.87	0.91	0.76	0.86	0.85
80 – 90 %	0.885	0.91	0.78	0.86	0.86
Highest 10 %	0.887	0.90	0.75	0.87	0.87
All Firms	*0.73*	*0.84*	*0.68*	*0.76*	*0.80*

Table 3.7: Mean Elasticity of Technical Efficiency with respect to Size and Age

Inefficiency Variable	*Mean Elasticity of Technical Efficiency*				
	1985-86	1990-91	1996-97	1998-99	2001-02
Size	0.1203 (0.002)	0.0457 (0.001)	0.0589 (0.001)	0.0665 (0.002)	0.0216 (0.0005)
Age	- 0.0085 (0.0006)	- 0.0155 (0.0007)	- 0.0051 (0.001)	- 0.0344 (0.0026)	- 0.0183 (0.0009)
Figures in the parentheses are the corresponding standard errors.					

Table 4.3: Estimated Regression Equations for Explaining Meta-Frontier (DEA) TE Scores of Firms (using State, Ownership and Organisation Dummies) for Selected Years

Regressor	*Estimated Coefficient*				
	1985-86	1990-91	1996-97	1998-99	2001-02
Gujarat D	0.011 (2.14)	0.022 (3.08)	- 0.051 (- 5.40)	- 0.002 (- 0.12)	- 0.035 (- 2.48)
Maharashtra D	0.008 (1.56)	0.018 (2.47)	- 0.058 (- 4.94)	- 0.017 (- 1.11)	- 0.012 (- 0.79)
Punjab D	0.015 (2.24)	0.045 (4.81)	0.015 (1.18)	- 0.051 (- 2.72)	- 0.017 (- 0.85)
Rajasthan D	0.020 (2.76)	0.032 (3.58)	- 0.042 (- 3.57)	- 0.013 (- 0.87)	0.001 (0.04)
Tamil Nadu D	- 0.002 (- 0.32)	- 0.011 (- 1.65)	- 0.072 (- 8.60)	- 0.033 (- 3.03)	- 0.022 (- 2.01)
West Bengal D	0.022 (2.22)	0.016 (1.13)	- 0.024 (- 1.25)	0.050 (2.43)	0.102 (4.76)
Public D	0.035 (5.51)	0.015 (1.68)	- 0.069 (- 4.97)	- 0.046 (- 2.74)	- 0.071 (- 3.97)
IP D	- 0.033 (- 5.68)	- 0.039 (- 3.97)	0.058 (3.61)	0.076 (3.06)	0.057 (2.08)
Partnership D	- 0.007 (- 1.35)	- 0.007 (- 0.84)	0.033 (2.25)	0.036 (1.66)	0.047 (2.03)
PULC D	0.103 (15.22)	0.091 (9.09)	- 0.029 (- 2.06)	0.006 (0.33)	0.043 (2.11)
PRLC D	0.059 (9.69)	0.047 (4.88)	- 0.056 (- 3.82)	0.014 (0.64)	0.025 (1.16)
Coops D	- 0.039 (- 4.92)	- 0.059 (- 5.23)	0.010 (0.61)	0.008 (0.38)	0.028 (1.14)
$\left(I/10^8\right)$	0.152 (47.19)	0.071 (26.91)	0.019 (18.58)	0.022 (18.87)	0.014 (14.33)
$\left(Age/10^2\right)$	0.058 (5.82)	0.082 (6.21)	0.007 (0.39)	0.008 (0.43)	0.015 (0.72)
Constant	0.094 (18.74)	0.320 (36.26)	0.238 (16.79)	0.155 (7.63)	0.465 (21.23)
$\overline{R}^2$ *(in percentage)*	46.75	29.97	14.95	24.46	16.55

Figure in the parenthesis is the corresponding t-ratio.
For a firm the value of the dummy variable of a given category is taken to be 1, if the firm belongs to that category and 0, otherwise.

Table 3.1: Estimated Regression Results (with State and Ownership Dummy Variables)

		Estimated Values of the Parameters				
Regressor	Associated Parameter	1985-86	1990-91	1996-97	1998-99	2001-02
Constant	β_0	9.57(19.83)	5.92(28.61)	9.67(13.15)	11.23(14.09)	2.97(6.15)
$\ln I$	β_1	- 0.78(- 11.13)	- 0.095(- 2.94)	- 0.537(- 6.06)	- 0.82(- 7.65)	0.63(8.3)
$\ln FA$	β_2	0.23(8.97)	0.12(6.71)	0.337(7.80)	0.23(3.45)	- 0.08(- 1.76)
$\ln L$	β_3	0.72(19.01)	0.56(22.38)	0.349(4.64)	0.72(6.96)	0.314(4.46)
$(\ln I)^2$	β_{11}	0.09(33.32)	0.06(35.08)	0.066(15.65)	0.08(16.95)	0.015(3.38)
$(\ln FA)^2$	β_{22}	0.012(8.37)	0.007(7.34)	0.011(6.64)	0.003(1.26)	0.0007(0.55)
$(\ln L)^2$	β_{33}	0.025(6.44)	0.029(11.45)	0.02(3.95)	0.02(3.93)	0.017(3.25)
$\ln I \times \ln FA$	β_{12}	- 0.034 (- 12.75)	- 0.016 (- 9.43)	- 0.0315 (- 6.95)	- 0.03 (- 3.8)	0.0045 (0.92)
$\ln FA \times \ln L$	β_{23}	0.0004 (0.11)	- 0.0018 (- 0.78)	- 0.006 (- 1.37)	0.02 (2.48)	- 0.0002 (- 0.04)
$\ln I \times \ln L$	β_{13}	- 0.072 (- 15.13)	- 0.062 (- 20.11)	- 0.036 (- 4.68)	- 0.08 (- 8.95)	- 0.033 (- 3.92)
Constant	δ_0	9.85(16.24)	11.33(13.18)	46.62(5.02)	5.93(4.6)	- 25.85(- 3.99)
$\ln I$	δ_1	- 0.87 (- 12.47)	- 1.365 (- 9.79)	- 4.77 (- 4.40)	- 0.24 (- 1.43)	2.63 (3.99)
$\ln Age$	δ_2	- 0.556 (- 3.04)	- 0.40 (- 3.92)	- 2.80 (- 2.65)	0.007 (0.03)	1.87 (2.99)
$(\ln I)^2$	δ_{11}	0.004 (1.73)	0.027 (5.63)	0.077 (2.66)	- 0.02 (- 4.13)	- 0.08 (- 4.93)
$(\ln Age)^2$	δ_{22}	0.09(5.02)	0.16(11.01)	0.92(5.84)	0.18(6.08)	0.16(3.29)
$\ln I \times \ln Age$	δ_{12}	0.0156 (1.06)	- 0.015 (- 1.73)	- 0.085 (- 1.72)	- 0.036 (- 2.27)	- 0.138 (- 4.17)
D_1	δ_{01}	- 0.20(- 4.11)	- 0.255(- 8.21)	0.101(2.63)	0.977(8.44)	0.625(7.32)
D_2	δ_{02}	0.929(12.41)	1.78(12.13)	1.23(1.27)	1.57(12.56)	1.86(11.95)
	$\sigma^2\left(=\sigma_u^2+\sigma_v^2\right)$	0.66(24.28)	0.60(17.5)	10.16(12.63)	1.21(11.88)	1.27(11.82)
	$\gamma\left(=\dfrac{\sigma_u^2}{\sigma^2}\right)$	0.91(201.55)	0.96(435.67)	0.995(2351.5)	0.96(214.23)	0.98(432.3)
Log-Likelihood Value		- 2502.49	178.27	- 2917.25	- 678.92	- 254.1
No. Of observations		5546	4750	3598	1423	1748
Mean TE		0.73	0.84	0.68	0.76	0.80
Figures in the parentheses are the corresponding t-ratios.						

Table 4.1: Average Technical Efficiency (TE) and Technology Closeness Ratio (TCR) of Firms in Each of Major Textile Producing States

Item	*State*	Year				
		1985-86	1990-91	1996-97	1998-99	2001-02
Percentage of Firms	Gujarat	16.73	16.55	16.26	10.42	12.30
	Maharashtra	17.94	14.29	8.56	9.71	9.94
	Punjab	8.64	7.73	6.81	5.85	4.66
	Rajasthan	7.14	8.48	8.78	10.35	7.53
	Tamil Nadu	18.10	18.40	22.10	25.98	28.62
	West Bengal	3.30	3.05	3.00	5.21	4.77
	All -India	100	100	100	100	100
Average TE Measured from Meta-Frontier	Gujarat	0.10	0.35	0.09	0.15	0.44
	Maharashtra	0.09	0.33	0.11	0.14	0.46
	Punjab	0.10	0.37	0.21	0.14	0.49
	Rajasthan	0.09	0.35	0.14	0.15	0.48
	Tamil Nadu	0.08	0.31	0.13	0.13	0.47
	West Bengal	0.15	0.40	0.13	0.20	0.60
	All- India (GM)*	0.09	0.33	0.13	0.15	0.47
	All- India (AM)*	0.15	0.38	0.22	0.20	0.52
Average TE Measured from Own Group Frontier	Gujarat	0.28	0.50	0.10	0.52	0.60
	Maharashtra	0.33	0.50	0.36	0.30	0.63
	Punjab	0.47	0.70	0.63	0.81	0.80
	Rajasthan	0.13	0.50	0.42	058	0.60
	Tamil Nadu	0.40	0.57	0.32	0.18	0.57
	West Bengal	0.66	0.77	0.53	0.69	0.84
CV** (in percentage)	Gujarat	88.20	40.76	253.42	45.15	40.35
	Maharashtra	72.09	51.61	83.04	98.45	36.14
	Punjab	50.38	24.43	29.91	23.58	23.92
	Rajasthan	214.02	48.64	64.36	39.71	41.11
	Tamil Nadu	68.79	34.51	77.31	111.37	32.03
	West Bengal	33.18	26.28	58.20	31.36	18.46
TCR	Gujarat	0.35	0.70	0.91	0.29	0.74
	Maharashtra	0.28	0.66	0.31	0.48	0.73
	Punjab	0.22	0.53	0.33	0.18	0.61
	Rajasthan	0.68	0.70	0.34	0.26	0.80
	Tamil Nadu	0.20	0.54	0.40	0.76	0.82
	West Bengal	0.23	0.51	0.24	0.29	0.72

**Average TE, which is computed and reported in this chapter, is obtained by taking geometric mean (GM) of TE scores of the constituent firms. We also report arithmetic mean (AM) of TE scores of these firms. In these two rows we have taken all textile firms.*

***CV refers to Coefficient of Variation in meta-frontier TE scores of firms within a group.*

Chapter 6

Efficiency of the Indian Leather Industry: A Comparison of Results Obtained through the SFA and the DEA

6.1 Introduction

The leather industry occupies a place of prominence in the Indian economy in view of its massive potential for employment, growth and exports.[1] In fact, backed by a strong raw-material base and a large reservoir of traditionally skilled and competitive labour force, the Indian leather industry has made significant strides during the past two decades.[2] Not only that, this industry has undergone a dramatic transformation from a mere exporter of raw materials (like tanned hides and skins) in the 1960's to that of value added finished products from the 1970's. Policy initiatives taken by the Government of India since 1973 have been quite instrumental in making such a transformation.

The structure of the Indian leather industry is quite interesting. It is spread along different segments namely tanning and finishing, footwear and footwear components, leather garments, leather goods including saddlery and harness etc.[3] The industry uses primarily indigenous natural resources with little dependence on imported resources. Hides and skins are the basic raw materials for the leather industry, which originate from the source of livestock. India has a very large share of the world bovine animal

[1] For instance, this industry accounted for 1.4 % of India's total industrial employment in 1998-99 and this figure had grown gradually over time, reaching 2.1% in 2007-08. During this period, however, its share in total industrial output had remained stagnant around 1%. Similarly, its share in India's total merchandise export was 2.1% in 2007-08. (*Data source*: Central Statistical Organization and Directorate General of Commercial Intelligence and Statistics, Government of India).

[2] For instance, export of leather and leather manufacturers (including leather footwear, leather travel goods and leather garments) went up from US $59 million in 1960-61 to US $493 million in 1980-81 and thereafter to US $1449 million 1990-91 and further to US $2323 million in 2004-05 (Government of India, 2004 - 05).

[3] Detailed discussion on the organisational structure of the industry starting from the stage of collection of raw materials to that of marketing of finished and semi-finished products can be found in Banerjee and Nihila (1999) and Mohapatra and Srivastava (2002).

population.[4] Further, an overwhelming proportion of the total production of this industry comes from the unorganised sector, i.e., small scale, cottage and artisan sector. The major production centres are spread over selected areas in a few states, e.g., selected places in Tamil Nadu, Kolkata in West Bengal, Kanpur and Agra in Uttar Pradesh, Jalandhar in Punjab and Delhi. And the major export market for the Indian leather goods is Germany, with an offtake of about 25 percent of India's domestic production, followed by the USA, the UK, France and Italy. The important export items are leather handbags, footwear and leather garments.

Official policies/programmes undertaken to facilitate the growth of the leather industry include de-reservations of 11 items (particularly semi-finished hides and skins, leather shoes and leather accessories for leather industry) in 2001 and abolition of the license system in case of manufacture of most of the leather items. Some items are still reserved for exclusive manufacture by the small-scale sector, but non-small scale units can also obtain necessary approval for manufacturing these items provided they meet an export obligation of 50 per cent of their annual production.[5]

Some intrinsic problems affect the leather firms also. The activities relating to the processing of leather generate pollution, particularly in the tanning and finishing stages of the production chain and hence, the leather firms have to bear increasing costs of production for undertaking pollution abating activities and/or relocating their establishments. There are however, some *favourable* factors also. Major world tanning firms are in the process of shifting their manufacturing base to developing countries due

[4] For instance, India's share in the world bovine animal population in 2005 was the highest (about 19%), followed by Brazil (13%), China (9%) and the USA (6%).

[5] In addition, a number of leather development programmes have been initiated in the recent past. A UNDP assisted National Leather Development Program (NLDP Phase I) was carried out from 1992 to 1998 to upgrade the training systems for design and manufacture of footwear, garments and leather goods and its second phase – called the Small Industries Development and Employment Programme (SIDE-NLDP) – from 1998 to 2002, with a view to promoting poverty alleviation and building linkages between the organised and unorganised sectors. To complement the above mentioned programmes a new plan scheme titled Indian Leather Development Programme (ILDP) started operation in 1992 to bridge critical gaps in infrastructure for integrated development of this industry, to undertake investment/trade development activities and build up an information base for leather industry. Productivity improvement programmes have also been launched for improving the manufacturing processes of footwear in the organised sector. A scheme for tannery modernisation was launched under ILDP in 2000 to provide the much needed financial help to the Indian tanneries for adoption of more efficient and cleaner process technologies for improving their performance in terms of productivity and pollution control.

to high wage levels and strict environmental norms in the developed countries. Factors such as sufficient availability of raw leather and cheap skilled labour with their long experience in the technical know-how of production and processing of leather items all work in India's favour. Further, given that the Indian leather industry is still dominated by household and small-scale sectors, more corporate presence may enhance the possibility of turning out quality leather products at smaller unit cost. All these present a large scope of expansion to the Indian leather industry.

Since there seems to be a large scope for expanding leather production and exporting such products abroad, the question arises whether the present structure of this industry is adequate enough to facilitate such an expansion and, if not, what additional measures are called for. All this needs a thorough examination of its production structure and related features, particularly those relating to productivity and efficiency of the leather firms.

The task, however, will not be complete by just measuring firm-level technical efficiency (TE). There remains the question of explaining it in terms of some firm specific variables. As already mentioned, size and age, among others, are two such variables emphasised in the literature. There are some other empirical issues which need to be addressed. For instance, one may like to know whether there is any significant variation in TE across firms in different regions and/or under different organisational structures. Further, production technology itself may be heterogeneous across firms due to such variations. These are some of the questions on which the present chapter seeks to throw some light.

It may be noted that we have come across only one empirical study in the context of measuring performance of the Indian leather industry. The study of Lall and Rodrigo (2001) fits a translog stochastic frontier to the plant level data for 1994 on each of four product groups, viz., leather product, motor vehicles, machine tools and electronics and computers. For instance, for the leather product group it finds the distribution of plant level efficiency to be highly negatively skewed with the mean value at 0.44 and further that such efficiency is positively related to the plant's energy use, but not much affected by its age or size.

The issues we have mentioned earlier about the Indian leather industry thus seem to have not yet been examined in detail and that is the primary focus of our analysis in this chapter. An additional feature of the present study is that it is based on the official firm level data collected under the ASI in India which are quite rich in coverage but have remained largely unused (presumably owing to the requirement of substantial processing time). We also use each of the two alternative methods of measuring TE, viz., *Stochastic Frontier Analysis* (SFA) and *Data Envelopment Analysis* (DEA) and seek to compare the results obtained through the two methods. However, the leather firms we examine here belong to the organised sector only (i.e., those covered by the ASI).

To put it summarily, the purpose of the present chapter is to use parametric as well as non-parametric methods to measure TE at the firm level for the Indian leather industry and then attempt to explain such efficiency in terms of firm specific factors. Since the two methodologies have been discussed in details in earlier chapters we skip the methodological parts. The plan of the chapter is thus as follows. Section 6.2 discusses briefly the data used in the study while section 6.3 reports our empirical findings. Section 6.4 gives concluding observations. A couple of Appendices to this chapter present some additional results.

6.2 Description of Variables, Equations and Data

The present study uses the micro-level data i.e., the data on a number of variables for different individual industrial units collected by the Central Statistical Organisation (CSO), Government of India through its Annual Survey of Industries (ASI) and made available in soft version. Since these data are not panel data and also quite expensive to procure, we have tried to fit the stochastic frontier function for *seven* selected years – two years in the mid-1980’s (viz., 1984-85 and 1985-86), two years immediately before economic reforms were initiated on a large scale in the early 1990’s (viz., 1989-90 and 1990-91) and three years after such initiation (viz., 1994-95, 1999-00 and 2002-03). We have considered the entire organised leather sector, i.e., the part of the industry for which ASI data are published by CSO on a regular basis.

The *five* variables considered in our empirical study are defined below along with the notation used for each; the notation for the i^{th} firm will be indicated by putting a subscript i.[6]

Output (***Y***): the total ex-factory value of products and by-products produced by the firm during the year in question.

Intermediate Inputs (***I***)**:** the value of inputs (both indigenous and imported ones, including power, fuels etc.) used by the firm during the year.

Capital (***FA***)**:** the net value of fixed assets of the firm at the beginning of a year.

Labour (***L***)**:** the total number of mandays worked during the year.

Age**:** the difference (in years) between the firm's current and initial year of production.

The stochastic frontier output of the i^{th} firm to be estimated in the present study has 3 input variables – value of intermediate inputs (I_i), amount of labour (L_i) and value of fixed capital (FA_i) used by it. Thus the equation takes the following form:

$$\begin{aligned}\ln Y_i = {} & \beta_0 + \beta_1 \ln I_i + \beta_2 \ln L_i + \beta_3 \ln FA_i + \beta_{11} (\ln I_i)^2 + \beta_{22} (\ln L_i)^2 + \beta_{33} (\ln FA_i)^2 \\ & + \beta_{12} (\ln I_i)(\ln L_i) + \beta_{13} (\ln I_i)(\ln FA_i) + \beta_{23} (\ln L_i)(\ln FA_i) + v_i - u_i \qquad (6.1)\end{aligned}$$

Further, there is also an inefficiency sub-model in which μ_i, the mean of u_i, is postulated to be determined by

$$\begin{aligned}\mu_i = {} & \delta_0 + \delta_1 \ln(I_i) + \delta_2 \ln(Age_i) + \delta_{11} \{\ln(I_i)\}^2 + \delta_{22} \{\ln(Age_i)\}^2 \\ & + \delta_{12} \{\ln(I_i)\}\{\ln(Age_i)\} + \delta_{01} SD_1 + \delta_{02} SD_2 + \delta_{03} OD \qquad (6.2)\end{aligned}$$

where SD_1 and SD_2 are the two (intercept) dummy variables used to distinguish firms located in two different groups of states. The dummy variable OD is used to distinguish firms under different organisational structures. The rationale of these dummy variables will be explained later.

[6] As in the case of textile firms, here also the definitions of the concepts like ex-factory value, fixed asset, manday etc are those used by the CSO. It would have been very useful if we had the panel data over a number of years. However, the lack of sufficient information did not allow one to construct a panel data set from this source.

6.3 Empirical Findings

Stochastic Frontier Analysis

The leather firms in India are seen to be concentrated in selected regions of a few states. However, the Indian states and union territories have their individual distinctive sociological, economic, political and infrastructural features. A priori then TE of firms may be supposed to vary across different regions. To examine this issue we consider two dummy variables, SD_1 and SD_2, in order to differentiate firms located in three different groups of states. These are defined below.[7]

SD_1 = 1, for a firm located in either West Bengal or Tamil Nadu,

= 0, for a firm located elsewhere.

SD_2 = 1, for a firm located in any one of the four northern states of India viz., Delhi, Haryana, Punjab and Uttar Pradesh,

= 0, for a firm located elsewhere.

Similarly, variability in TE among individual firms under different types of organisations has been sought to be captured by introducing an organisation dummy variable (OD) which takes the value 1 for a firm that is either a partnership firm or a private limited company or a public limited company, and the value zero, otherwise.

The maximum likelihood estimate (MLE) of each of the parameters of the frontier model defined by equations (6.1) and (6.2) are obtained for each of the seven years under consideration, using the computer program FRONTIER **4.1**. These estimates are shown in Table 6.1A. An important point that is observed is that the coefficients of the input variable FA as well as those of its products with I and L have not turned out to be significant except in a few cases. This leads us to be skeptic about the importance of variation in fixed assets across leather firms in accounting for variation in their production behavior. For this reason, equations (6.1)-(6.2) have been re-estimated excluding FA as an input in the production frontier and the corresponding MLE's of the parameters are shown in Table 6.1B. The two regression equations – one with FA (Table

[7] The procedure followed for combining a number of states (organisations) into a given *group* of states (organisations) is the same as discussed in Chapter 3.

6.1A) and the other excluding *FA* (Table 6.1B) – yield two series of firm-level TE's; the scatter diagrams (given in the Appendix 1) between these two sets of values show that the points are on or around the 45^0 line for almost all the years. In addition, on the basis of the results of these two regression equations, generalised likelihood-ratio (LR) tests have been carried out which also fail to reject in any year the null hypothesis, $H_0 : \beta_3 = \beta_{33} = \beta_{13} = \beta_{23} = 0$, against the alternative hypothesis that H_0 is *not true*.[8] The point that emerges is that so far as the explanation for inter-firm variation in frontier output is concerned, intermediate inputs and labour seem to be relatively more important inputs than fixed assets or, to be more specific, inter-firm variation in *FA* does not seem to be relevant. We, therefore, drop *FA* as an explanatory variable and consider regression results given in Table 6.1B.

We observe from Table 6.1B that the coefficient of the state dummy SD_2 is not significant although the coefficient of SD_1 as well as that of *OD* are significant for each sample year (the latter except for a couple of years). We, therefore, carry out the LR test of null hypothesis of no effect of SD_2 on TE ($H_0 : \delta_{02} = 0$) which fails to get rejected.[9] Thus the final version of the set of equations (6.1)-(6.2) that we choose for further analysis is the one obtained by dropping *FA* and SD_2 (i.e., setting $\beta_3 = \beta_{13} = \beta_{23} = \beta_{33} = \delta_{02} = 0$). The regression results corresponding to this version are given in Table 6.1.

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[8] The estimated values of generalised LR statistic under H_0 are given below (the corresponding critical value at 1% level being 13. 28) :

Year	1984-85	1985-86	1989-90	1990-91	1994-95	1999-00	2002-03
LR statistic	0.00	4.74	1.60	1.00	4.80	2.76	11.98

[9] The estimated values of generalised LR statistic under H_0 are given below (the corresponding critical value at 1% level being 6.64) :

Year	1984-85	1985-86	1989-90	1990-91	1994-95	1999-00	2002-03
LR statistic	0.60	0.40	1.40	0.20	0.60	0.22	0.16

To begin our discussion on the fitted frontier, we note that some individual parameter estimates in Table 6.1 are not statistically significant. We have, therefore, carried out generalised LR tests of hypotheses regarding exclusion of various explanatory variables, taking one at a time and the results are presented in Table 6.2. The first row of this table indicates that Cobb-Douglas type function does not seem to provide a reasonable representation of production frontier for the Indian leather industry. Thus the elasticities of frontier output with respect to various inputs are likely to depend on the values of the parameters as well as the values of the explanatory variables – a feature sought to be captured in the present study by fitting a translog production frontier.

The second row of Table 6.2 shows rejection (for each year) of the null hypothesis of no technical inefficiency in firms. Thus, given that the technology can be described by a translog stochastic frontier, firms cannot all be supposed to be technically efficient. In fact, the parameter γ, i.e., $\sigma_u^2 / \left(\sigma_u^2 + \sigma_v^2\right)$, measures the proportion of the total variability in output (across firms with the same input quantities) due to variation in technical inefficiency alone and the estimated value of γ (as shown in Table 6.1) clearly indicates that each year almost the entire part of such variability is due to variation in technical inefficiency. The next two tests reported in Table 6.2 are concerned with hypotheses regarding exclusion of size and age variables from the inefficiency model. The null hypothesis of no effect of a firm's size on its TE is rejected for each year while that of a firm's age on its TE is rejected for all but two years (fourth row of Table 6.2).

To begin our analysis of the regression results, note that equation (6.2) explains μ_i, the mean of the *inefficiency* variable u_i and hence, a higher μ_i indicates a lower expected value of TE. Table 6.1 shows that the coefficient of SD_1 is significant and positive for each year under consideration, implying thereby that a firm (with given values of explanatory variables) located in either Tamil Nadu or West Bengal is technically less efficient than an identical firm located elsewhere in India. Again, the coefficient of the organisation dummy (OD) is positive and significant for each year (except 1990-91). Thus a partnership firm or a private limited company or a public limited company has lower level of TE compared to an otherwise identical firm belonging to other types of organisations.

Given the fitted function, TE's of individual firms are computed and (arithmetic) mean of these values is then calculated for each year. These mean values, given in the last row of Table 6.1, indicate that TE of firms, on an average, has increased over time (except for a drop in 1994-95).

Finally, since we have fitted a translog production frontier (equation (6.1)), one has to verify whether the fitted function is well behaved. The function is well behaved, if the following two properties of the fitted function are satisfied at a majority of observations viz., *monotonicity* (non-negative elasticity of output with respect to each input) and *quasi-concavity* (negative semi-definite bordered Hessian matrix of first and second derivatives with respect to inputs). We have computed these quantities on the basis of our fitted function (given in Table 6.1) and the results (reported in Table 6.3) show that for each year the two regularity conditions are satisfied for the majority of the firms.

Data Envelopment Analysis

Using the computer program DEAP **2.1**, output-oriented TE has been calculated, following the DEA methodology, for each individual firm for each sample year relative to the frontier constructed on the basis of the data on all firms in the industry (or, what we have called in Chapter 4 the *meta-frontier*). For the sake of brevity, we shall call it a firm's DEA-TE (and that obtained through SFA, its SFA-TE). Subsequently, a (geometric) average of these TE values is computed over all firms for each year. These averages are given in the last row of Table 6.6. Such average DEA-TE's are lower than the corresponding average SFA-TE's (given in the last row of Table 6.1), but display similar inter-temporal behavior as the latter.

We have also tried to examine whether DEA-TE's show any variation across firms in different groups of states and types of organisations. For this purpose, we have considered the same kind of grouping as in the case of our SFA exercise, namely two groups of states and one group of organisations. The results are given in Table 6.4. One observes that an average firm in Tamil Nadu or West Bengal had a smaller DEA-TE than an average firm in the four northern states of India or even in all-India, particularly in the pre-liberalisation period. However, not much differences are observed in the values of

DEA-TE's across firms under different organisations, as can be assessed by comparing the values for the group OG vis-a-vis the corresponding ones for all firms (Table 6.4, second block).

Attempts have also been made to find explanation for inter-firm differences in DEA-TE's. For instance, some authors (e.g., Aly et al, 1990) adopt a two-stage procedure in this regard and try to find determinants of TE values through regression analyses at the second stage, having estimated these through DEA at the first stage.[10] We have followed this approach here by regressing DEA-TE value of a firm on its size (log I) and age (log *Age*) as well as two state dummies SD_1 and SD_2 and one organisation dummy OD (dummies being the same as those considered for our SFA exercises) and the results are given in Table 6.5. We observe that the coefficient of SD_2 is not significant while that of SD_1 is significant and negative for many years, corroborating our findings of SFA in this respect. The coefficient of OD is, however, significantly negative, if at all, only after the mid-1990's. (It may be noted that a negative coefficient here should correspond to a positive coefficient in the context of SFA, as the latter seeks to explain (mean of) technical *inefficiency*.)

We have examined one additional issue in the context of our DEA exercise, namely a comparison between a firm's TE relative to its own frontier (i.e., the one constructed on the basis of observations on firms within its *own* group only) and its TE relative to the *meta-frontier* and referred to as its DEA-TE. (Geometric) average of each of these two series of TE's is computed over all firms within a given group. Table 6.4 gives these averages for the different groups of firms. Finally, we compute the *technology closeness ratio* (TCR) of each group which seeks to measure the extent of closeness of a group's *own* technology towards the *industry* technology. (This concept has been discussed at length in Chapter 4). These values are shown in Table 6.4. In effect, such *TCR* values reflect, at least to a large extent, how differences in infrastructural and other constraints arising out of differences in physical, legal, cultural and similar factors affect the productivity of a given group relative to the other groups.

[10] Aly et al (1990) used as determinants of efficiency indices variables like degree of urbanisation, firm's size and product diversity etc. for a sample of 322 independent banks in the USA.

One observes quite high *TCR* values for both groups of states for many years, but not for all the years. Also no definite pattern emerges in this respect. However, not much difference is there in technologies available to different types of organisations, as shown by the relevant rows in Table 6.4.

Some Additional Analysis: Firm Size, Firm Age and TE

An important aspect of our enquiry is to ascertain how a firm's size and age affect its TE. To examine the first relationship we, first of all, arrange individual firms in *ascending* order of size and then classify them into different decile groups like the lowest ten per cent, next ten per cent and so on up to the highest ten per cent. Then mean values of TE's of firms in each decile group for each year is computed. Such decile group-wise mean TE's are given in Table 6.6 for TE's computed through DEA. One observes that in any given year TE increases with firm size, thereby pointing to a positive relationship between the two and that this increase is quite sharp across the upper size groups. A similar exercise with the TE scores obtained through SFA has also been done and the results (not reported here) show a similar pattern of behavior of TE's across size classes of firms each year.

Another way of examining the relationship between firm size and TE in the context of SFA exercise is to compute the elasticity of TE with respect to size for each firm (say, $\hat{e}_i$, for firm *i*) in a year on the basis of the estimated stochastic frontier (given in Table 6.1). As mentioned in Chapter 3 this elasticity depends on the amounts of inputs and output of the firm in question. For each year we then compute such firm-level elasticities using the estimated frontier given in Table 6.1 and average these values across firms to find mean elasticity, $\bar{\hat{e}}$ and also compute its standard error. This result (given in the first row of Table 6.7), along with those stated in the preceding paragraph, clearly indicates that as far as the Indian leather industry is concerned, there is a positive relationship between firm size and TE.

To investigate whether there is any such systematic relation between a firm's age and TE we classify firms into four different age groups, viz., very old, old, young and very young, according as they were established twenty years ago, within the preceding eleven to twenty years, within the preceding six to ten years and within the last five years, respectively. We then take an average of the individual values of TE (computed through DEA) across all firms in each group for each year. Such average TE's (not shown here) do not show any systematic increasing or decreasing tendency across age group of firms. A similar analysis using the SFA estimates of TE's also yields a similar result (not reported here). In the latter case we have also computed mean elasticity of TE with respect to firm's age for each year (see the second row of Table 6.7). Although it is significant in some cases (as shown by its standard errors), no clear picture of positive or negative relationship between the two emerges. There might have been a positive relation, but only after the late 90's. First two rows of Table 6.5 also reconfirm these findings about the relation between firm size and its TE and that between firm's age and its TE.

6.4 Concluding Remarks

The leather industry is being considered as one of the most promising industries of India with excellent prospects for growth and export. The government is particularly interested in its promotion in view of its large potential for generating employment and income, with relatively low inputs of capital. A large part of this industry is in the unorganised sector about which very little systemic information is available. To examine some features of the production behaviour of this industry we have, therefore, no other alternative but to consider the organised part of this industry – the part on which information is available regularly from the Annual Survey of Industries (ASI).

The industry – at least the part covered by the ASI – grew very fast in the last two decades despite some erratic behaviour of its production in the 1990s. To secure a reasonable position in the export market the industry needs to be efficient in production. The purpose of the present chapter is to examine the extent of TE prevailing among the Indian leather firms as well as behaviour of such TE across time and across groups of firms, applying each of the two alternative tools used widely for this purpose, viz., the *stochastic frontier analysis* (SFA) and the *data envelopment analysis* (DEA). We have considered firm-level data for seven years – four years (viz., 1984-85, 1985-86, 1989-90 and 1990-91) before and three years (viz., 1994-95, 1999-2000 and 2002-03) after – the initiation of economic reforms on a large scale in India. The main results of our study may be summarised as follows.

We have applied both DEA and SFA – the two alternative techniques for measuring TE's of different firms and hence obtained two series of TE's for each year. Patterns displayed by these two sets of TE's are similar except in a few cases. For one thing, each year the mean value of DEA-TE's is much lower than that of SFA-TE's (see the last row of Table 6.1 and that of Table 6.6). Further, the results differ in the nature of the frequency distribution of firms by levels of TE. If, for instance, one constructs *histograms*, taking say twenty class intervals of TE values viz., 0 – 0.05, 0.05 – 0.1, … up to 0.95 – 1.0 and label them as 1, 2, ..., up to 20, respectively, one finds that for almost every year histogram of SFA-TE's displays a negatively skewed distribution while that of DEA-TE's is broadly a two-tail distribution. We have shown such histograms for some years in Figure 6A.2 in the Appendix 6.1. However, as we have already noted in Chapter 5, such a direct comparison may not be valid, as the TE scores obtained through SFA come from a model which has already taken into account inefficiency effects (equation (6.2)) due to some firm-specific factors like size, age, location etc. whereas the DEA scores are computed on the basis of the frontier constructed, using only the observed output and input values of firms. As in Chapter 5 here also we have recomputed, what we have called there, the modified DEA-TE scores, to make these comparable with their corresponding SFA-TE scores, to the extent possible. The method of such modification has already been described in Chapter 5 in details. Following this method we have computed the modified DEA-TE scores of the individual firms of the Indian leather industry. The histograms showing distribution of the modified DEA-TE scores for some years are given in Figure 6A.3 along with that of the SFA-TE scores. The result is more or less similar as that observed for the textile firms in Chapter 5.

There are, however, many other results which are common to both sets of TE's. We have considered a few possible determinants of firm level TE's. One is size of a firm. Both sets of TE's show a positive relation each year between size and TE of a firm – higher the size, larger is the firm's efficiency. However, neither series of TE's shows any clear relation between age and TE of a firm. If at all there is a relation, it is likely to be a positive one and that too only after the 1990's or the late 1990's.

Table 6.1A: Estimated Stochastic Frontier with *FA* as One Explanatory Variable

		*Estimated Values of the Parameters**						
Regressor	*Parameter*	1984-85	1985-86	1989-90	1990-91	1994-95	1999-00	2002-03
Constant	β_0	4.221 (3.570)	6.442 (6.538)	4.075 (3.684)	3.743 (4.143)	7.462 (3.462)	2.012 (2.036)	2.665 (3.057)
$\ln I$	β_1	0.085 (0.354)	- 0.430 (- 3.333)	0.309 (1.913)	0.392 (3.096)	- 0.498 (- 1.523)	0.680 (4.128)	0.486 (4.013)
$\ln FA$	β_3	0.031 (0.178)	0.489 (3.421)	0.031 (0.327)	0.065 (0.592)	0.246 (1.384)	0.017 (0.163)	0.024 (0.291)
$\ln L$	β_2	0.730 (3.013)	0.450 (2.101)	0.424 (2.978)	0.285 (2.009)	0.987 (4.175)	0.259 (1.366)	0.504 (4.034)
$(\ln I)^2$	β_{11}	0.055 (3.312)	0.068 (7.410)	0.036 (4.700)	0.022 (2.713)	0.072 (4.797)	0.002 (0.217)	0.021 (3.454)
$(\ln FA)^2$	β_{33}	0.001 (0.072)	0.011 (1.246)	- 0.004 (- 0.527)	- 0.005 (- 0.950)	- 0.016 (- 2.077)	- 0.005 (- 0.728)	0.001 (0.288)
$(\ln L)^2$	β_{22}	0.043 (1.773)	0.016 (0.835)	0.030 (1.935)	0.009 (0.630)	0.048 (2.534)	0.015 (1.577)	0.026 (2.390)
$\ln I \times \ln FA$	β_{13}	- 0.002 (- 0.118)	- 0.039 (- 2.942)	0.001 (0.140)	0.006 (0.632)	0.005 (0.353)	0.019 (1.293)	0.005 (0.665)
$\ln FA \times \ln L$	β_{23}	- 0.003 (- 0.126)	- 0.020 (- 0.999)	0.007 (0.439)	- 0.002 (- 0.199)	0.016 (0.899)	- 0.016 (- 0.988)	- 0.013 (- 1.056)
$\ln I \times \ln L$	β_{12}	- 0.092 (- 2.475)	- 0.026 (- 0.844)	- 0.063 (- 3.400)	- 0.025 (- 1.343)	- 0.122 (- 4.900)	- 0.014 (- 0.750)	- 0.042 (- 3.084)
Constant	δ_0	20.53 (1.107)	11.94 (2.521)	5.583 (1.892)	32.03 (2.361)	- 0.172 (- 0.084)	- 2.248 (- 1.920)	37.26 (3.531)
$\ln I$	δ_1	- 2.136 (- 0.966)	- 0.903 (- 1.170)	- 0.720 (- 1.356)	- 3.338 (- 2.038)	1.374 (3.475)	0.098 (0.327)	- 3.496 (- 2.801)
$\ln Age$	δ_2	- 0.550 (- 0.229)	- 1.300 (- 1.491)	3.182 (3.007)	- 3.297 (-1.361)	- 1.968 (- 1.899)	- 1.081 (- 0.603)	- 4.934 (- 9.052)
$(\ln I)^2$	δ_{11}	- 0.018 (- 0.321)	- 0.052 (- 2.421)	- 0.029 (- 1.592)	0.029 (0.592)	- 0.114 (- 8.463)	- 0.038 (- 1.529)	0.055 (1.606)
$(\ln Age)^2$	δ_{22}	- 0.774 (- 3.561)	- 0.743 (- 3.808)	- 0.450 (- 5.418)	- 0.256 (- 1.068)	0.012 (0.098)	0.0002 (0.0003)	0.031 (0.444)
$\ln I \times \ln Age$	δ_{12}	0.278 (1.531)	0.341 (4.906)	- 0.026 (- 0.437)	0.303 (2.829)	0.181 (3.011)	0.042 (0.179)	0.258 (7.203)
SD_1	δ_{01}	3.856 (4.900)	2.520 (4.918)	2.677 (7.303)	3.558 (7.729)	1.803 (4.851)	1.084 (1.123)	1.715 (3.833)
SD_2	δ_{02}	- 0.775 (- 1.429)	0.057 (0.122)	- 1.623 (- 4.116)	- 0.228 (- 0.433)	0.336 (0.889)	0.700 (0.927)	0.028 (0.089)
OD	δ_{03}	2.769 (5.442)	2.443 (4.866)	2.163 (5.359)	0.110 (0.244)	1.224 (3.349)	3.420 (4.783)	0.665 (3.642)
$\sigma^2 \left(= \sigma_u^2 + \sigma_v^2\right)$		4.972 (6.532)	3.253 (6.722)	3.229 (8.454)	4.843 (7.078)	3.196 (8.798)	3.122 (5.630)	1.344 (8.167)
$\gamma \left(= \sigma_u^2 / \sigma^2\right)$		0.9888 (414.6)	0.9918 (633.7)	0.9947 (937.4)	0.9961 (1294.5)	0.9734 (279.5)	0.9925 (545.0)	0.9847 (480.0)
Log-Likelihood Value		- 320.2	- 275.03	- 193.3	- 231.0	- 433.5	- 81.55	15.45
No. Of Firms		413	470	493	533	562	321	523
Mean TE (%)		66.93	70.21	73.23	73.23	66.83	78.20	82.89

** Figures in parentheses are the corresponding t-ratios.*

Table 6.1B: Estimated Stochastic Frontier *Dropping FA* from the List of Explanatory Variables

		*Estimated Values of the Parameters**						
Regressor	*Parameter*	1984-85	1985-86	1989-90	1990-91	1994-95	1999-00	2002-03
Constant	β_0	3.990 (3.845)	16.222 (13.535)	4.369 (4.422)	3.762 (3.793)	7.826 (3.299)	1.776 (1.845)	2.510 (2.569)
$\ln I$	β_1	0.167 (0.816)	- 1.341 (- 8.561)	0.264 (1.447)	0.456 (3.052)	- 0.347 (- 1.109)	0.736 (4.659)	0.571 (3.935)
$\ln L$	β_2	0.695 (3.040)	0.702 (3.628)	0.479 (2.749)	0.272 (1.698)	1.008 (4.545)	0.232 (1.350)	0.430 (3.427)
$(\ln I)^2$	β_{11}	0.052 (3.655)	0.080 (8.072)	0.039 (4.256)	0.022 (2.782)	0.066 (5.581)	0.012 (1.729)	0.020 (2.973)
$(\ln L)^2$	β_{22}	0.045 (1.904)	- 0.005 (- 0.349)	0.034 (3.098)	0.006 (0.526)	0.045 (2.909)	0.014 (1.445)	0.018 (2.177)
$\ln I \times \ln L$	β_{12}	- 0.094 (- 2.792)	- 0.034 (- 1.385)	- 0.065 (- 3.792)	- 0.022 (- 1.312)	- 0.107 (- 4.718)	- 0.025 (- 1.841)	- 0.040 (- 2.963)
Constant	δ_0	2.118 (1.658)	16.705 (3.339)	6.054 (5.807)	12.615 (11.340)	1.026 (0.309)	- 5.956 (- 3.888)	28.484 (28.708)
$\ln I$	δ_1	- 0.072 (- 0.210)	- 1.007 (- 1.483)	- 0.876 (- 2.992)	- 0.853 (- 2.752)	1.171 (2.795)	0.552 (2.706)	- 2.497 (- 12.98)
$\ln Age$	δ_2	1.894 (1.878)	- 2.115 (- 2.393)	3.323 (3.353)	- 2.529 (- 2.337)	- 1.767 (- 1.165)	- 1.684 (- 1.884)	- 4.655 (- 4.604)
$(\ln I)^2$	δ_{11}	- 0.070 (- 4.912)	- 0.048 (- 2.809)	- 0.023 (- 1.735)	- 0.046 (- 2.580)	- 0.106 (- 7.414)	- 0.053 (- 5.649)	0.029 (3.121)
$(\ln Age)^2$	δ_{22}	- 0.827 (- 4.805)	- 0.462 (- 2.857)	- 0.433 (- 1.927)	- 0.402 (- 1.178)	0.021 (0.163)	0.051 (0.400)	0.103 (0.454)
$\ln I \times \ln Age$	δ_{12}	0.118 (1.681)	0.329 (3.897)	- 0.034 (- 0.455)	0.306 (2.406)	0.166 (2.065)	0.071 (1.337)	0.232 (3.626)
SD_1	δ_{01}	3.671 (6.080)	1.687 (4.001)	2.836 (3.039)	2.868 (3.149)	1.768 (4.875)	1.059 (3.487)	1.661 (2.422)
SD_2	δ_{02}	- 0.459 (- 0.791)	0.064 (0.147)	- 1.542 (- 1.775)	- 0.262 (- 0.262)	0.213 (0.562)	0.348 (1.201)	- 0.145 (- 0.181)
OD	δ_{03}	2.680 (7.180)	1.208 (4.346)	2.362 (2.727)	0.422 (0.425)	1.254 (3.540)	3.242 (7.520)	0.704 (0.984)
$\sigma^2 \left(= \sigma_u^2 + \sigma_v^2\right)$		4.814 (7.750)	2.429 (8.178)	3.380 (4.923)	4.090 (5.040)	3.193 (8.833)	3.405 (8.349)	1.218 (5.049)
$\gamma \left(= \sigma_u^2 / \sigma^2\right)$		0.9873 (419.4)	0.9894 (512.0)	0.9947 (739.0)	0.9955 (936.3)	0.9720 (184.9)	0.9931 (735.1)	0.9822 (240.2)
Log-Likelihood Value		- 320.2	- 277.4	- 194.1	- 231.5	- 435.9	- 82.93	9.46
No. Of Firms		413	470	493	533	562	321	523
Mean TE (%)		66.83	65.40	73.14	72.81	66.99	78.08	83.00

** Figures in parentheses are the corresponding t-ratios.*

So far as regional variation in firm's TE is concerned, both series show that there is some variation and that in particular an average firm in West Bengal or Tamil Nadu, the two largest leather goods producing states, is technically less efficient than its counterpart in other areas. The two series also show some variation in TE's across firms under different types of organisation. In particular, a partnership firm or a private limited company or a public limited company has, on an average, lower level of TE compared to an otherwise identical firm belonging to other types of organisations.

There are some exercises which could be/have been done only for a specific method. One such exercise relevant in the context of SFA is finding a suitable parametric representation of production technology of firms. As far as the Indian leather firms are concerned, the Cobb-Douglas production function, in which elasticities of output with respect to individual inputs remain constant, does not seem to be appropriate. A flexible form like translog production frontier appears to fit the observed data better.

India is a vast country with a number of states and union territories with their inherent and distinctive sociological, economic, political and infrastructural features. These factors may lead to some variation in production technology used by different units. We have made an attempt to examine whether there is any technological heterogeneity across states and/or types of organisation. Our DEA analysis in this respect shows that some technological heterogeneity (as reflected in values of TCR) prevails across firms in different groups of states, but not so much across firms under different types of organisations.

Finally, do economic reforms initiated in the early nineties have made any perceptible impact on the efficiency levels of leather firms? The question is not easy to answer as we do not have any panel data set, i.e., data on variables corresponding to a *given set* of firms for several years – the kind of data which may help one to find how the extent of efficiency of a given firm or a group of firms has undergone changes. It is then quite likely that the firms that we observe/examine in a year are the relatively better firms, the inefficient firms having failed to survive through. The best that one can do under these circumstances is to examine the inter-temporal behavior of average TE of firms. We find that both series of average TE's of firms – series estimated through SFA as well as DEA – show a slightly increasing trend over time despite some decline in the immediate post-reform year(s) (presumably owing to the effects of structural adjustments to the new economic regime).

Table 6.1: Estimated Stochastic Frontier *Dropping FA* and *SD_2* from the List of Explanatory Variables

		*Estimated Values of the Parameters**						
Regressor	*Parameter*	1984-85	1985-86	1989-90	1990-91	1994-95	1999-00	2002-03
Constant	β_0	3.981 (3.933)	16.504 (15.208)	5.021 (5.204)	3.937 (4.909)	7.441 (3.256)	1.809 (1.833)	2.706 (3.532)
$\ln I$	β_1	0.144 (0.712)	- 1.350 (- 8.834)	0.168 (1.049)	0.419 (3.183)	- 0.293 (- 0.937)	0.735 (4.569)	0.547 (4.764)
$\ln L$	β_2	0.723 (3.218)	0.668 (3.349)	0.501 (3.735)	0.290 (2.113)	0.995 (4.320)	0.227 (1.430)	0.432 (4.488)
$(\ln I)^2$	β_{11}	0.053 (3.650)	0.080 (7.885)	0.042 (5.726)	0.024 (3.538)	0.063 (4.987)	0.013 (1.813)	0.021 (3.675)
$(\ln L)^2$	β_{22}	0.043 (1.773)	- 0.003 (- 0.260)	0.033 (3.117)	0.007 (0.680)	0.044 (2.709)	0.015 (1.539)	0.018 (2.112)
$\ln I \times \ln L$	β_{12}	- 0.094 (- 2.704)	- 0.034 (- 1.539)	- 0.066 (- 4.517)	- 0.025 (- 1.666)	- 0.105 (- 4.254)	- 0.026 (- 2.066)	- 0.040 (- 3.234)
Constant	δ_0	3.820 (1.416)	15.933 (3.223)	29.171 (3.200)	35.056 (2.305)	- 0.112 (- 0.036)	- 5.545 (- 4.056)	34.257 (6.150)
$\ln I$	δ_1	- 0.458 (- 0.969)	- 0.845 (- 1.363)	- 3.759 (- 3.368)	- 3.827 (- 1.984)	1.312 (2.524)	0.694 (3.780)	- 3.176 (- 4.728)
$\ln Age$	δ_2	2.303 (2.193)	- 2.251 (- 2.018)	1.790 (1.424)	- 2.730 (- 1.034)	- 1.693 (- 1.694)	- 2.166 (- 2.262)	- 4.715 (- 10.53)
$(\ln I)^2$	δ_{11}	- 0.057 (- 4.656)	- 0.052 (- 3.474)	0.059 (1.817)	0.045 (0.763)	- 0.110 (- 6.261)	- 0.059 (- 6.270)	0.048 (2.360)
$(\ln Age)^2$	δ_{22}	- 0.910 (- 4.697)	- 0.420 (- 2.597)	- 0.318 (- 2.864)	- 0.305 (- 1.367)	0.022 (0.192)	0.094 (0.712)	0.086 (0.994)
$\ln I \times \ln Age$	δ_{12}	0.114 (1.139)	0.324 (3.525)	0.031 (0.471)	0.278 (2.302)	0.159 (3.349)	0.088 (1.476)	0.237 (5.398)
SD_1	δ_{01}	4.114 (7.261)	1.592 (4.841)	3.762 (9.147)	3.892 (6.218)	1.682 (5.160)	0.923 (4.175)	1.663 (7.437)
OD	δ_{03}	2.781 (8.041)	1.150 (3.257)	2.466 (9.692)	0.191 (0.447)	1.309 (3.507)	3.043 (17.264)	0.662 (3.616)
$\sigma^2 \left(= \sigma_u^2 + \sigma_v^2\right)$		5.186 (5.618)	2.303 (6.770)	3.826 (8.929)	4.912 (7.528)	3.178 (12.96)	3.190 (8.767)	1.274 (11.406)
$\gamma \left(= \sigma_u^2 / \sigma^2\right)$		0.9881 (381.6)	0.9892 (496.1)	0.9952 (1042.7)	0.9962 (1216.6)	0.9717 (231.8)	0.9924 (675.5)	0.9830 (439.9)
Log-Likelihood Value		- 320.5	- 277.6	- 194.8	- 231.6	- 436.2	- 83.04	9.38
No. Of Firms		413	470	493	533	562	321	523
Mean TE (%)		66.92	65.10	73.17	73.19	66.94	78.07	83.03
** Figures in parentheses are the corresponding t-ratios.*								

Table 6.2: Generalised Likelihood-Ratio Tests of Null Hypotheses for Parameter Values in the Estimated Stochastic Frontier Production Function

Null Hypothesis	*Estimated value of generalised likelihood ratio statistic*[a]							*Critical Value*	
	1984-85	1985-86	1989-90	1990-91	1994-95	1999-00	2002-03	*at 1% level*	*at 0.5% level*
$\beta_{11} = \beta_{12} = \beta_{22} = 0$ (Cobb-Douglas Function)	12.26	134.04	39.48	20.40	21.52	4.84+	13.36	11.34	12.84
$\gamma = \delta_0 = \delta_1 = \delta_2 = \delta_{11} = \delta_{12} = \delta_{22} = \delta_{01} = \delta_{03} = 0$ (No Inefficiency Effect)	240.76	373.88	451.16	452.52	280.10	191.84	299.34	22.53[b]	24.49[b]
$\delta_1 = \delta_{11} = \delta_{12} = 0$ (No Size Effect)	48.98	128.20	97.84	62.96	103.58	8.66*	66.70	11.34	12.84
$\delta_2 = \delta_{22} = \delta_{12} = 0$ (No Age Effect)	4.82+	13.00	18.70	13.24	10.86*	0.26+	18.96	11.34	12.84
$\delta_{01} = 0$ (SD_1 is *not* significant)	22.10	15.70	34.12	18.66	11.32	6.46*	9.78	6.64	7.88
$\delta_{03} = 0$ (No Organisation Variation)	10.74	7.38	15.20	2.68+	6.36*	16.30	3.60+	6.64	7.88

a The values marked with a plus sign(+) and an asterisk (*) are respectively non-significant and significant at 5% level. All other values are significant even at lower than 5% level.

b The critical value for the test involving γ is taken from Table 6.6.1 of Kodde and Palm (1986, p. 1246).

Table 6.3: Percentages of Firms Satisfying Regularity Conditions in Different Years

Regularity Condition	*Percentage of Firms Satisfying the Condition in sample year*						
	1984-85	1985-86	1989-90	1990-91	1994-95	1999-00	2002-03
Monotonicity	90.80	92.98	88.03	73.36	79.72	99.38	99.43
Quasi-Concavity	58.84	94.26	59.63	57.41	51.60	94.08	94.46
Both	58.84	92.77	59.63	57.41	51.60	94.08	94.46

Table 6.4: Average Technical Efficiency (TE) and Technology Closeness Ratio (TCR) of Leather Firms (Obtained through DEA Method) by Group*

Item	*Group*	*Year*						
		1984-1985	1985-1986	1989-1990	1990-1991	1994-1995	1999-2000	2002-2003
Percentage Of Firms	SG1	51	54	45	47	49	36	32
	SG2	25	24	25	24	27	33	41
	OG	71	72	77	79	82	81	84
	All Firms	100	100	100	100	100	100	100
Average TE Measured from Meta-Frontier (called *DEA-TE* in the text)	SG1	0.25	0.33	0.45	0.37	0.19	0.45	0.55
	SG2	0.34	0.44	0.56	0.45	0.21	0.45	0.58
	OG	0.27	0.37	0.50	0.42	0.20	0.43	0.56
	All Firms	0.28	0.37	0.49	0.41	0.20	0.44	0.55
Average TE Measured from *Own* Group Frontier	SG1	0.33	0.37	0.71	0.53	0.28	0.51	0.61
	SG2	0.56	0.52	0.61	0.46	0.27	0.61	0.69
	OG	0.28	0.40	0.57	0.42	0.20	0.54	0.56
TCR	SG1	0.75	0.91	0.87	0.69	0.70	0.89	0.90
	SG2	0.61	0.84	0.91	0.98	0.78	0.74	0.84
	OG	0.97	0.92	0.97	1.00	1.00	0.80	0.99
	All Firms	1.00	1.00	1.00	1.00	1.00	1.00	1.00

* Location and types of organisations are the two criteria used for classifying firms. In the case of the former, the following two groups of states have been considered:
SG1: Tamil Nadu and West Bengal; SG2: Delhi, Haryana, Punjab and Uttar Pradesh. In the latter case, only one broad group has been considered viz. OG which includes all partnership firms, private limited companies and public limited companies.

Table 6.5: Estimated Regression Equations Seeking to Explain DEA-TE of a Firm

Explanatory Variable	*Estimated Coefficient**						
	1984-85	1985-86	1989-90	1990-91	1994-95	1999-00	2002-03
$(\ln I)$	0.080 (15.71)	0.094 (19.24)	0.052 (10.94)	0.045 (11.20)	0.068 (15.03)	0.035 (6.310)	0.056 (15.40)
$(\ln Age)$	0.004 (0.476)	- 0.014 (- 1.374)	- 0.006 (- 0.663)	0.013 (1.748)	0.021 (2.614)	0.011 (0.823)	0.011 (1.446)
SD_1	- 0.060 (- 2.839)	- 0.029 (- 1.322)	- 0.049 (- 2.474)	- 0.055 (- 3.322)	- 0.033 (- 1.686)	- 0.005 (- 0.220)	- 0.027 (- 1.527)
SD_2	- 0.058 (- 2.360)	- 0.012 (- 0.458)	0.001 (0.031)	- 0.004 (- 0.207)	- 0.006 (- 0.257)	0.011 (0.457)	- 0.011 (- 0.654)
OD	- 0.011 (- 0.604)	- 0.027 (- 1.379)	- 0.026 (- 1.273)	- 0.004 (- 0.219)	- 0.038 (- 1.864)	- 0.094 (- 3.594)	- 0.031 (- 1.765)
Constant	- 0.784 (- 10.78)	- 0.863 (- 11.53)	- 0.181 (- 2.453)	- 0.229 (- 3.647)	- 0.869 (- 11.33)	- 0.052 (- 0.577)	- 0.354 (- 6.044)
$\overline{R}^2$	0.39	0.45	0.20	0.21	0.30	0.12	0.34
** Figures in parentheses are the corresponding t-ratios.*							

Table 6.6: Distribution of Average DEA-TE of Firms by Size Group

Size Group of Firms (in deciles)	*Average DEA-TE (%)*						
	1984-85	1985-86	1989-90	1990-91	1994-95	1999-00	2002-03
Lowest 10 %	15.51	13.15	28.43	31.47	8.41	44.27	35.95
10 –20 %	14.52	19.61	37.97	28.57	7.27	38.69	41.49
20 – 30 %	17.84	23.07	41.96	32.09	10.45	39.86	51.81
30 – 40 %	18.74	26.21	43.13	32.89	12.06	37.39	50.47
40 – 50 %	32.85	40.91	52.62	39.75	19.88	38.12	52.83
50 – 60 %	28.20	43.01	47.54	36.53	25.31	39.36	57.59
60 – 70 %	28.87	56.62	55.34	44.78	27.71	41.86	59.29
70 – 80 %	41.26	59.88	63.70	50.04	34.03	46.89	66.33
80 – 90 %	42.78	69.12	67.49	54.46	40.86	52.80	66.77
Highest 10 %	71.04	80.18	73.93	71.27	56.85	69.67	80.92
All Firms	*27.75*	*37.26*	*49.49*	*40.67*	*19.70*	*44.14*	*55.06*

Table 6.7: Estimated (Average) Elasticity of SFA-TE with respect to Firm Size and to Firm Age

	Elasticity of TE *						
Inefficiency Variable	1984-85	1985-86	1989-90	1990-91	1994-95	1999-00	2002-03
Firm-Size	0.0857 (0.0028)	0.1719 (0.0086)	0.0891 (0.0057)	0.0627 (0.0032)	0.1224 (0.0037)	0.0272 (0.0004)	0.0454 (0.0041)
Firm's Age	0.0062 (0.0041)	- 0.0120 (0.0089)	- 0.0338 (0.0026)	- 0.0034 (0.0015)	- 0.0626 (0.0017)	0.0072 (0.0005)	0.0255 (0.0036)
** Figures in parentheses are the corresponding standard errors.*							

Appendix 6.1

Figure 6A.1: Scatter Diagrams of Two Series of Firm TE's Computed from Two Alternative Stochastic Frontiers – One with FA as One Explanatory variable (*Vertical Axis*) and the Other Excluding it (*Horizontal Axis*)

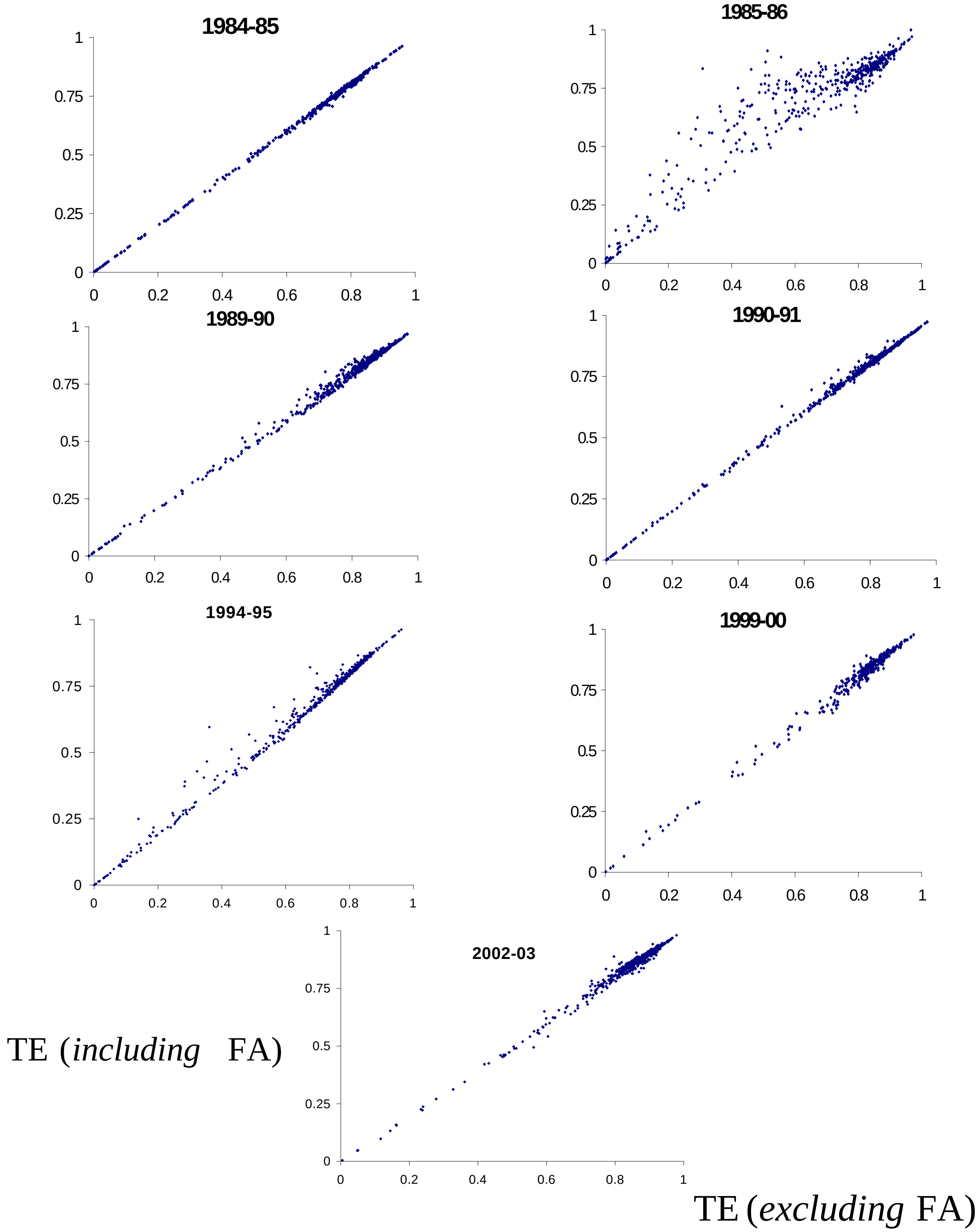


Figure 6A.2: Histograms Showing Proportions of Firms (*Vertical Axis*) in Different Class Intervals of Technical Efficiency Scores (*Horizontal Axis*): Selected Years

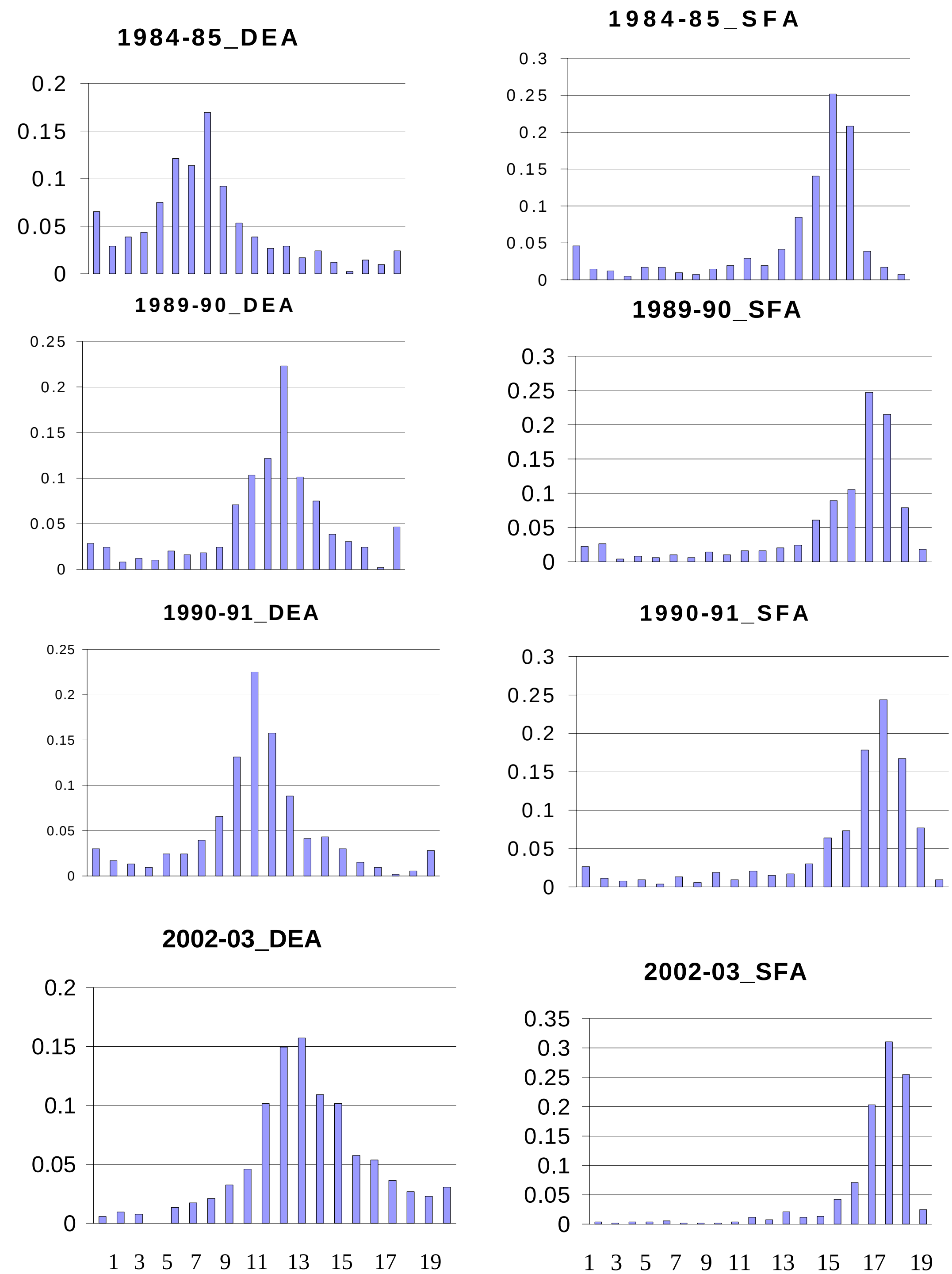
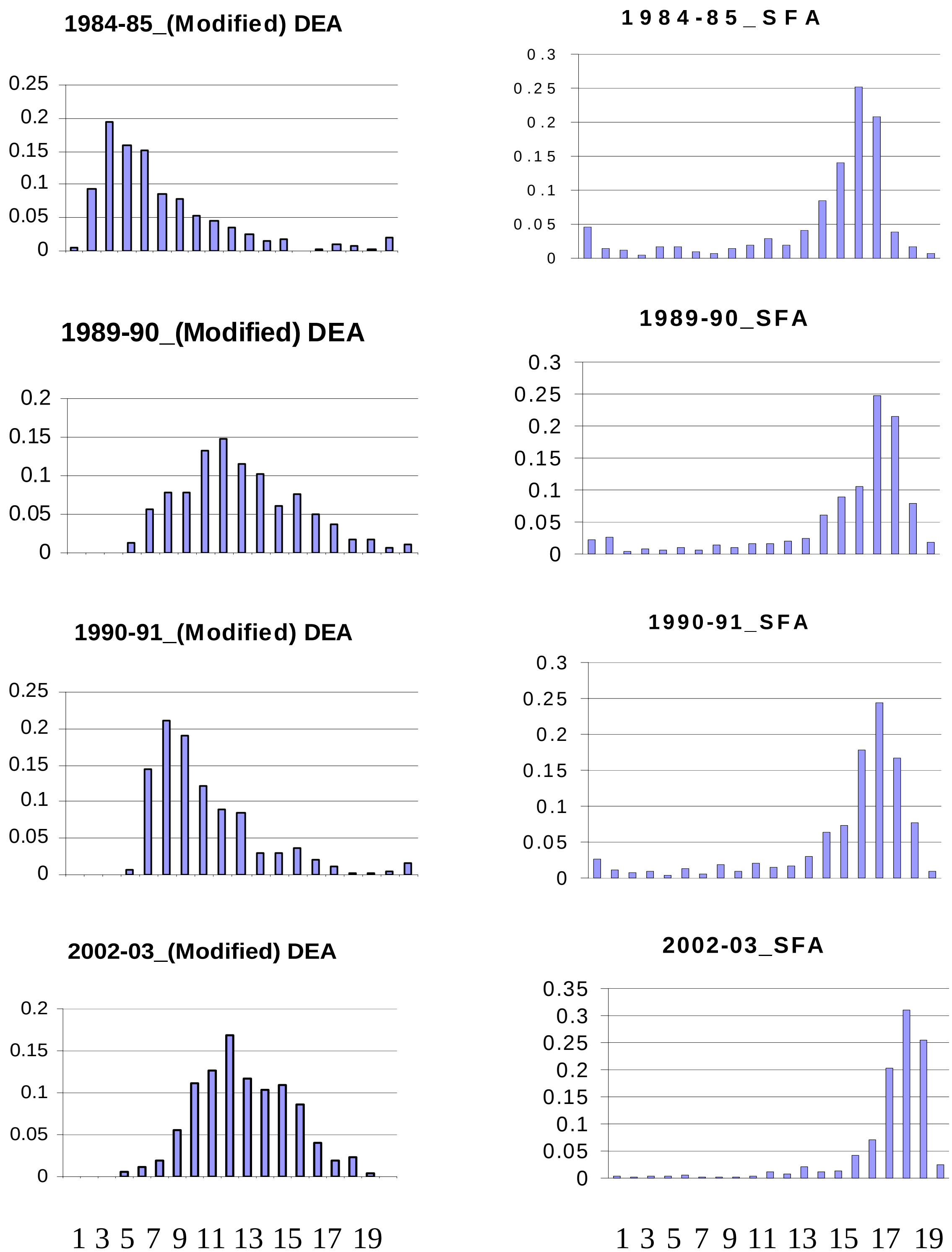


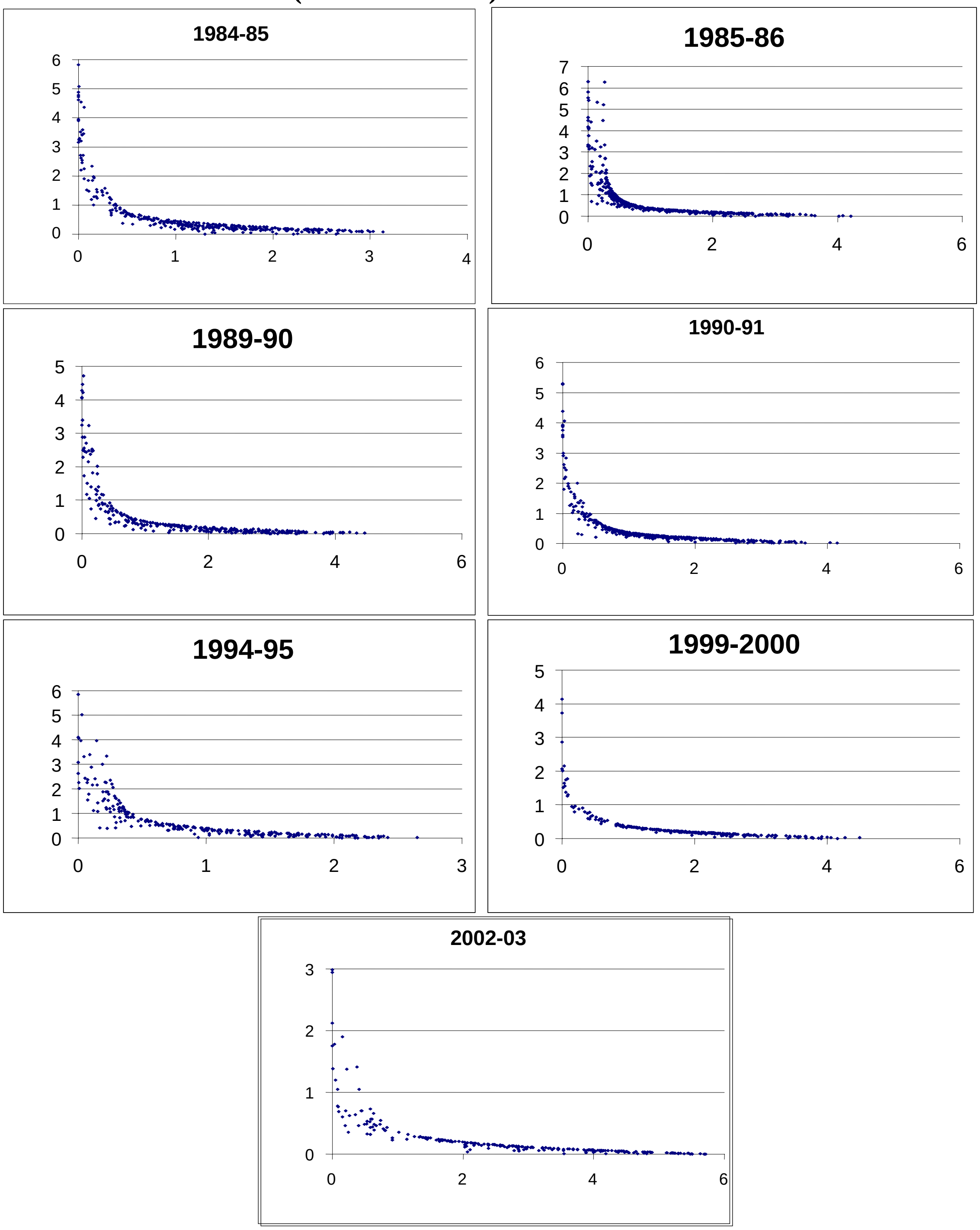
Figure 6A.3: Histograms Showing Proportions of Firms (*Vertical Axis*) in Different Class Intervals of Technical Efficiency Scores (*Horizontal Axis*): Selected Years



Appendix 6.2

Here we show the distribution of the estimated inefficiency error term (obtained by using the results presented in Appendix 3.2 earlier) for the Indian leather manufacturing firms for each of the sample years we have considered.

Figure 6A.4: Scatter Diagram of Probability Density of $\hat{u}$ (Vertical Axis) against $\hat{u}$ (Horizontal Axis) for Different Years



Chapter 7

Concentration and Profitability in the Indian Industries: Some Empirical Results

7.1 Introduction

A description of market structure indicates the number of sellers in the market, degree of their product differentiation, their cost structure, the degree of vertical integration and so on. And market structure determines what is called market conduct, i.e., the behavioural rules followed by the various agents – the buyers, the sellers or even the potential entrants – to choose the variables under their control. Finally, market performance (like efficiency, price-cost margin, profit etc.) is the result of market conduct. Such market 'structure-conduct-performance' (S-C-P) paradigm has been an area of active research for a long time and a large number of studies – both theoretical and empirical – have come up in this domain of industrial organisation.

The purpose of the present chapter is humble, namely to study empirically a part of this paradigm in the context of the Indian industries. In particular, we would like to examine, to what extent profitability of Indian industries has been affected by various features of industrial structure like concentration, advertising intensity, R & D intensity and so on.

The plan of the chapter is as follows. Section 7.2 outlines the relevant theoretical analysis as well as some important empirical studies in this area. Section 7.3 describes the data set and the variables used in the present work. Section 7.4 describes the analytical framework used and the empirical results obtained in the present study. Section 7.5 makes final observations.

7.2 Theory and Some Empirical Studies

Theoretical Structure

The pioneering work in this area was done by Bain (1951, 1956). In an attempt to measure the effects of concentration and entry barriers on economic performance of a sample of U. S. industries, Bain observed that profit rates were substantially higher in the highly concentrated industries and further that high entry barriers also affected profit rates favourably. The study of Mann (1966) also suggested that barriers to entry and concentration were the two important variables affecting profitability separately and favourably.

Before presenting our empirical results, let us turn to some analytical discussion on the issue. A perfectly competitive firm has no influence on the price of its product and hence, cannot earn more than normal profit. In contrast, by exercising control on price/production, a monopolist or even an oligopoly firm earns super-normal profit. Thus, profitability is closely related to the market power of firms. To derive such a relation algebraically, let us consider an oligopolistic industry in which say N firms produce a homogeneous good. Suppose, p is price of the good, x_i is output of firm i and X is industry output: $X = \sum_{i=1}^{N} x_i$. Let $X = F(p)$ be the demand function faced by the industry for this good. In other words, the (inverse) demand function is: $p = F^{-1}(X) \equiv f(X)$, say. The firm i, with its cost function $C_i(x_i)$, maximises profit

$$\Pi_i = x_i p - C_i(x_i) = x_i f(X) - C_i(x_i) \tag{7.1}$$

and the first-order condition for profit maximisation is given by

$$p - C_i'(x_i) = -x_i f'(X)\frac{dX}{dx_i} = -\frac{x_i}{X} X f'(X)\frac{dX}{dx_i} = \frac{s_i}{\varepsilon}\frac{dX}{dx_i} f(X) \tag{7.2}$$

where $s_i = (x_i / X)$ is the output share of firm i and ε is the (absolute value of) price elasticity of demand $[\text{i.e.}, -X f'(X)/f(X) = 1/\varepsilon]$. Given that $X = \sum_{i=1}^{N} x_i$,

$$\frac{dX}{dx_i} = 1 + \frac{d\left(\sum_{j \neq i} x_j\right)}{dx_i} = 1 + \lambda_i, \tag{7.3}$$

where $\lambda_i \left(\equiv d\left(\sum_{j \neq i} x_j\right)/dx_i\right)$ measures i^{th} firm's perception or belief about output responses of all other firms taken together to its own output changes.

A measure of market power of firm i is provided by the Lerner index, L_i, which is defined to be the excess of price over its marginal cost $C_i'(x_i)$ as a proportion of price and hence, in view of (7.2) and (7.3), depends on s_i, ε and λ_i:

$$L_i = \frac{p - C_i'(x_i)}{p} = \frac{s_i}{\varepsilon}\frac{dX}{dx_i} = \frac{s_i}{\varepsilon}(1+\lambda_i) \tag{7.4}$$

In a *perfectly competitive* industry with a large number of firms profit maximisation requires price (taken as given by a firm) to be equal to its marginal cost so that Lerner index, $L_i = 0$ (which is obtained by putting $dX/dx_i = 0$ in equation (7.4)). The *other extreme* case is *monopoly* in which both s_i and dX/dx_i are equal to unity and hence, $L_i = 1/\varepsilon$. These two are the lowest and highest values of Lerner index obtaining in two extreme types of market structure. In between, of course, we have the Cournot duopoly – a structure where only two firms operate and each firm believes that the other firm will *not* change its output when it changes its own and hence $dX/dx_i = 1$ and $\lambda_i = 0$ where the Lerner index equals $L_i = s_i/\varepsilon$.

However, once we move out of these extreme or simple forms of market structure, profitability or price-cost margins are affected by other features as well, e.g., the degree of concentration, the extent of product differentiation, entry barrier and so on. To see how, say, degree of concentration affects profitability, consider expressions (7.3) and (7.4) and assume the following conjectural behaviour (introduced by Dixit and Stern, 1982, in the context of a homogeneous good industry), namely that a one per cent change in i^{th} firm's output is believed to induce a θ per cent change in the output of each, and hence, the total output, of the remaining firms. Thus, for each $j \neq i$, we have[1]

$$\frac{dx_j}{dx_i} = \theta\,\frac{x_j}{x_i} = \theta\,\frac{s_j}{s_i} \tag{7.5}$$

[1] Note that $\theta = 0$ corresponds to the case of Cournot behaviour and $\theta = 1$, to that of complete collusion. The case $\theta < 0$ may also arise when, say, the firms agree to adjust their output for keeping price constant. We, however, consider here the case of positive θ only.

and hence, $$\lambda_i = \frac{d\left(\sum_{j\neq i} x_j\right)}{dx_i} = \sum_{j\neq i}\left(\frac{dx_j}{dx_i}\right) = \theta\ \frac{\sum_{j\neq i} s_j}{s_i} = \theta\ \frac{1-s_i}{s_i} \qquad (7.5)'$$

The Lerner index now also depends on θ:

$$L_i = \frac{p - C_i'(x_i)}{p} = \frac{s_i}{\varepsilon}(1+\lambda_i) = \frac{s_i}{\varepsilon}\left[1+\theta\frac{1-s_i}{s_i}\right]$$

$$= \frac{1}{\varepsilon}\left[s_i + (1-s_i)\theta\right] = \frac{1}{\varepsilon}\left[\theta + (1-\theta)s_i\right] \qquad (7.6)$$

Can we have some expression for the average rate of profit in an industry? To simplify the expressions let us assume that for each firm i, its marginal cost $\left(C_i'\right)$ coincides with its average cost (say, c_i). Since $\sum s_i = 1$ and $x_i = s_i X$, one gets the following expression for an industry's profit (Π), by using equation (7.6):

$$\Pi = pX - \sum_i c_i x_i = X\left(p - \sum_i c_i \frac{x_i}{X}\right) = X\left(\sum_i p s_i - \sum_i c_i s_i\right) = pX\sum_i\left(\frac{p-c_i}{p}\right)s_i = pX\sum_i L_i s_i$$

$$= pX\frac{1}{\varepsilon}\sum_i\left[\theta s_i + (1-\theta)s_i^2\right] = pX\frac{1}{\varepsilon}\left[\theta + (1-\theta)H\right] \qquad (7.7)$$

The symbol H on the extreme right hand side is the Hirfindahl-Hirschman index of concentration, being given by the sum of the squares of shares of firms, $H = \sum s_i^2$. (It may alternatively be interpreted as the (share weighted) averaged share of the firms in an industry ($H = \sum (s_i) s_i$), where the weight attached to a firm is its share). Now writing $pX = R$, i.e., total revenue, we get a very simple relation among profitability, θ, ε and concentration index in an industry:

$$\frac{\Pi}{R} = \frac{\theta}{\varepsilon} + (1-\theta)\frac{H}{\varepsilon} \qquad (7.8)$$

If we assume θ to be a nonnegative fraction $(0 \le \theta < 1)$, profitability (strictly speaking, profit as a proportion of revenue, Π/R) is a weighted average of $1/\varepsilon$ and H/ε and hence would increase whenever θ and/or H would increase. Further, quite expectedly profitability would fall if, *cet. par.*, price elasticity were to rise.[2]

We have shown above how concentration of market power affects industrial profitability in a homogeneous good industry. We now consider models in which not only concentration but the extent of product differentiation also affects profitability. Assuming that different firms produce different brands, with the i^{th} firm selling its brand at price p_i, Clarke, Davies and Waterson (1984) considered the following relation:

$$\frac{\partial p_i}{\partial x_j} = \psi \frac{\partial p_i}{\partial x_i}, \; 0 \le \psi \le 1 \tag{7.9}$$

in which the parameter ψ is taken to represent the degree of closeness as regarded by the consumers across various brands – a higher value of ψ indicating a higher degree of similarity. The market share of firm i and collusive parameter θ are now defined as follows:

$$s_i = \frac{p_i x_i}{\sum_j p_j x_j} \text{ and } \frac{dx_j}{dx_i} = \theta \frac{s_j}{s_i}, \; 0 \le \theta < 1 \tag{7.10}$$

Using profit-maximising condition for firm i and writing c_i for its marginal as well as average cost, its Lerner index can be shown to be equal to[3]

$$L_i = \frac{p_i - c_i}{p_i} = \frac{1}{s_i \, \varepsilon_i}\left[\theta\psi + \left(1 - \theta\psi\right) s_i\right] \tag{7.11}$$

[2] Interestingly, as (7.6) would reveal, even *within* an industry, profitability is larger for a larger firm (i.e., one with a larger output share, s_i).

[3] With the i^{th} firm's profit equaling $p_i x_i - c_i x_i$, its profit-maximisation condition is

$$p_i - c_i = -x_i\left[\frac{\partial p_i}{\partial x_i} + \sum_{j \ne i}\frac{\partial p_i}{\partial x_j}\frac{dx_j}{dx_i}\right] = p_i\left[-\frac{x_i}{p_i}\frac{\partial p_i}{\partial x_i} - \frac{x_i}{p_i}\sum_{j \ne i}\psi\frac{\partial p_i}{\partial x_i}\frac{dx_j}{dx_i}\right] \text{(using (7.9)).}$$

$$= p_i\left[\frac{1}{\varepsilon_i} + \frac{\psi}{\varepsilon_i}\sum_{j \ne i}\frac{dx_j}{dx_i}\right] = \frac{p_i}{\varepsilon_i}\left[1 + \psi\theta\frac{\sum_{j \ne i} s_j}{s_i}\right] = \frac{p_i}{s_i \varepsilon_i}\left[s_i + \psi\theta\left(1 - s_i\right)\right] \text{ (since } \sum_{j \ne i} s_j = 1 - s_i \text{).}$$

$$= \frac{p_i}{s_i \varepsilon_i}\left[\psi\theta + \left(1 - \psi\theta\right)s_i\right].$$

where ε_i is (the absolute value of) the price elasticity of demand for i^{th} firm's product.

The weighted average of margins given in (7.11), where the weights are firms' market shares, then yields the industry profit-revenue ratio:

$$\frac{\Pi}{R}=\sum_i\left(\frac{p_i-c_i}{p_i}\right)\frac{p_i x_i}{\sum_i p_i x_i}=\sum_i L_i s_i=\sum_i\left[\frac{1}{\varepsilon_i}\left(\theta\,\psi+(1-\theta\psi)\ s_i\right)\right] \tag{7.12}$$

We observe that the basic predictions of the previous model namely that profitability rises whenever s_i and/or θ rise (s) carry over. As it is clear, the equation (7.11) does not imply a monotonic relationship between profitability and market share nor does equation (7.12) imply a monotonic relationship between industry profitability and concentration. However, such results can be obtained if we consider a special case where $s_i\varepsilon_i$ is the same for all firms within a particular industry. This assumption along with the assumption of product differentiation (equation (7.9)) is consistent with the following demand function for the i^{th} firm's product

$$x_i=A_i+\frac{B}{p_i}-\psi\sum_{j\neq i}x_j \tag{7.13}$$

Since, $\varepsilon_i=-\dfrac{p_i}{x_i}\dfrac{\partial x_i}{\partial p_i}=\dfrac{p_i}{x_i}\dfrac{B}{p_i^2}=\dfrac{B}{p_i x_i}=\dfrac{B}{s_i\sum p_i x_i}$ we have

$$s_i\varepsilon_i=B/R \tag{7.14}$$

where R is the total revenue of all firms within the industry. In this special case the expression for the Lerner index given in (7.11) becomes

$$L_i=\frac{p_i-c_i}{p_i}=\frac{R}{B}\left[\theta\psi+(1-\theta\psi)s_i\right] \tag{7.15}$$

And hence, the profit-revenue rate given in (7.12) changes to

$$\frac{\Pi}{R}=\sum_i L_i s_i=\frac{R}{B}\left[\theta\psi+(1-\theta\psi)H\right] \tag{7.16}$$

which depends on not only H and θ, but also the degree of product differentiation as reflected in ψ. We further assume a special case where R/B remains fixed across industries which obtains, if the average price elasticity of demand in an industry, ε (defined to be the share-weighted elasticities of demand for different firms' products, i.e.,

$\varepsilon \equiv \sum_i \varepsilon_i s_i$) is proportional to the total number of firms within the industry. Since (7.14) yields that $\varepsilon \equiv \sum_i \varepsilon_i s_i = N(B/R)$, R/B remains constant across industries and hence profitability across industries varies accordingly as θ, ψ and H vary:

$$\frac{\Pi}{R} = \text{Constant} \times \left[\theta\psi + (1-\theta\psi)H\right] \tag{7.17}$$

We have sought to explain rate of profit/return across industries.[4] We could get an expression of the rate of profit from the relation (7.17) by multiplying Π/R by $R\big/p^k K$, where $p^k K$ is the value of capital, with K denoting the (column vector of) physical quantity (quantities) of its capital good (s) and p^k, the (row vector of) corresponding price (s). If we now express our relation (7.17) in terms of rate of profit we get

$$\frac{\Pi}{p^k K} = \frac{\Pi}{R} \times \frac{R}{p^k K} = \text{Constant} \times \left[\theta\psi + (1-\theta\psi)H\right] \times \frac{R}{p^k K} \tag{7.18}$$

Thus, the rate of profit varies positively with each of θ, ψ and H, but inversely with the capital-output ratio (in value terms), $p^k K \big/ \sum p_i x_i$.

As we have mentioned earlier, ψ is a measure of degree of product differentiation. In our empirical analysis we have considered a number of variables to capture effects of product differentiation as well as entry barriers on profitability of an industry, viz., advertisement to sales ratio, research and development expenditure (as a proportion of value of output) and so on.

Some Empirical Studies

Bain's hypothesis was that firms in an industry with high concentration could earn excess profits and more so if they were protected by entry barriers. A different view, known as the *Chicago School's hypothesis* (pioneered by Demsetz, 1973), states that high profits are in fact a consequence of greater or differential efficiency of some firms in the

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[4] An alternative dependent variable, widely used in the literature, is the price-cost margin. Since we do not readily get information on such margins from the data set used, viz., Prowess database, we could not try this as an alternative dependent variable.

industry. These firms capture a large proportion of market share on account of their relative efficiency and consequently market concentration increases and efficient firms earn economic rent. This view also implies that market concentration and industry profit are positively related.

However, Bain's (1956) results were corroborated in many subsequent works, e.g., Caves (1974), Comanor and Wilson (1967), Connor and Mueller (1982), Mann (1966), Orr (1974, 1974a), Porter (1979) to mention a few. Most of the above studies have, however, been carried out for the developed countries like the UK, the USA and Canada while that of Connor and Mueller (1982) was for the US multinationals operating in developing economies like Brazil and Mexico. An exhaustive survey of these studies can be found in Chakravarty (1995). However, studies on inter-industry differences in profitability in the context of developing economies are not large in number. We survey below a few such studies for the Indian economy.

Studies on the Indian industries have produced mixed results. On the basis of the Annual Survey of Industries (ASI) data and some relevant information from earlier studies of Saluja (1968) and Panchamukhi (1974), Katrak (1980) finds that price-cost margin is higher in Indian manufacturing industries with relatively little import competition, high export orientation and high rate of protection. He also observes this margin to increase with the increase in concentration up to a certain level and fall thereafter. The study by Siddharthan and Dasgupta (1983) observes that inter-industry differences in skill and advertisement intensity are the two major determinants of differences in profitability across Indian industries while such differences in R&D intensity and concentration ratio are not. Kumar (1990) uses an unpublished database on 43 (three-digit) Indian manufacturing industries for the years 1976-77 through 1980-81 compiled by the RBI and observes that the degree of seller concentration, advertisement intensity and protection from imports accorded to the local (Indian) industries are not related to their profitability. He, however, finds knowledge (skill and technology) intensity to be an effective entry barrier variable for the multinational enterprises and intra-industry structure (in terms of strategic heterogeneity) to have played an important role in affecting industry profitability. Agarwal (1991) considers vehicles manufacturing industry (like jeeps, trucks, buses etc.) in private sector for the years 1966-67 to 1986-87 but fails to find much support for either the S-C-P paradigm or the relative efficiency hypothesis. On the other hand, the study by Kambhampati and Parikh (2003) observes profit margins in the Indian industries to be significantly influenced by the market structure variables like market shares, advertising, R&D and exports. In particular, both advertisement and R&D intensity are observed to have favorable effect on profit margins. Kambhampati (1996) surveys a few additional Indian studies in this area.

7.3 Data Set and Variables

Our empirical exercises use Prowess database made available by the Centre for Monitoring Indian Economy (CMIE). This source releases company-level annual data on several important economic variables for different industries. Data on thirty-seven industries are available for years spanning almost one and a half decade since the early nineties and hence a panel data set may be constructed. That is exactly what we have done. Different industries are taken to be the individual units in the present study. A list of the industries included in the present study is given in Table 7.3. We give below a brief description of the variables we have considered (along with the corresponding notations used) in the present study.

Three measures of performance have been proposed in the literature on market structure-conduct-performance: *rate of return*, *price-cost margins* and *Tobin's q* (Tobin, 1969, 1980). The available data do not directly provide any information on price-cost margins or *Tobin's q* at the firm level. So, we have compiled information on profit and used rate of return as our primary variable for explanation.

Rate of Return (*ROR*): Bain (1951) carried out the first empirical study relating *ROR* to concentration for 42 U. S. industries. Several profit variables could be constructed from our data set such as profit after tax, profit before tax, profit before depreciation and tax etc. We have used mainly 'profit after tax' (PAT) variable to compute rate of return of a firm/industry. Interestingly, Bain (1951) also used PAT to define *ROR*.[5]

[5] In the study of Bain (1951) the numerator of the *ROR* variable was PAT, but the denominator was the book value of stockholder's equity. In the present exercise, we have used paid-up equity capital for the latter.

Concentration (*Con*): Several alternative measures of economic concentration have been suggested in the literature, of which *k*-firm concentration ratio and Herfindahl Index (H) are the two most popular ones. Of these two again, the former is the most widely used one, with the value of k depending on the choice of the researcher. If s_i be the share of the i^{th} firm in the total output of an industry with N number of firms, then the *k*-firm concentration ratio is given by the sum of the s_i's of the k largest firms, while H is defined as the sum of the squares of the shares of all firms: $H = \sum_{i=1}^{N} s_i^2$. In our exercise, we have considered both the alternative measures and for the first one, we have considered the 4-firm concentration ratio (to be denoted by $CR4$). Net sales rather than outputs of the individual firms have been used for computing individual shares (s_i's).

Advertising Intensity (*Adv*)*:* Product differentiation plays a dual role in the S-C-P paradigm. It directly influences the character of competition among established firms and has been used widely as an effective entry barrier variable in the literature. *Advertising intensity* is usually measured by the ratio of the advertising expenditure made by a firm (all firms in an industry) to the firm's (industry's) net sales. We have also followed this method. To reiterate, this variable is presumed to measure, at least indirectly, the extent of product differentiation within an industry and also the extent of goodwill. As Bain (1956) pointed out, in markets with differentiated products consumers usually prefer the existing brands to the unfamiliar brand of a new entrant. Therefore, an entrant would have to offer its product at a price substantially lower than the ones charged by the existing firms and also have to undertake heavy advertisement to nullify such preference barrier. If the existing firms themselves do high levels of advertisement, it then becomes all the more difficult for a new comer

Minimum Efficient Scale (*MES*)*:* A second entry barrier variable usually considered in the literature is the minimum efficient scale (*MES*) of an enterprise. By *MES* of a plant we mean the point at which average cost is minimised. It is argued that if an analysis of inter-temporal movement in size distribution of firms reveals that the firms are moving into one particular size class, then the size class that gains is likely to contain the *MES* (Shepherd, 1967; Stigler, 1968; Rees, 1973). The usual scenario is that an entrant faces greater difficulty in raising money from the capital market compared to an existing firm which probably operates at an *MES* size. Alternative measures of *MES* of an industry have been suggested/used in the literature. Firms or plants are arranged first in descending order of their values of outputs, starting with the plant yielding the largest output. The plants are then classified into two halves – the upper and the lower halves and plants in the upper half (i.e., the half producing fifty per cent of industry's output or more) are only considered. One measure of *MES* is the *average size* of plants in the upper half. An alternative measure, also used by some authors, is the value of output of the *smallest* plant in the upper half. In our analysis we have used the former measure. We have also used some additional explanatory variables. These will be mentioned when we discuss the empirical findings of our study.

7.4 Econometric Framework and Empirical Findings

Standard regression techniques for the panel data have been used for our empirical exercises. To give a brief idea about this technique, suppose we have a balanced panel data, i.e., observations on N units for each of T number of time periods.[6] Let the panel data regression model involving L explanatory variables be written as

$$y_{it} = \sum_{j=1}^{L} \beta_j x_{jit} + a_i + u_{it} \qquad (i = 1, 2, 3, \dots, N; \quad t = 1, 2, 3, \dots\dots, T) \qquad (7.19)$$

where y_{it}, x_{jit}, and u_{it} are respectively the value of the dependent variable, the j^{th} explanatory variable and the idiosyncratic error term, corresponding to the i^{th} unit in the t^{th} period. Equation (7.19) also includes the case where a time invariant factor, a_i, may affect y_{it}. The u_{it} is assumed to be uncorrelated with each explanatory variable across *all* time periods and distributed, conditional on x's and a_i, as identical and independent normal variable with zero mean and constant variance.

In the case of panel data the literature suggests the selection of an appropriate regression equation from two alternative models – *fixed effect* (FE) model and *random*

[6] The estimation methodology discussed here is also applicable to the case of the so-called 'unbalanced' panel data set in which the total number of observations falls short of NT.

effect (RE) model. When a_i is likely to be correlated with some explanatory variable (s) in any time period, FE model appears to be the proper one. Estimates of the various parameters could then be obtained through a pooled ordinary least squares (OLS) regression based on the following modified form of the equation (7.19):

$$\ddot{y}_{it} = \sum_{j=1}^{L} \beta_j \ddot{x}_{jit} + \ddot{u}_{it} \tag{7.20}$$

where each variable is expressed as deviation from its mean value (over the total time period T), such deviations being denoted by putting two dots $(\bullet\bullet)$ over the corresponding symbol (e.g., y_{it} is replaced by $\ddot{y}_{it}$, where $\ddot{y}_{it} = y_{it} - \bar{y}_i$ and $\bar{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it}$). However, if we have reasons to believe that a_i is uncorrelated with *each* explanatory variable in *all* time periods, then the use of a transformed/modified model so as to eliminate the effect of a_i would result in inefficient estimators. Hence one has to use the RE model in that case and the generalised least squares (GLS) estimation procedure may be used to obtain consistent estimates of the regression parameters. (Wooldridge (2003) presents some detailed discussion on panel data models.)

Thus, as far as choice between a RE and FE approach is concerned, the key consideration is whether or not a_i and x_{jit}'s are correlated. Hence, it is important to have a method for testing this assumption. Hausman (1978) proposed a test for accepting/rejecting null hypothesis, $H_0 : RE$ model, against the alternative hypothesis, $H_1 : FE$ model, on the basis of a test statistic – known as Hausman Statistic. This statistic, as reported in most of the econometric packages, is distributed asymptotically as χ^2 with L degrees of freedom under H_0.

We have fitted both FE as well as RE models and then used the Hausman test to arrive at the appropriate model for estimating the parameters of regression equation. Statistical package **TSP** (version **4.5)** has been used for our empirical exercises. To facilitate our subsequent discussion we write below the general form of the regression equation involving all possible explanatory variables we have tried:

$$y_{it} = \alpha_i + \beta_C\, Con_{it} + \beta_M\, MES_{it} + \beta_A\, Adv_{it} + \beta_R\, RD_{it} + \beta_V\, Vas_{it} + \beta_K Kas_{it} + u_{it} \tag{7.21}$$

where three additional explanatory variables are also considered, viz., *RD*, *Vas* and *Kas.* These will be defined and explained when we discuss our regression results.

Regression Results

As far as our regression exercises are concerned, we have proceeded in a step-by-step fashion. We have not introduced at one go all explanatory variables listed in equation (7.21). Rather we bring in these variables one by one and examine at each stage whether regression result improves in terms of the value of $\overline{R}^2$ and the levels of significance of the estimated coefficients of the different explanatory variables. We have proceeded in this fashion and eventually ended up with an equation in which explanatory variables included have coefficients which are of expected signs and statistically significant (at least at ten percent level).

For an equation at each stage regression results for both the random effect (RE) model and fixed effect (FE) model are obtained first and then the appropriate model is chosen using the test results for the estimated value of the associated Hausman Statistic.

As mentioned earlier, we have considered two alternative measures of concentration – Herfindahl index (denoted by H) and 4-firm concentration ratio (denoted by $CR4$). To begin discussion on our regression exercises we note, first of all, that whenever concentration is used as the only explanatory variable, $CR4$ has fared much better than H. This is clear from the first regression equation of Tables 7.1 and 7.2. In fact, $CR4$ alone explains about 49 per cent of total variation in profitability across industries and its coefficient is expectedly positive and significant. When *Adv* or *MES* are added as additional explanatory variables, the coefficient of $CR4$ turns out to be *not significant*. And the estimated coefficient of concentration variable remains *nonsignificant*, even if $CR4$ is replaced by the alternative measure, H.

We have initially considered two alternative advertisement variables – advertising ratio during the previous year[7] and that in the current year. However, we have finally settled for the former, in view of not only its better performance but also the argument that presumably there should be some lag between initiation of advertisement and its effect on sale. Coming to report our empirical results involving *MES* as another explanatory variable, we note that when we use as additional explanatory variable (s) advertisement-sales ratio (*adv*) or minimum efficient scale (*MES*) either one at a time or jointly, regression results improve – in respect of both the values of $\overline{R}^2$ and the t-ratio of the estimated coefficient of the concentration variable (second and third equations of either Table). One other important observation is that the coefficient of the constant term in each of these equations now turns out to be *nonsignificant*.

We next consider R&D intensity (*RD*) of an industry. It is defined as the ratio of aggregate expenditure on research and development (R&D) activities of an industry to its aggregate net sales. More and more R&D expenditure incurred by any producing unit (relative to its net sales) is likely to have a higher prospect of inventing and adopting advanced method of production which helps to lower its unit cost of production, and/or improve the quality of its product. Thus, an increased R&D intensity for all existing firms in general is likely to act as an effective entry-barrier to a potential new entrant into the industry. When we add RD (i.e., R&D expenditure in the preceding year as a proportion of sales) as an additional explanatory variable, the result improves marginally in terms of the value of $\overline{R}^2$, but now the $t-$ratio of the coefficient of $CR4$ exceeds 2.

The proportion of value added in the total value of output of a firm (*Vas*) indicates the extent to which the firm has to depend on outside supply for raw materials/intermediate inputs needed for its production. The less it has to depend, the larger is likely to be the stability and smoothness of its production process. At an industry level this ratio reflects the degree of vertical integration of the industry, and is likely to act as an effective entry barrier. In fact, vertical integration, by assuring timely availability of inputs, yields distinct advantages and higher the degree of vertical

[7] In fact, as mentioned earlier, advertisement-sales ratio has been found to be an important determinant of profit in the study by Siddharthan et al (1983). However, Kumar (1990) notes that product differentiation through advertisement is effective mainly in the case of consumer goods industry.

integration in an industry, less favorable is likely to be the platform for a potential entrant, owing to its cost disadvantage relative to the existing rivals. When *Vas* is introduced as an additional explanatory variable, value of $\overline{R}^2$ improves considerably, the coefficient of *Vas* is of expected sign and highly significant and the coefficients of other explanatory variables remain significant with expected signs (equations 5 and 6 of Tables 7.1 and 7.2).

Our final form of rate of return includes capital-output ratio as another explanatory variable. In fact, as equation (7.18) shows, other things remaining unchanged, higher the capital-output ratio, the lower is expected to be the rate of return. In our regression exercises, we have to use capital-sales ratio (*Kas*). When we bring in this as an additional explanatory variable, its coefficient is observed to be negative and significant, as expected. The overall regression result, i.e., the value of $\overline{R}^2$, improves, level of significance of the estimated coefficient of each of the remaining explanatory variables including concentration increases and is also of expected sign (equations 7 and 8 of Tables 7.1 and 7.2).[8]

7.5 Concluding Remarks

Most of the empirical works regarding concentration-profitability relation in India have been done for the pre-liberalised Indian economy. Our principal concern in this chapter is to ascertain whether the conventional S-C-P paradigm is valid for the industries in the post-reform period. Specifically, we have sought to examine how market concentration along with some important entry-barrier variables like advertisement-sales ratio, minimum efficient scale of a firm etc. affect profitability of the Indian industries. There are other factors that constitute the elements of 'market conduct' such as R&D expenses, degree of vertical integration, capital-sales ratio etc. which have considerable implications for profitability. Results suggest that market structure variable like industry

[8] In this connection it may be noted that *Kas* has been used by a number of researchers to explain price-cost margin of an industry and many of them have come up with positive sign of coefficient of *Kas* (Ornstein, 1975; Liebowitz, 1982; Domowitz et al, 1986; Martin, 1988); presumably the underlying argument is that *Kas* also acts as an entry barrier variable. In our case the dependent variable is not price-cost margin, but rate of return and it stands to reason that the rate of return would be lower if, other things remaining unchanged, capital-output (or its proxy capital-sales) ratio were higher.

concentration has a significant positive effect on industry profitability in India. This is in contrast to some of the empirical findings for the Indian industries surveyed in section 2 and also for other countries. The entry barrier variables like advertisement intensity, minimum efficient scale, R&D intensity, degree of vertical integration etc. are also observed to have affected profitability significantly with theoretically proper signs. Needless to say, the results obtained here could have been enriched by including some other explanatory variables considered by some authors. But limitations of availability of suitable data did not allow us to carry out these exercises. However, the limited exercise we could carry out here seems to confirm, by and large, the prevalence of the conventional S-C-P paradigm in the Indian industries.

Table 7.1: Estimated Linear Regression Equation for Rate of Return (*ROR*) using 4-Firm Concentration Ratio (*CR4*) as the Measure of Concentration

Regression Equation	Independent Variables							
	Constant	*CR*4	*Adv*	*MES*	*RD*	*Vas*	*Kas*	$\bar{\bar{R}}^2$
1	0.192 (1.530)	0.374 (1.958)						0.49
2	0.117 (0.925)	0.267 (1.404)	12.110 (4.332)					0.51
3	0.068 (0.579)	0.284 (1.578)	10.713 (4.072)	0.00001 (5.033)				0.52
4	- 0.037 (- 0.316)	0.374 (2.094)	9.849 (3.841)	0.00001 (5.186)	22.492 (2.962)			0.53
5	----	0.448 (2.074)	7.106 (2.002)	0.00002 (5.539)		3.527 (7.902)		0.62
6	----	0.501 (2.308)	6.895 (1.948)	0.00002 (5.492)	16.266 (2.035)	3.484 (7.825)		0.62
7	----	0.531 (2.580)	10.410 (3.056)	0.00002 (6.195)		3.459 (8.155)	- 0.478 (- 6.951)	0.66
8	----	0.591 (2.864)	10.215 (3.014)	0.00002 (6.155)	18.207 (2.400)	3.411 (8.074)	- 0.484 (- 7.071)	0.66

Figure in parenthesis is the corresponding t-ratio.
The equations with the constant term correspond to the RE models and those without it, the FE models.

Table 7.2: Estimated Linear Regression Equation for Rate of Return (*ROR*) using Herfindahl Index (*H*) as the Measure of Concentration

Regression Equation	Independent Variables							
	Constant	*H*	*Adv*	*MES*	*RD*	*Vas*	*Kas*	$\bar{\bar{R}}^2$
1	0.364 (4.561)	0.224 (0.970)						0.49
2	0.236 (2.806)	0.144 (0.636)	12.600 (4.477)					0.51
3	----	0.427 (1.690)	16.212 (4.466)	0.00001 (3.702)				0.56
4	0.132 (1.749)	0.230 (1.065)	10.479 (4.066)	0.00002 (5.177)	20.333 (2.696)			0.53
5	----	0.617 (2.600)	7.681 (2.162)	0.00002 (5.633)		3.608 (8.071)		0.62
6	----	0.621 (2.626)	7.474 (2.108)	0.00002 (5.560)	14.302 (1.805)	3.567 (7.991)		0.62
7	----	0.726 (3.219)	11.119 (3.264)	0.00002 (6.320)		3.554 (8.377)	- 0.483 (- 7.047)	0.66
8	----	0.732 (3.259)	10.919 (3.217)	0.00002 (6.247)	15.902 (2.118)	3.508 (8.293)	- 0.487 (- 7.135)	0.66

Figure in parenthesis is the corresponding t-ratio.
The equations with the constant term correspond to the RE models and those without it, the FE models.

Table 7.3: List of the Industries Considered in the Study

1. Beverages & tobacco
2. Books & cards
3. Cement
4. Clocks & watches
5. Communication services
6. Construction
7. Cosmetics, toiletries, soaps & detergents
8. Drugs & pharmaceuticals
9. Dyes & pigments
10. Electrical machinery
11. Electricity
12. Electronics
13. Fertilisers
14. Financial services
15. Food products
16. Health services
17. Hotels & tourism
18. Inorganic chemicals
19. Leather products
20. Metals & metal products
21. Mining
22. Non-electrical machinery
23. Organic chemicals
24. Other non-metallic mineral products (except Cement)
25. Paints & varnishes
26. Paper & paper products
27. Pesticides
28. Petroleum products
29. Plastic products
30. Polymers
31. Rubber & rubber products
32. Textiles
33. Trading
34. Transport equipment
35. Transport services
36. Tyres & tubes
37. Wood

Chapter 8

Conclusion

The domestic as well as the international economic scenario has started changing for India ever since she tried to respond, in a number of ways, to the major economic crisis of the early 1990's. The response has come mainly in the form of new economic policies advocating and introducing reforms in various areas of economic activities like foreign trade, foreign investment, industrial licensing and so on. The so-called 'new economic policies' have had various dimensions but one common objective was to improve the efficiency of the system and make the various sectors competitive and comparable to the international standard. As far as the industrial sector is concerned, the focus has been on improving the productive efficiency of the various units irrespective of whether they are in the public or private sectors. Thus emphasis is being placed on good performance of a unit, as it is supposed to be a prerequisite for growth or even mere survival. Given this backdrop, the present dissertation takes up some selected features of the Indian industrial sector for detailed analysis. The purpose of the present chapter is to summarise the major findings of our dissertation and indicate some potential areas of future research and also some limitations of the present study. Much of what we are going to say here has already been discussed in details in the text or concluding sections of the preceding chapters. In that sense, the present chapter merely tries to put these findings together in a somewhat concise and unified fashion.

As we have stated above, the objective of the present dissertation is to take up a couple of aspects of the Indian industrial sector for a detailed analysis. The *first aspect* which the dissertation has tried to examine is efficiency of industrial firms. For this purpose, the study has considered two major mass consumption good industries in India, viz., textile and leather and attempted to measure, applying two very well known methods to the official micro level data, the extent of technical efficiency (TE) of individual firms in each of these two industries. It has also sought to explain the extent of temporal variation in TE across firms in each industry.

The *second aspect* which has been taken up for analysis deals with the entire industrial sector, as an attempt has been made here to find any plausible association between market structure and profitability in the Indian industries. The conventional market Structure-Conduct-Performance (S-C-P) paradigm has been enriched much by the pioneering work of Bain (1956) which relates profitability to the degree of seller concentration and the stiffness of entry barriers in the market. It has been an area of important research in many countries ever since Bain (1956) made his study. We have sought to examine this issue for the Indian industries. We summarise below the major findings of our study on these two aspects.

The study has examined some micro-aspects of textile and leather industries, the two relatively large and old Indian industries accounting for a substantial proportion of industrial employment and occupying a significant position in the economy from the point of view of foreign exchange earnings. Technical efficiency and other related issues have been examined for these two industries for some selected years spanning over the period from the mid-1980's to the beginning of the present century, using both the parametric stochastic frontier analysis (SFA) and mathematical programming-based data envelopment analysis (DEA).

The major findings of our SFA exercise on the *textile industry* may be summarised first. For each sample year, a significant variation in firm-level technical efficiency (TE) has been observed across different states and ownership patterns. For instance, firms located within the states of Gujarat and Maharashtra (as well as Karnataka and Kerala) are found to have performed better than the group of firms located in the remaining states during the pre-liberalisation period. But the picture turned out to be the opposite for the later period. As far as the ownership pattern is concerned, privately owned firms are found to have been relatively more efficient than firms under public ownership. Size and age of a firm are each found to be important factors affecting its TE, the relation being positive in case of the first, but negative in the case of the second. Finally, the average firm level TE seems to be on a rising trend during the post-liberalisation era.

Our DEA exercises on this industry seem to corroborate the major findings obtained through the SFA method with a couple of exceptions. As in the case of our SFA exercise, here also we find a positive relation between firm size and efficiency for each sample year as well as significant effects of a firm's regional location and ownership pattern on its TE. Although we have considered a somewhat different group of states here, our observations on Gujarat and Maharashtra remain the same as in the case of our SFA exercise. In addition, we observe that textile firms in West Bengal and Punjab, though relatively small in numbers, have displayed relatively better and *stable* performance over time. Once again, firms under public ownership are found to be relatively less efficient. We have attempted two additional exercises applying the DEA. One exercise is concerned with ascertaining whether organisational structure as such has had a role in affecting performances of firms and we find that it did have a role. A second additional exercise is concerned with finding the existence of any possible technological heterogeneity among textile firms; such heterogeneity presumably might result from factors such as differences in regional locations, ownership patterns or organisational types. Our exercises on (own) group TE and meta-frontier TE pointed to the prevalence of such technological heterogeneity across groups of firms, as shown by the values of technology closeness ratio (TCR) of the different groups. Once again, average firm level efficiency is seen to have risen in the post-liberalisation period. However, unlike our findings in the SFA exercise, the DEA exercise does not find any possible effect of a firm's age on its efficiency.

The main findings for the Indian leather industry are found to be more or less the same as observed for the Indian textile industry. However, one notable exception in the case of the translog production frontier estimated through SFA method is that fixed capital has not come out to be a significant variable in explaining inter-firm variation in output. Once again, the findings are broadly similar whichever method of analysis is used, SFA or DEA. Each year the TE level of a leather firm is found to be positively correlated with its size but not with its age. The TE level is also found to have varied across firms located in different states. Indeed, either method reveals that an average firm located in Tamil Nadu or West Bengal has performed relatively worse than an otherwise identical firm located elsewhere. Finally, average firm level efficiency of the Indian leather industry is found to show some mild tendency to rise over the years.

The present dissertation has also tried to analyse another aspect of the Indian industrial sector. This aspect involves the conventional structure-conduct-performance (S-C-P) relation in industries and the present study has sought to examine whether such a relation is tenable empirically in India in its post-reform period. The study uses the panel data on the relevant economic variables of the different industries for this purpose and finds that the major variables which are generally emphasised in the literature to describe the structure of an industry, along with an index of concentration, have all turned out to be significant (with expected signs) in explaining variation in the rate of return across different industries. The set of the explanatory variables considered includes, in particular, *minimum efficient size* of a plant in an industry (measured by the average size, in terms of output, of the upper half of the firms in the industry where the upper and lower halves have been obtained by first arranging firms in descending order of size and then considering upper firms producing at least fifty percent of the industrial output), its *advertisement* and *R&D intensity* (seeking to capture the extent of product differentiation in an industry, being measured respectively by the industry's advertising expenditure and expenditure on research and development each as a proportion of its net sales), the *degree of vertical integration* (within the industry) etc.

An empirical study generally has a number of limitations and ours is not an exception. To point out some of these limitations, we understand that it is very useful to measure technical efficiency of a fixed set of producing units and to examine inter-temporal behaviour of the efficiency level of each individual unit in order to assess, for instance, whether it follows an increasing or decreasing trend over time. This would have been feasible, if panel data were available. Our data are the firm-level data thrown up by the Annual Survey of Industries (ASI) in India. Although it is a reliable *official* source of information, it does not disclose the individual identity of any unit. Therefore, construction of any panel data set was not feasible. In such a situation perhaps the best that one could do is to make a cross-sectional analysis of firms for a number of consecutive years and compute (average) efficiency over time. That is what we have tried to do here except that these data being quite expensive to procure and also requiring substantial processing time in order to be in useable form, we could analyse data for some selected years only.

Further, the analysis of the type of structure-conduct-performance of the Indian industries that we have tried to do in the present study is an old area of interest and might have gone out of active research now in the context of the developed countries. However, we do not have many studies for the Indian industrial sector. The idea behind whatever limited investigations we have been able to do here is to add to this small literature. In addition, a distinguishing feature of our study is that it uses panel data which might help one to feel a little bit more confident about the validity of conventional S-C-P paradigm for the Indian industries. Another distinguishing feature is that most of the studies on the characteristics of industrial structure and its performance in India have been done for the period prior to the 1990's. Ours is one which is based on the data for the post-reform period.

In this connection we may briefly discuss some other related exercises which might be an interesting extension in the spirit of the present investigation. *First*, it might be extremely useful, if one could compare efficiency of the Indian textile and leather firms with that of their counterparts in countries which are our competitors in the international markets in these products. However, we do not have any ready access to these micro data of the other countries, even if they were available. *Second,* we could have carried out a comparative analysis of group frontier vs. meta-frontier TE in the context of leather and textile firms following SFA also. This has not been attempted here. *Third* and perhaps the most important point is that the present study considers the organised sector of each industry – the sector on which data are available from the ASI in India. It would have been extremely interesting, if similar issues – in particular, measures of unit-level TE and their possible determinants – were investigated for the unorganised part of these industries as well so that a comparative analysis of productivity and efficiency could have made for these two different parts of a given industry. However, for this purpose one has to find data from other sources like the data thrown up by the sample surveys conducted by the National Sample Survey Organisation (NSSO) of India. These data are available only for some selected years (i.e., rounds). However, that work is beyond the limited scope of the present study. Further, the use of firm-size as a variable affecting firm-TE's in our SFA exercises, may render the inefficiency variable, *u*, to be heteroscedastic. We have not considered this case in our study.

Fourth, any industrial production activity generates some pollution. In particular, one of our selected industries, viz. leather, is generally a polluting one. The analysis would have been more interesting, if some allowances were made for such pollution generation. One approach could be to include such pollution as *bad* in the list of products. However, inclusion of more than one output in the conventional parametric production function approach is not feasible. A second alternative is to redefine output by making allowance for some pollution abatement cost. But then such costs are to be estimated satisfactorily and there are no reliable data either on pollution generation or on its abatement cost which one can make use of. Of course a multi-output – multi-input analysis could have been carried out in the DEA framework. But that again requires reliable estimates of either quantum of pollution generation or amount of abatement costs. So this exercise cannot be done in any meaningful way.

Finally, in our DEA exercise we have sought to compare performances of different groups of firms (groups being formed on the basis of firms' regional locations/ownership types/internal organisational structures) in terms of only mean levels of' efficiency scores of the different groups. Banker (1993) and Banker and Natarajan (2004) have developed statistical methods to test whether these means are significantly different from each other or not. Hence, the way we have tried to compare performances of different group of firms could have been improved upon. However, we have not taken up this task in the present exercise.

Our exercises have also some policy implications. We have considered several variables as potential determinants of TE of a firm. Among these, *firm size* has turned out to be an important determinant. To be specific, larger firms are seen to be relatively more efficient than their smaller counterparts and this result holds good for both the industries we have studied namely, textile and leather and, for each of the sample years we have considered. From such a stable positive relation between size of a firm and its level of TE, one may recommend, first of all, that large scale production in both textile and leather industries in India should be encouraged, so that the constituent firms become technically more efficient. This will surely go a long way in improving their competitiveness in the international market. Secondly, we have observed that Fixed Asset (FA) is not an important factor of production in the leather industry in India. This may be a reflection of the fact that the overwhelming majority of the leather manufacturing firms here are still practicing some relatively primitive (labour intensive) techniques of production. One might, therefore, argue that more corporate presence with advanced machinery and technical know-how would help Indian leather industry to produce quality products with higher technical efficiency. We have noted in Chapter 6 that the Indian leather industry has massive potential for generating export-led growth and that its major export markets are the developed countries like Germany, the UK, the USA, France and Italy. Since these are relatively high income countries, minimum acceptable quality with even some higher price, rather than poor quality cheap products, may help Indian leather industry to capture markets in these countries. Thus, one feels that official attempts should be made to attract large domestic as well as international ventures into the industry by providing them, to the extent possible, with some basic infrastructural facilities. It is interesting to note the recent effort on the part of central government in this regard. Recently, the Cabinet Committee on Economic Affairs, Government of India, gave its nod for the development of a leather park under the Indian Leather Development Programme (ILDP) and earmarked INR3000 million for it. The aim of the sub-scheme is to provide infrastructure facilities for setting up leather units across product categories so as to attract large domestic joint venture and foreign investments into the leather manufacturing sector. A leather park set up under this sub-scheme is expected to cover all sectors of leather industry – tannery, all products categories and leather machinery (The Hindu *Business Line*, October 23, 2009). Finally, more research work should be encouraged in this area, especially to identify the factors causing production infrastructural heterogeneity across different states/organizations so that appropriate steps could be undertaken to remove them.

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