FARMER EFFICIENCY: THE FRONTIER APPROACH APPLIED TO RICE FARMING IN BANGLADESH

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ABSTRACT

In this study, we have attempted to empirically assess the efficiency of a sample of Bangladeshi farmers in the cultivation of rice, the most important crop in the country. That sample is drawn from Khilghati, a village lying about 95 miles north of the capital city of Dhaka. Our empirical analysis is based on survey data collected by Khandker (1982) for the 1981-82 crop year.

The importance of farmer efficiency in Bangladeshi agriculture cannot be overstated given the predominance of agriculture in the economy, low crop yields and limited land supplies relative to population. While the adoption of "Green Revolution" technologies involving the use of more productive seed varieties and fertilizer inputs are undoubtedly important for increasing yields, and while progress has been made in that direction, attention also needs be paid to improving the efficiency of farmers within the framework of any technology, be it of the traditional or more modern kind. The data for Khilghati provides an opportunity to examine this question. In particular, we construct indices to assess the efficiency of Khilghati farmers in the cultivation of the traditional, wet-season "Aman" and "Aus" rice crops, and the dry season, new-technology "Boro" rice crop.

Several efficiency indices are estimated for each crop. Thus, we construct multi-factor indices of technical and allocative efficiency, as well as factor-specific efficiency indices which are indicators of the efficiency of individual factor usage. Technical efficiency refers to the efficiency of factor use in the physical sense and is an attribute of the production function, while allocative efficiency is a cost concept, and is associated with the question of whether a firm utilizes inputs in the "right" (that is, cost-minimizing) proportions.

Technical and allocative efficiency can be modeled and estimated in different ways [Schmidt (1986)]. In this study, given the nature of the data available, the efficiency indices are constructed from deterministic and stochastic Cobb-Douglas production frontiers. In the deterministic case, all departures from the frontier are taken to represent inefficiency, while stochastic frontiers additionally allow for statistical noise. The estimation of the production frontier generally (though not always) involves assumptions about the distribution of the technical inefficiency term in the deterministic case, and additionally statistical noise in the stochastic case. To examine the sensitivity of the estimates, we consider two alternative assumptions about the technical inefficiency term - one, that it follows a half-normal distribution and two, that it follows an exponential distribution. These distributions imply that technical inefficiency places the firm on or below the deterministic/stochastic frontier. In the stochastic case, we assume that the disturbance term reflecting statistical noise is normally distributed with zero mean and constant variance.

The deterministic frontier is estimated by two versions of the corrected least squares (COLS) as well as by linear and quadratic programming techniques, while the stochastic frontier is estimated by the COLS and maximum likelihood methods. The distributional assumptions stated earlier are critical aspects of the estimation strategy, particularly in the stochastic case where they are needed in order to separate technical inefficiency from statistical noise. Our results indicate that the efficiency estimates are somewhat sensitive to estimation method and distributional assumptions, though primarily in the deterministic case. More importantly, we find that the relative ranking of farmers along the technical or allocative efficiency spectrum is largely independent of estimation method and distributional assumptions under the deterministic and stochastic approaches. The major difference between the two approaches is that, under the latter, the average level of technical efficiency is clearly higher, with statistical noise being an important reason for departures from the deterministic kernel. This points to the importance of allowing for statistical noise. The following discussion deals with estimates obtained from the stochastic frontier, unless noted otherwise.

The estimates of technical efficiency suggest that Khilghati farmers are highly efficient in the cultivation of all crops, with at least 70 percent of farmers having a technical efficiency index in excess of 80 percent. Average technical efficiency is about 90 percent in Aman, and about 85 percent in Aus and Boro cultivation. In allocative terms, farmers are markedly less efficient, and the inter-crop variation is also greater. Thus, average allocative efficiency is in the 70-75 percent range for Aman and Boro, but only about 50 percent for Aus. Alternative distributional assumptions have only a minor impact on the allocative efficiency estimates and a somewhat larger impact on the technical efficiency estimates.

We used our estimates of technical and allocative efficiency to examine a number of issues. Thus, correlation analysis provides limited evidence to indicate that a farm household's technical (allocative) efficiency indices are related across crops, indicating perhaps that efficient cultivation practices are crop-specific, and that farmers' growing experience and/or learning by doing also vary across crops. We also found little evidence to support the view that technically more efficient farmers are also allocatively more efficient. In addition, we examined the widely held view that better educated farmers are relatively more efficient in the technical and/or allocative senses, in a regression context. Only allocative efficiency in Aman cultivation and technical efficiency in Boro cultivation were found to bear a statistically significant positive relationship with farmer education.

Our factor-specific estimates of efficiency suggest that farmers are least efficient, in the physical sense, in the use of labour (the relatively abundant factor), and generally most efficient in the use of land (the relatively scarce factor). The inefficiency of labour usage is substantial; however, the greatest gain (in terms of cost saving) would be realized through the elimination of inefficiency in land or other inputs, and not labour.

Several implications follow from our findings. Farmers appear to be as efficient in the new-technology Boro crop as in the traditional Aman and Aus crops. A policy of encouraging the adoption of such HYV crops is thus well-founded. However, attention clearly needs to be paid to improving farmer skills within the existing crops. For instance, rural development policies could be geared to improving allocative skills, perhaps through rural education, and more effective management of extension services and rural co-operatives. Our estimates point to a substantial cost saving via such an improvement. Those policies would probably have to take account of possible differences in efficient cultivation practices across crops. Policies aimed at improving the efficiency of highly scarce inputs such as land could also go a long way towards improving the overall efficiency of farmers. In fact, since the relative price of land can be expected to increase over time, the cost reductions by improving the efficiency of land use could be substantial. Finally, it may be that institutional constraints on individual behaviour foster inefficiency. For example, the lack of access of smaller farmers to credit, government-supplied chemical fertilizer and public services may lead them to make inefficient choices. Ensuring greater access to those farmers could be important in promoting greater efficiency.

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Needless to say, I alone am responsible for all remaining errors.

For

Kunwar K. Dar
Jura Smith

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CHAPTER 1

THE NATURE AND ORGANIZATION OF THE STUDY

The focus of this study is on the measurement of efficiency of farmers in Bangladesh, a primarily agricultural economy. Schultz's 1964 contention that farmers in developing countries are poor but efficient provided a strong impetus to empirical studies in the area.[1] Earlier studies by Tax (1953) and Hopper (1957) appeared to confirm this contention.[2] The tests for efficiency also gave rise to numerous studies which explored the role of various factors in fostering greater efficiency. In this context, the role of education, both formal and informal, was explored by many investigators. As the survey article by Lockheed (1980) suggests, better educated farmers tend to be more efficient than uneducated ones.[3] The exploration of static efficiency soon spilled over into questions pertaining to dynamic efficiency. That is, notwithstanding the static efficiency of farmers (i.e. within the framework of a given technology) in developing countries, the questions being posed were: do farmers adapt to changing technology, how successful are they, and what are the factors explaining their response.[4] This is an important set of questions in countries like Bangladesh where the government has actively sought to encourage the adoption of "Green Revolution" technologies.

In the context of poor, agriculture-based economies, the question of efficiency is an extremely important one. Clearly, whether farmers are more or less efficient in any sense could mean significantly different standards of living, given the dominance of farming in economic activity. Thus, if farmers are inefficient, government policies aimed at increased efficiency could be extremely important in fostering higher standards of living for a large proportion of the population. It is, therefore, also important to explore the reasons underlying that inefficiency so that the appropriate policies for reducing it can be fashioned. The significance of these issues should not be understated for Bangladesh agriculture, the focus of this study.

Bangladesh is a predominantly agricultural economy, characterized by extremely high population pressure and very low standards of living. Population growth has averaged about 2.1 percent per annum through the eighties, and the density of population was a high 769 per square kilometer in 1989. In spite of the decline in the share of agriculture in gross domestic product through the seventies and eighties, agriculture accounted for close to 50 percent of gross domestic product by the mid-eighties, and continues to be the source of livelihood for a majority of the population.[5] The production of foodgrains, particularly rice, is the major agricultural activity. Thus, while rice and wheat together accounted for an average of more than 83 percent of gross cropped area during the 1980-1982 period, rice itself accounted for 80 percent of cropped area, and for 93 percent of foodgrains produced over that period.[6] Jute is the other major crop grown; it competes with rice for productive resources, as their growing seasons overlap. While Bangladesh is a net importer of foodgrains, jute is the major export commodity. Thus, agriculture plays a significant role, not only in supplying the wage-goods for the population at large, but as the major source of the foreign exchange required to develop the industrial sector sector of the country so that the vast surpluses of labour in agriculture can be absorbed. Consequently, rapid agricultural growth can be expected to play a leading role in determining the standard of living of the vast majority of the populace. This can be achieved through faster capital accumulation and increased productivity. However, given that Bangladeshi agriculture is based on small landholdings, and the potential supply of cultivatable land is limited, increased farmer productivity acquires even greater significance, and greater efficiency of resource use is a potentially important channel through which increases in productivity can be attained. This requires not only greater efficiency within the framework of older technologies, but also a rapid and efficient adaptation to the newer ones.

The government initiated the spread of "Green Revolution" technologies during the early sixties, and since then there has been an impressive increase in fertilizer use, irrigated area and the cropped area under high-yielding seed varieties, particularly in the production of rice.[7] Nevertheless, Bangladesh agriculture is still primarily based on largely traditional farming practices, and agricultural yields are among the lowest in the world. The unequal access of small farmers to important, new technology inputs, as a result of a number of social and institutional barriers, has undoubtedly been one important factor in impeding the efficient adoption of the new technology, particularly in the production of the high-yielding winter rice crop which requires timely availability of water supplies and inputs such as fertilizer [see, for instance, Ahmed and Freedman (1982)]. Whether that inefficiency is significant, and whether it varies to an appreciable degree between high-yielding and other crops in Bangladesh agriculture, remains an empirical issue, and one which we attempt to address in this study.

Our study examines empirically the efficiency question, using as our sample a group of farmers taken from the village of Khilghati, which lies some 95 miles north of the capital city of Dhaka. The data for this village for the three cropping seasons, running from April 1981 through March 1982, were collected by Khandker (1982) through three sets of interviews conducted during the July 1981-March 1982 interval. Khilghati is quite typical of villages in

Bangladesh, though in contrast to some other villages it specializes mainly in the production of rice which occupies almost 90 percent of the cropped area, a figure well above the national average. It grows three rice crops during the year, the cultivation of the high-yielding winter rice reflecting the adaptation to new technologies. Our primary focus is on the measurement of the efficiency of Khilghati farmers, both in the technical and allocative senses, and the determination of whether there is a pattern to the variation in efficiency across crops, and of what factors appear to explain inter-farm efficiency differentials.

The concept of efficiency lies at the very foundations of economic theory. Several types of efficiency can be identified, each corresponding to different aspects of the production process. Thus, technical efficiency can be represented by the production function/frontier, which shows the maximum output producible from any given set of inputs, while economic efficiency is represented by the cost function/frontier and subsumes both technical and allocative efficiency, the latter requiring the correct factor proportions to produce any level of output. The broadest concept of efficiency is illustrated by the profit frontier which requires not only that the firm is economically efficient (that is, technically and allocatively efficient), but also scale-efficient, in that it chooses the profit maximizing level of output.[8] The conditions for efficiency can also be extended to deal with multiple output technologies. At the theoretical level, the production, cost and profit functions are all frontiers in that each specifies the maximum/minimum attainable values. From the empirical viewpoint, therefore, the problem is to estimate those functions, such that actual output or profit does not exceed frontier output or profit, and actual cost is no less than frontier cost.

In his pioneering study, Farrell (1957) showed how one could measure technical, allocative and economic efficiency by estimating a non-parametric production frontier, characterized by constant returns to scale. However, frontier estimation, particularly of the parametric type, did not receive much attention for many years after that. In 1968, Aigner and Chu showed how a parametric production frontier could be estimated by programming methods. However, even their work was followed by only a relatively few attempts to empirically measure parametric frontiers. It is only over the past decade or so that the measurement of such frontiers has attracted considerable attention but there is now a substantial literature on the subject. Much of the earlier empirical literature on frontier estimation viewed the frontier as being deterministic, so that all departures from that frontier were attributed to inefficiency [Farrell (1957), Aigner and Chu (1968), Timmer (1970), are some examples]. A more general approach was suggested subsequently by Aigner et al. (1977) and Meeusen and van den Broeck (1977), who regarded the frontier itself as being stochastic. As a result, departures from the deterministic kernel could represent both random factors beyond the control of the firm (that is, statistical noise) as well as inefficiency. Parametric, stochastic frontiers are now commonly used in empirical studies, even though theoretical frontiers are deterministic. The primary advantage of stochastic frontiers stems from the fact that their use reduces the danger of inefficiency being confused with statistical noise.[9] On the other hand, they suffer from the drawback that specific distributional assumptions about the statistical noise and inefficiency terms are needed in order to estimate firm-specific efficiency, and the estimates can be sensitive to those assumptions. This problem can be dealt with more satisfactorily if panel data are available [see, for instance, Schmidt and Sickles (1984), Cornwell, Schmidt and Sickles (1990), and Kumbhakar (1990)]. However, the sample used in this study is cross-sectional;

consequently, in order to obtain firm-specific estimates of efficiency, we have had to make distributional assumptions about the statistical noise and inefficiency terms. We, nevertheless, consider alternative assumptions to examine the sensitivity of our results.

As stated earlier, our interest in this study lies in the measurement of technical and allocative efficiency in rice farming in the Bangladeshi village of Khilghati. As a consequence, we do not consider questions pertaining to scale efficiency and profit frontiers. Either the cost frontier or the production frontier can serve as the basis for measuring a farmer's technical and allocative efficiency [see, for instance, Kopp (1981), Lovell and Schmidt (1979) and Kopp and Diewert (1982)]. This is straightforward when the technology is self-dual. The use of the cost frontier as the relevant efficiency standard is ruled out in this study in view of the absence of sufficient factor price variation among the farm households in our sample. Thus, we estimate a production frontier and construct farm-specific technical and allocative efficiency indices for each of the three dominant crops in Khilghati. These are the "Aus" (spring), the broadcast "Aman" (summer) and the high-yielding "Boro" (winter) rice crops grown over the crop cycle beginning in March. In addition, these indices are constructed from both deterministic and stochastic production frontiers. The production frontier yields two alternative measures of technical efficiency. One is an output-based index and the other is a generalized Farrell, input-based index [see Kopp(1981)]. Since the two are identical only under rather special conditions, we compute both indices. The allocative efficiency indices computed are those suggested by Kopp, and are also generalizations of the Farrell index. The input-based technical and allocative efficiency indices additionally enable us to estimate the extra cost resulting from both technical and allocative mistakes. The aforementioned indices of technical and allocative efficiency are multi-factor indices, in that they cannot tell us anything about the relative efficiency of different factors. It is possible, however, to estimate both factor-specific technical and allocative efficiency indices for each farm household, and this we also do for each farm household and crop, using the approach suggested by Kopp.

The estimation of parametric production frontiers raises some special considerations, apart from those that are common to all empirical studies. Among the latter is the important question of functional form. In this study, the production function is assumed to take the Cobb-Douglas form. While, on prior grounds, a more general specification (e.g translog) would be preferable, many frontier studies have successfully applied the simpler Cobb-Douglas function. In addition, as we argue in Chapter 2, the latter is not without some advantages in a frontier setting, particularly in the context of the measurement of allocative efficiency. Once the functional form is specified, the production frontier can be estimated in a number of different ways. To begin with, the deterministic frontier need not be estimated by statistical methods, and thus requires none of the assumptions associated with single equation econometric estimation. Thus, following Aigner and Chu (1968), we minimize (i) the absolute sum and (ii) the sum of squares of the difference between frontier and actual output, each under the constraint that actual output is no greater than frontier output at each observation. With a Cobb-Douglas frontier, the former is a linear programming problem and the latter is one of quadratic programming. Of course, since we merely compute the frontier, it has the drawback of having no formal statistical properties. As it turns out though, the linear programming and quadratic programming "estimators" are in fact identical to the maximum likelihood estimators, under the assumption that the disturbance in the log-linear Cobb-Douglas function follows an exponential and half- normal distribution respectively [Schmidt (1976)].[10] However, the usual properties of maximum likelihood estimators do not apply since one of the regularity conditions upon which those properties depend is violated.[11]

We also estimate the deterministic frontier by statistical methods. We assume that the disturbances in the frontier function are identically and independently distributed, that the input quantities are independent of those disturbances, that technical inefficiency is unknown to the farmers, and that farmers maximize expected or median profits. Under those assumptions, ordinary least squares gives consistent estimates of all parameters except the intercept term.[12] However, ordinary least squares does not estimate a frontier, so we modify that method and adopt what can be termed the "corrected" least squares method (COLS for short). We consider two alternative versions of COLS. Both give consistent estimates of the intercept as well [see Greene (1980)]; however, one requires an explicit assumption about the distribution of the disturbance term and does not guarantee that actual output will not exceed frontier output. In light of the fact that the results can be sensitive to that specification, we consider two alternative distributions - the exponential and half-normal - to represent technical inefficiency.

The estimation of the stochastic frontier depends upon distributional assumptions in a more fundamental way. A distributional assumption is required for both components of the disturbance term - one reflecting statistical noise and the other reflecting technical inefficiency. The former is assumed to follow a normal distribution, while the latter is assumed to follow, as in the deterministic case, either an exponential or a half-normal distribution. In this study, the production frontier is first estimated by the COLS method, and then by the asymptotically more efficient maximum likelihood method. Because the maximum likelihood function, in this case, is not the standard type, analytical formulae for the parameters cannot be derived. Solutions have to be sought through numerical optimization. Whether we use the COLS or maximum likelihood method, the distributional assumptions stated above are crucial requirements for separating technical inefficiency from statistical noise, in order to estimate the stochastic frontier at the level of the individual farm.

The study is organized as follows. In chapter 2, we discuss three sets of issues. First, in Section 2.2, we present an overview of the theoretical concepts of technical, allocative, economic and price efficiency. Section 2.3 contains a detailed discussion of the alternative approaches to the measurement of efficiency, the starting point being the non-parametric approach first suggested by Farrell (1957); this material is provided in sub-section 2.3.1. Sub-section 2.3.2 discusses the notion of parametric frontiers as efficiency standards, drawing a distinction between deterministic and stochastic frontiers, and how they can be used to model inefficiency. The methods and problems of measuring technical and allocative efficiency from a knowledge of either the production or cost frontier, as well as those of measuring factor-specific technical and allocative efficiency are also discussed. We conclude this sub-section by examining some of the problems that arise for the measurement of allocative efficiency when a firm's actual output, the basis for efficiency measurement, differs from the output the firm expected to produce. This is a potentially important problem and appears to have been largely ignored in the literature. We discuss some of the major measurement issues raised by this problem.

In Section 2.4 we examine the problems of specification and estimation of frontiers. Our purpose here is to review those aspects of specification and estimation that are somewhat unique to frontiers. Sub-section 2.4.1 addresses the problem of specification in the broad sense. Thus, we discuss not only the question of functional form, but also the implications of various distributional assumptions and how the problem of separating statistical noise from technical inefficiency can be dealt with. The estimation methods (alluded to in the foregoing pages), and the assumptions underlying them are reviewed in sub-section 2.4.2. Section 2.5 concludes by summarizing the main points of the chapter.

The purpose of Chapter 3 is twofold. First, in Section 3.2, we present an outline of our sample economy, the village of Khilghati. Our discussion is brief and we concentrate on those characteristics of Khilghati that have a direct bearing on this study, such as the structure of economic activity [discussed in sub-section 3.2.1] and the nature of tenancy arrangements, factor markets and employment [discussed in sub-section 3.2.2]. The second objective of this chapter is to provide a clear presentation of our models and the estimation strategy. This is done in Section 3.3 . We first discuss the considerations governing our choice of production frontier for Khilghati, the input set included and the problems of measuring factor prices needed for the measurement of allocative efficiency; this discussion is provided in subsections 3.3.1 and 3.3.2. In sub-section 3.3.3 we outline our estimation strategy, as well as the computational procedure for obtaining each of our efficiency indices. Section 3.5 is a summary of the chapter.

In Chapters 4 and 5, we present and evaluate our findings. Chapter 4 deals with the results based on a deterministic frontier, while those from the stochastic frontier are examined in Chapter 5. One of the questions we attempt to address in these chapters pertains to the likely causes for inter-farm as well as inter-crop variations in allocative and technical efficiency. In particular, we examine whether factors such as farmer education and/or membership in agricultural co-operatives are important in this context, and whether their role varies significantly across crops. In Chapter 6, we summarize our findings and point to some important implications that follow from them.

FOOTNOTES TO CHAPTER 1

1. Schultz (1964).

2. For a contrary view, see Shapiro (1983).

3. Lockheed et al.'s examination of thirteen studies suggests that education does have a positive impact on technical efficiency, and that the likelihood of a positive impact is greater the more modernizing the environment. While some writers like Phillips (1986) have questioned some aspects of the Lockheed et al. interpretation of these studies, the growing evidence is that there is a threshold education level, below which education has only a minor impact on technical efficiency.

4. See, for instance, Jamison and Moock (1981).

5. Thus, up until the early eighties, about 75 percent of the labour force was engaged in agriculture. See Khandker (1982), p. 157, footnote 1.

6. These figures are taken from Alauddin and Tisdell (1988), p. 199.

7. Ibid., p. 200.

8. The term allocative efficiency is often used to imply profit maximization. In this study, we use it to signify equality between the ratio of marginal products of any pair of factors and their respective prices, which corresponds to cost minimization.

9. Deterministic and stochastic frontiers have been surveyed by Forsund, Lovell and Schmidt (1980) and Schmidt (1986). Recent developments in the area are the subject of a paper by Bauer (1990). The literature surveyed in these papers deals primarily with the econometric estimation of parametric frontiers. In the operations research/management science fields, however, a parallel literature, emphasizing a non-parametric, mathematical programming approach has also grown rapidly. This alternative approach, popularly known as "Data Envelope Analysis" (DEA), was pioneered by Charnes, Cooper and Rhodes (1978, 1981), and has recently been surveyed by Seiford and Thrall (1991). DEA represents a non-parametric extension of Farrell (1957) and utilizes mathematical programming techniques to construct frontiers. It, therefore, imposes no functional form nor distributional assumptions on the data. However, it has the drawback that statistical noise is ignored (all frontiers are deterministic), and the statistical properties of the estimates are unknown. In our study, the focus is largely on econometric frontiers. We do, however, estimate some deterministic frontiers by programming methods.

10. In the deterministic frontier, a one-sided disturbance term is required to represent technical inefficiency. The exponential and half-normal distributions meet this requirement. In the stochastic frontier, a specific assumption about the distribution of the variable reflecting statistical noise is also required.

11. Schmidt (1976).

12. See, for instance, Kumbhakar (1987).

CHAPTER 2

THE MEANING AND MEASUREMENT OF EFFICIENCY: A REVIEW

2.1 INTRODUCTION

In this chapter, our purpose is to review the major theoretical and empirical issues pertaining to the measurement of firm efficiency. We begin with a brief discussion of various ways in which the efficiency of a firm can be characterized (Section 2.1). Section 2.2 deals with the various approaches to modeling and measuring efficiency, and their problems. In that section, the discussion proceeds on the assumption that the relevant efficiency standard used for measuring firm efficiency is known. The problems relating to the specification and estimation of those efficiency standards are discussed in Section 2.3. Section 2.4 summarizes the chapter.

2.2 THE CONCEPT AND TYPES OF EFFICIENCY: A THEORETICAL OUTLINE

In theory, firm efficiency can be of three types, depending upon which aspect of the firm's productive process is being referred to. These can be described in precise fashion by considering a firm that produces a single output with the help of a vector of production factors.[1] We assume that the firm buys the services of factors and sells its output at fixed prices. It is further assumed that the underlying technology can be represented by the production function:

$$y = f(x) \qquad (1)$$

where y is output and x is the vector of production factors. The production function of a firm depicts the maximum output that can be produced from any given vector of inputs. In that sense, the function described by (1) depicts an efficient transformation of inputs into output. More formally, a production plan $\{y^o, x^o\}$ is technically efficient if $y^o = f(x^o)$, and technically inefficient if $y^o < f(x^o)$. That is, any plan that places the firm below the frontier represented by (1) is inefficient in a technical sense. Technical inefficiency could arise if the technology is not fully known, or if it is poorly implemented (bad management), or a combination of both. In view of the fact that the production function is the primary constraint on the firm's behaviour, technical efficiency (or the lack of it) is a critical factor in the overall efficiency of the firm.

If the production function (1) is well behaved, a firm's efficiency can also be studied in terms of its dual - the cost function - which is:

$$C = C(y, r) \tag{2}$$

where C stands for cost and r is the vector of factor prices. The cost function shows the lowest cost for producing any given output, given factor prices and the underlying technology (1). If the production plan of a firm satisfies (2), then that plan can be said to be economically efficient. More formally, a production plan $\{y^o, x^o\}$ is economically efficient if $r'x^o = C(y^o, r)$, and economically inefficient if $r'x^o > C(y^o, r)$.

A third representation of efficiency can be made in terms of the profit function, on the assumption of profit maximization given (1), (2) and a fixed product price p. Under this assumption, we can write the profit function as:

$$\Pi = \Pi(p, r) \tag{3}$$

where Π stands for profit. The profit frontier shows the maximum profit attainable, given the technology and product and factor prices. The production plan $\{y^o, x^o\}$ can be said to be price efficient if $(p^o y^o - r' x^o) = \Pi(p,r)$. Price inefficiency thus arises if the profit earned from a given production plan is less than the maximum attainable profit.

Each of the above functions represents a particular type of efficiency, and in light of the fact that each embodies optimality of some kind, each can be viewed as a frontier in that no production plan that is feasible can place the firm above it in the case of the production or profit frontier, or below it in the case of the cost frontier. Frontiers have come to occupy a central place in the study of firm inefficiency. In particular, once a frontier can be estimated such that all observations are bounded by it, firm inefficiency of a particular type can be evaluated in terms of departures from that frontier.

It follows from the foregoing discussion that price efficiency is the broadest of the three types of efficiency dealt with. In particular, the existence of price efficiency implies economic efficiency, while the latter implies technical efficiency. On the other hand, technical efficiency is necessary but not sufficient for economic efficiency, and the latter is necessary but not sufficient for price efficiency. Clearly, economic efficiency requires something more than technical efficiency, and price efficiency requires something beyond economic efficiency. These additional requirements for economic and price efficiency necessitate two additional efficiency concepts - namely, allocative and scale efficiency. These can be illustrated as follows.

In order for a production plan to be economically efficient, the given output must be produced at minimum cost. If that plan is inefficient in a technical sense (input use is in excess of the minimum required), this would translate into extra costs and hence economic inefficiency. However, even if the production plan is technically efficient, costs could be above the minimum if the inputs are not used in the "right" proportions. Thus, economic efficiency requires not only that the production plan be technically efficient, but that it also involve using inputs in the "right" proportions. The latter requirement is known as allocative efficiency, and is met if the ratio of marginal products of any pair of factors equals the ratio of their prices. That is,

$$f_i(x) \,/\, f_j(x) \;=\; r_i \,/\, r_j \quad \text{for all } i \text{ and } j \tag{4}$$

where f_i and f_j are the marginal products of factors i and j respectively. Thus, technical and allocative efficiency imply (and are implied by) economic efficiency, and departures from the cost frontier (economic inefficiency) could reflect technical or allocative mistakes, or both.

A production plan that is economically inefficient (due to technical or allocative mistakes, or both) must also be price inefficient, since then the firm could not be maximizing profits. However, even if the plan were economically efficient, that would not be sufficient for maximum profits, since the firm could be producing the wrong output. Economic efficiency guarantees that the chosen output is produced at minimum cost, but it does not guarantee that that output maximizes the difference between revenue and cost. To ensure the latter, the firm must additionally choose the correct output (scale). This requirement is known as scale efficiency, and is met if, under our assumption of a fixed product price p, marginal cost equals product price.

That is, if $p = C_y$, where C_y is marginal cost. Thus, technical, allocative and scale efficiency imply (and are implied by) price efficiency. It follows, therefore, that departures from the profit frontier (price inefficiency) could reflect technical inefficiency, allocative inefficiency, scale inefficiency, or some combination thereof.

The brief sketch above provides the basic theoretical framework that underlies most empirical approaches to efficiency measurement, whether or not those approaches adopt the theoretical concept of a frontier. In this study, we do not deal with the non-frontier approach to efficiency measurement.[2] It is assumed that efficiency standards can be represented by the relevant frontiers, and our discussion in the rest of this chapter looks at the problems of modeling inefficiency and the specification and estimation of frontiers. Further, since the primary focus is on technical and allocative efficiency, we do not discuss scale, and hence price, efficiency. In most cases, our discussion can be modified and extended to deal with the latter type of efficiency or with more general multiple-output technologies.

2.3 THE MEASUREMENT OF EFFICIENCY: A REVIEW OF ALTERNATIVE MODELS

Approaches to the measurement of efficiency differ according to the choice of efficiency standard, the manner in which inefficiency is modeled and the methods used to estimate the standard. The purpose of this section is to present an overview of the issues relating to the choice of the efficiency standard and the modeling of technical and allocative efficency.[3] We begin with the pioneering , non-parametric work of Farrell (1957), which was the precursor of the newer and more general parametric frontier approaches.

2.3.1 THE FARRELL APPROACH

In his now classic 1957 article, Farrell proposed indices that could be used to measure both the technical and allocative efficiency of a firm. He chose as the efficiency standard the unit isoquant, which under his assumption of constant returns to scale is fully representative of the entire technology. Empirically, the efficiency standard was the outer envelope of the convex hull for one unit of output, constructed from the observed input-output ratios by linear programming techniques. In the two input case, Farrell's efficiency standard can be represented by the curve abcd in Figure 1 below. This could be replaced by a smooth isoquant without changing the analysis. Farrell used this unit isoquant to propose measures of technical, allocative and economic efficiency.

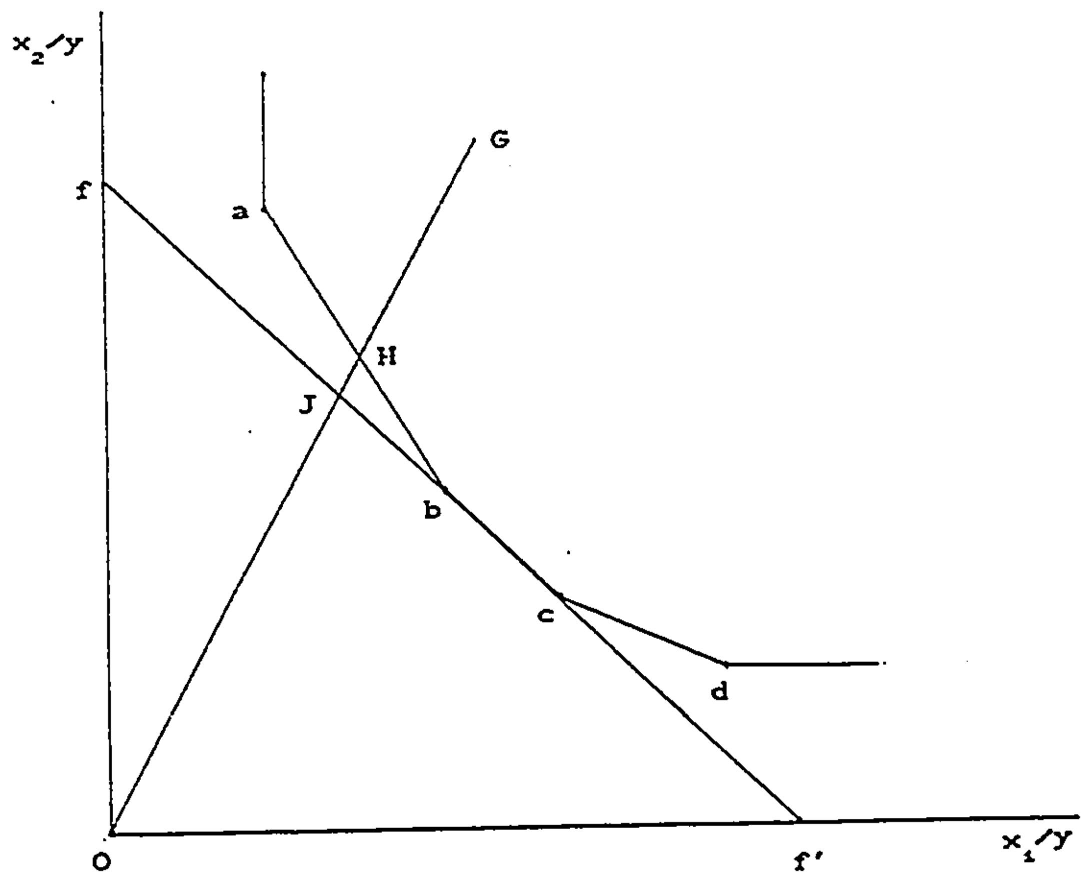
Consider an actual factor combination - say that given by point G in the figure. Farrell proposed that the technical efficiency of G , denoted by TE(G) can be measured as

$$TE(G) = OH/OG \tag{5}$$

where H is the technically efficient production plan whose factor ratio is identical to that of G. Note that $0 < TE(G) < 1$ and $[1 - TE(G)]$ represents the proportionate reduction in both inputs required to eliminate technical inefficiency, holding the factor ratio constant.

Farrell also proposed a measure of the allocative efficiency at G that was independent of the technical inefficiency at that point. Suppose that factor prices are such that the isocost line ff' is tangent to the linear segment bc. Any factor combination on that segment is an optimal one. Farrell's index of

FIGURE 1



allocative efficiency, AE(G), is then:

$$AE(G) = OJ/OH \tag{6}$$

where J uses the same factor ratio as G and costs no more or less than any of the optimal combinations along bc. This measure of allocative efficiency is clearly independent of the degree of technical inefficiency at G, and thus measures the inefficiency arising only out of allocative mistakes. Indeed, [1 -AE(G)] measures the proportionate cost saving that would be achieved by eliminating allocative inefficiency by moving from factor ratio H to any ratio consistent with the segment bc. Note that, in this framework, TE(G) can also be given a cost interpretation. In particular,[1 - TE(G)] measures the proportionate cost saving possible by eliminating technical inefficiency (that is, by moving from G to H).

On the basis of these measures, Farrell proposed that the overall economic efficiency of G, EE(G), would be indicated by the product of TE(G) and AE(G). That is,

$$EE(G) = (OH/OG)(OJ/OH) = OJ/OG \tag{7}$$

It is clear that [1 - EE(G)] measures the proportionate cost reduction resulting from the elimination of technical and allocative inefficiency. Alternatively, this cost reduction can be viewed in terms of its components as follows:

$$\text{Overall cost reduction} = 1 - EE(G) = JG/OG$$

$$\text{But } JG/OG = (JH + HG)/OG = JH/OG + HG/OG$$

$$= [1 - TE(G)] + [1 - AE(G)]$$

In summary, the Farrell approach is to estimate a non-parametric efficiency frontier and, under the assumption of constant returns to scale, to propose input-based measures of technical and allocative efficiency. Attempts to extend the approach to non constant returns and/or nonhomogeneous technologies proved cumbersome.[4] As a result, Farrell's measures were not applied much. An important step in the development of efficiency measurement, itself a consequence of Farrell's work, was the specification of the efficiency standard in mathematical form. This fostered the development of the now commonly-used parametric approaches to efficiency measurement. While most of the newer parametric approaches involve measures of efficiency that are not of the Farrell type (that is, are not input-based), Kopp (1981), in a useful paper, showed how generalized Farrell indices of technical and allocative efficiency could be obtained from a parametric frontier function that was not restricted to constant returns to scale and/or homogeneous technologies.[5] These generalized Farrell indices are discussed later in this section.

2.3.2 PARAMETRIC FRONTIERS AND EFFICIENCY MEASUREMENT

A logical extension of Farrell's non-parametric approach was the specification of the relevant efficiency standard in mathematical form. This permitted the analysis to be generalized to non-homogeneous technologies, and facilitated the development of alternative measures of efficiency. Once the form of the parametric frontier is specified, it can be estimated by statistical, and in some cases by non-statistical methods from sample data and the efficiency of actual production plans can then be evaluated in terms of departures from the relevant frontier. In particular, the production frontier can be used to measure technical efficiency, while the cost and profit frontiers enable the estimation of economic and price efficency. Since our primary interest in this study is on technical efficiency and allocative efficiency, our discussion will deal primarily with those types. Nevertheless, much of this discussion carries over (with minor modifications) to price efficiency.

Deterministic vs. Stochastic Frontiers as Efficiency Standards

Parametric frontiers as efficiency standards can be either deterministic or stochastic.[6] Much of the earlier literature on the subject [see for instance Aigner and Chu (1968) and Timmer 1971)] dealt with frontiers that were assumed (implicitly) to be deterministic.[7] Under this scheme all departures from the relevant frontier represented inefficiency. Thus, considering the case of production, the technical efficiency of any production plan can be measured by the following index:

$$w = y/f(x) \tag{8}$$

where y is the actual output and $f(x)$ the frontier output associated with the production plan, and the technical efficiency index w lies in the zero-one interval. Notice that w is an output-based measure of technical efficiency, focusing as it does on the proportionate amount by which output could be increased by eliminating that inefficiency. It is thus conceptually different from the Farrell input-based index, which measures technical efficiency in terms of the degree of excessive input usage. Under the Farrell restriction of constant returns to scale the two indexes are identical, but under more general conditions this would no longer be true, a point discussed in greater depth later in the chapter. With minor modifications, the above discussion carries over to the measurement of economic efficiency in terms of departures from the deterministic cost frontier. Of course, those departures indicate inefficiency arising from both technical and allocative mistakes. A deterministic cost frontier with economic inefficiency can be written as

$$C = C(y, r)v \tag{9}$$

where C is actual cost, C(.) is the cost frontier, r is the vector of factor prices and v is an indicator of economic efficiency. An index of economic efficiency is then simply (1/v) which lies in the zero-one interval, and indicates the proportionate cost saving possible through the elimination of economic inefficiency. However, the additional costs separately attributable to technical and allocative mistakes cannot, in general, be ascertained from a knowledge of actual costs and the cost frontier alone, just as a knowledge of an actual production plan and the production frontier alone tells us nothing about allocative inefficiency. We turn to these issues shortly.

Our discussion thus far has dealt with the measurement of efficiency under the assumption of deterministic frontiers. Their primary drawback, from the empirical viewpoint, is that they attribute all departures from the relevant frontier to inefficiency. However, in light of the fact that departures from frontiers may well reflect factors of a random nature, entirely outside the control of the firm, the deterministic approach is clearly simplistic from an empirical viewpoint. We thus turn to the logical generalization of the deterministic frontier - the stochastic frontier developed by Meeusen and van de Broeck (1977) and by Aigner et al. (1977).

A stochastic frontier permits departures from the deterministic kernel to result both from inefficiency and from random factors beyond the control of the firm. It is nevertheless possible to isolate these two types of departure, and hence to measure technical and economic efficiency in terms of those departures from the relevant frontiers. The basic idea behind stochastic frontiers can best be illustrated by considering a stochastic production frontier, though our exposition applies equally to cost or profit frontiers. A stochastic frontier that embodies technical inefficiency can be expressed as

$$y = f(x)e^{v-u} \tag{10}$$

where the production frontier is now stochastic and represented by $f(x)e^{v}$ and e^{-u} represents technical inefficiency. The index of technical efficiency is now modified to

$$e^{-u} = y/f(x)e^{v} \tag{11}$$

Thus, once the stochastic frontier is known, the technical efficiency of any production plan can be obtained. More specifically, under certain assumptions and the appropriate estimation methods (to be discussed later), it is possible to estimate both u and v and thus measure the technical efficiency of each firm. The above composite-error model has been used extensively to model inefficiency in the many empirical studies undertaken since the earlier work of Muesen and van den Broeck and Aigner et al.[8] However, production and cost frontiers (deterministic or stochastic) in themselves indicate only the degree of technical and allocative inefficiency, respectively. Nevertheless, it is possible to use either frontier to measure both technical and allocative efficiency. We turn next to this and related issues.

Measuring the Technical and Allocative Components of Economic Inefficiency

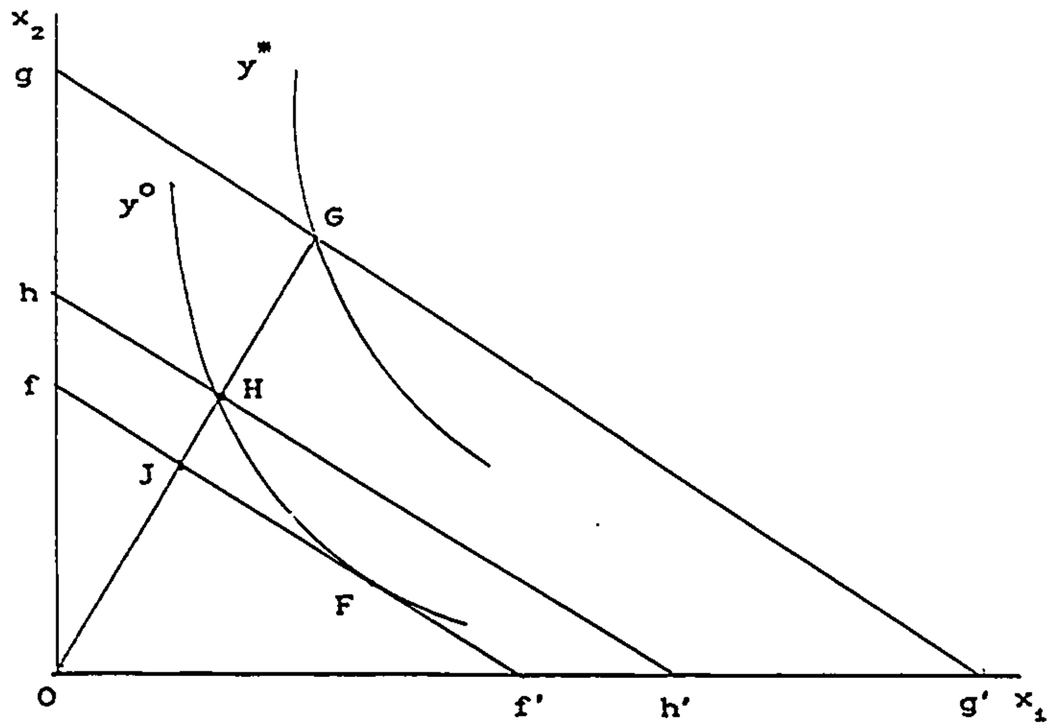
In principle, the measurement of both technical and allocative efficiency can proceed in two (not entirely independent) ways. First, one can generalize the Farrell approach to allow for non-constant returns to scale or non-homogeneous technologies and measure either type of efficiency using either the production frontier or the cost frontier along the lines suggested by Kopp (1981), Kopp and Diewert (1982) and Zeischang (1983). Secondly, one can explicitly model allocative inefficiency in much the way that technical inefficiency is modeled. This approach was first suggested by Schmidt and Lovell (1979), and subsequently extended or used by Schmidt and Lovell (1980) and Kumbhakar (1987).

Kopp (1981) showed that a parametric production frontier, restricted neither by constant returns to scale nor homogeneity, could be used to obtain Farrell-type measures of technical and allocative efficiency.[9] These generalized Farrell measures can be illustrated with the help of Figure 2 below for the two-input case. Consider the production plan (y^o, x^o). This plan is depicted by point G and the isoquant labelled y^o in the figure. In order to assess G's inefficiency without imposing constant returns to scale or homogeneity, output effects have to be removed. This is achieved by comparing the actual factor combination with the technically efficient combination required to produce the same output at the same factor ratio. The latter combination is H, and in line with Farrell, a measure of technical efficency is

$$TE(G) = OH/OG \qquad (12)$$

Notice that this input-based measure would in general differ from the

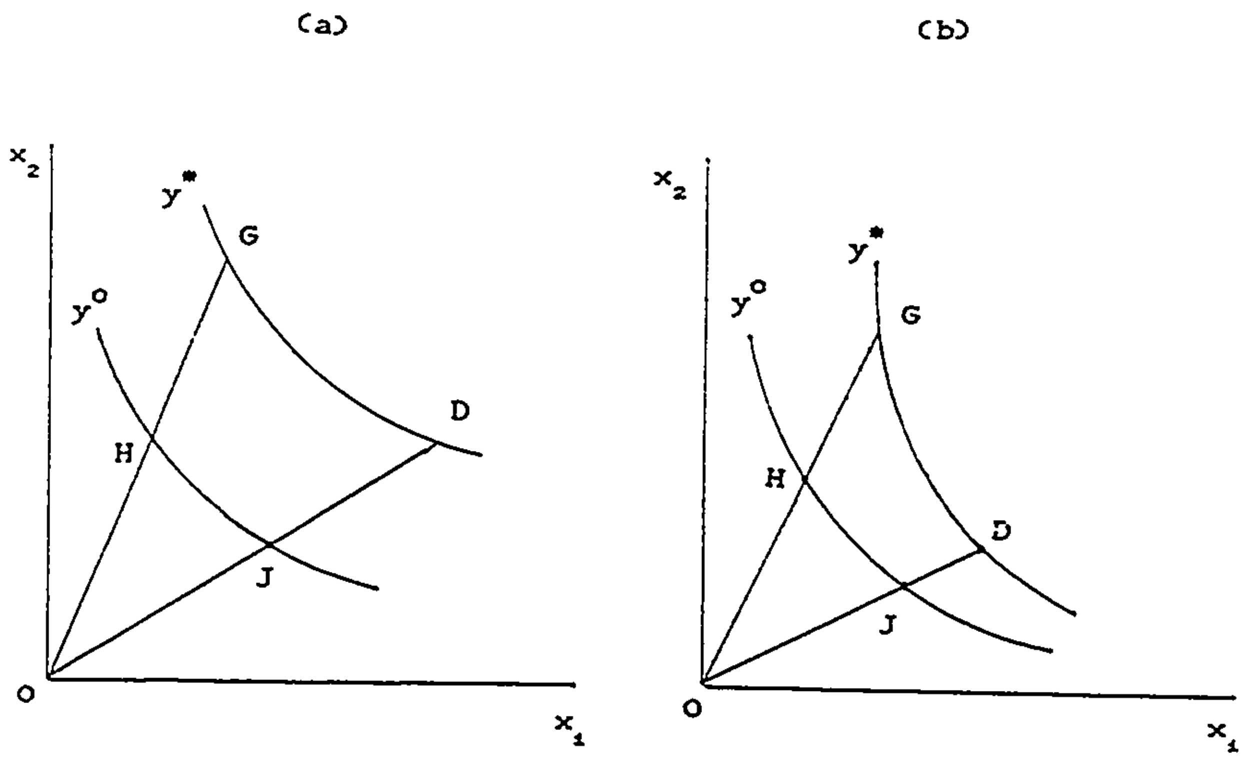
FIGURE 2



output-based measure given by either (8) or (11). Thus, suppose the frontier function implies an output of y^* for combination G. This is depicted by the isoquant y^* in the figure. Let $y^* = \lambda y^o$, $(\lambda > 1)$. Then the output-based technical efficiency measure is simply $(1/\lambda)$. Suppose further that OG = ϕ OH, $\phi > 1$. Then the input-based measure of technical efficiency is simply $(1/\phi)$. The two would be identical iff $\lambda = \phi$. But it is evident that this would occur only when the returns to scale are constant. Thus, the technical efficiency of G as measured by the output-based measure would be higher (lower) than that based on the input-based measure accordingly as the returns to scale were decreasing $(\lambda > \phi)$ or increasing $(\lambda < \phi)$.

While it is expected that the input- and output- based measures would differ under general conditions, the important issue pertains to the ranking of two firms or alternative production plans by each of these measures. Consider, by way of example, two firms that produce the same output y^o but with different factor combinations. Let us suppose at first that the frontier technology is homogeneous but displays non-constant returns. In this case, the output-based and input-based measures would differ, but they would rank the firms identically. Thus in Figure 3 (a) below, G and D represent the observed factor combinations of firms 1 and 2, respectively, y^o is the identical output produced, and y^* is the technically efficient output that could be produced by G and D. Clearly, here both firms are equally inefficient according to either measure, even though the degree of efficiency depends upon which measure one looks at. Consequently, if it is the ranking of firms one is interested in, either measure would do. However, if the frontier technology is not homogeneous, the two measures could rank the same pair of production plans differently. This situation is described in Figure 3 (b). Here, while the output-based measure would assign both firms the same efficiency ranking, the

FIGURE 3



input-based measure would not. In the particular case shown, firm 2 is relatively more efficient according to the input-based measure.

The radial nature of the generalized Farrell index of technical efficiency means that it can be given a straightforward cost interpretation. Thus, given factor prices, we can draw the isocost lines gg' and hh' in Figure 2. Then 1 - TE(G) shows the percentage cost saving attainable through the elimination of technical inefficiency, since this is simply the proportional reduction in both inputs required to eliminate technical inefficiency. The output-based measure, on the other hand, cannot be given that interpretation. In particular, $(1 - y^{o}/y^{*})$ is, in general, not the percentage cost saving possible by eliminating technical inefficiency. However, we can exploit the relationship that exists between the input-based and output-based measures (for a homogeneous technology) to show that

$$1 - TE(G) = (1/RTS)\,(1 - y^{o}/y^{*}) \qquad (13)$$

That is, the generalized Farrell input-based technical efficiency measure can indirectly provide information as to the extra cost resulting from technical inefficiency.[10]

Kopp has shown that it is also possible to construct a Farrell type measure of a production plan's allocative efficiency from a knowledge of the production frontier. Thus, consider again the production plan represented by factor combination G and output y^{o} in Figure 2. For the given output, the technically and allocatively efficient combination is F. To isolate allocative inefficiency, we merely need to locate the combination J which costs the same as the allocatively and technically efficient combination F but which involves the same factor ratio as G. The measure of G's allocative efficiency (AE) is then given by:

$$AE(G) = OJ/OH \tag{14}$$

The logic behind this index can easily be explained as follows. Technical and allocative mistakes are costly. In terms of Figure 2 this results in extra costs equal to fg. However, a part of this cost can be attributed to excessive input usage (technical inefficiency). This is simply hg, since had the firm been technically efficient, it would have chosen H and hence reduced cost by that amount. However, H is allocatively inefficient, and the cost reduction possible by eliminating this inefficiency (by moving to F) is then simply fh = fg - hg. It is easily seen that in proportionate terms this cost reduction is simply 1 - AE(G), so that AE(G) can readily be interpreted as an index of the degree to which the given production plan is allocatively efficient. It is then possible to combine the generalized Farrell measures of technical and allocative efficiency to obtain a measure of the economic efficiency (EE) of the given production plan. This measure is

$$EE(G) = TE(G).AE(G) = (OH/OG)\ (OJ/OH) = OJ/OG \tag{15}$$

Notice that 1 - EE(G) is the proportionate cost saving possible through the elimination of both technical and allocative inefficiency. Thus, the Farrell approach can be extended to obtain measures of technical, allocative and economic efficiency for non-constant returns, non-homogeneous technologies from a knowledge of the production frontier. Given the cost interpretation of these measures, all that is needed are the costs of combinations F, H, G and J once the production frontier is known. Of course, G and y^o, along with factor prices, are given by the data. It is then possible to solve for F, H and J using the equation for the y^o isoquant, the factor ratio corresponding to G and the first order conditions for cost minimization. The computations are straightforward for the Cobb-Douglas case even in the multiple input case, though with other flexible-form and/or non-homogeneous technologies the required solutions would typically involve numerical methods.[11]

So far we have discussed how the Farrell approach can be generalized to give measures of allocative and technical efficiency from the production frontier. But Kopp and Diewert (1982) and Zeischang (1983) show how these measures can be distilled from a knowledge of only the cost frontier. For self-dual frontiers this is not surprising. The main contribution of these studies is that their methodology can be used even when one considers flexible-form frontiers that do not display the self-dual property. We illustrate the Kopp-Diewert methodology for the two input case with the help of Figure 2 , though it can easily be extended to many inputs. The essence of the problem is to identify the points F, H, and J with a knowledge of only the cost frontier, the actual combination G, the factor price ratio and output.[12] The point F is easily identified because according to Sheppard's Lemma

$$x_i^F = \partial C(y^o, r_1, r_2)/\partial r_i \qquad i = 1,2. \tag{16}$$

The point J can be identified as follows. By definition

$$r' x^J = C^F \tag{17}$$

where C^F is the cost of combination F. Also, we have

$$x_1^J / x_2^J = x_1^G / x_2^G \qquad (18)$$

These two equations can be solved for the combination J, yielding

$$x_i^J = [C^F / C^G] \; x_i^G \qquad i = 1, 2 \qquad (19)$$

where the superscript G is for factor combination G.[13] The next step is to obtain the technically efficient combination H. Again, from Sheppard's Lemma we know that

$$x_i^H = \partial C(y^O, r_1^H, r_2^H) / \partial r_i \qquad i = 1,2. \qquad (20)$$

where r_i^H are the factor prices at which combination H would place the firm on its cost frontier. We also know that

$$x_1^H / x_2^H = x_1^G / x_2^G \qquad (21)$$

(20) and (21) thus represent a system of three equations in four unknowns, the two factor quantities and their respective prices. However, since only relative prices are needed to determine H, we can normalize by setting the price of any one factor to unity. This ensures equality between the number of equations and the number of unknowns. Thus a solution for the remaining price and the two factor quantities represented by H can be obtained. The generalized Farrell indices of technical and allocative efficiency can be obtained in the usual way.

An alternative approach to measuring both technical and allocative efficiency is to independently model allocative inefficiency by permitting departures from the first order conditions for cost minimization [see Schmidt and Lovell (1979)]. Thus, the model incorporating technical and allocative inefficiency can be written as

$$y = f(x)\, e^{v-u} \tag{22}$$

$$f_i(x) \,/\, f_1(x) = (r_i / r_1)\, \tau_i, \quad i = 2,3,\ldots,n \tag{23}$$

where the τ_i measure allocative inefficiency. Note that once the production frontier is known, the τ_i can easily be calculated by using (23). The rationale then, of specifying the entire system given by (22) and (23), is primarily empirical. That is, instead of estimating only (22) and measuring allocative efficiency by applying the results obtained therefrom to (23), the entire system is estimated to account for the cross-equation constraints. Theoretically speaking, however, the extra cost of each of technical and allocative inefficiency is the same as that implied by the corresponding generalized Farrell indices discussed above, when the frontier is self-dual. This can be seen by considering, for instance, the Cobb-Douglas frontier case. Because of the self-dual nature of this function, it is easy to show that the cost function with both technical and allocative inefficiency using (22) and (23) is[14]

$$C = B\, \Pi\, p_i^{\alpha_i/\delta}\, y^{1/\delta}\, e^{v}\, e^{(1/\delta)u}\, e^{D-\ln\delta} \tag{24}$$

where the α_i are the output elasticities, $\Sigma\alpha_i = \delta$ is the returns to scale parameter, and $D = \sum (\alpha_j/\delta)\, \tau_j + \ln \left[\alpha_1 + \sum \alpha_j e^{-\alpha_j} \right]$. It can be seen from (24) that the impact of technical efficiency on cost is given by $e^{(1/\delta)u}$, while the impact of allocative inefficiency is $e^{D-\ln\delta}$. It follows that the proportionate increase in cost due to technical inefficiency alone is

$$\Delta C/C = (1/\delta)u$$
$$= (1/\delta)\,[y^{*}/y^{o} - 1] \qquad (25)$$

because from (22) it follows that $u = \ln(y^{*}/y^{o}) = (y^{*}/y^{o}-1)$.[15] But, as we saw earlier [see (13)], the right hand side of (25) is simply (1 - TE). Similarly, it can be noted from (24) that the proportionate increase in cost above frontier cost due to allocative inefficiency alone is $D - \ln\delta$. But this is precisely the interpretation of (1 - AE), where AE is the generalized Farrell allocative efficiency index given by (14) above. Note that the measurement of the extra cost of technical and allocative inefficiency, using the equation system (22) and (23), is possible because the cost function can be derived given the self-dual nature of the Cobb-Douglas production function. However, in the event that the technology is not self-dual, the cost function cannot be derived. In this case, one can use the production frontier to evaluate technical and allocative efficiency according to (12) and (14). Alternatively, when only the cost frontier is known, one can use the Kopp-Diewert method outlined above to obtain both technical and allocative efficiency.

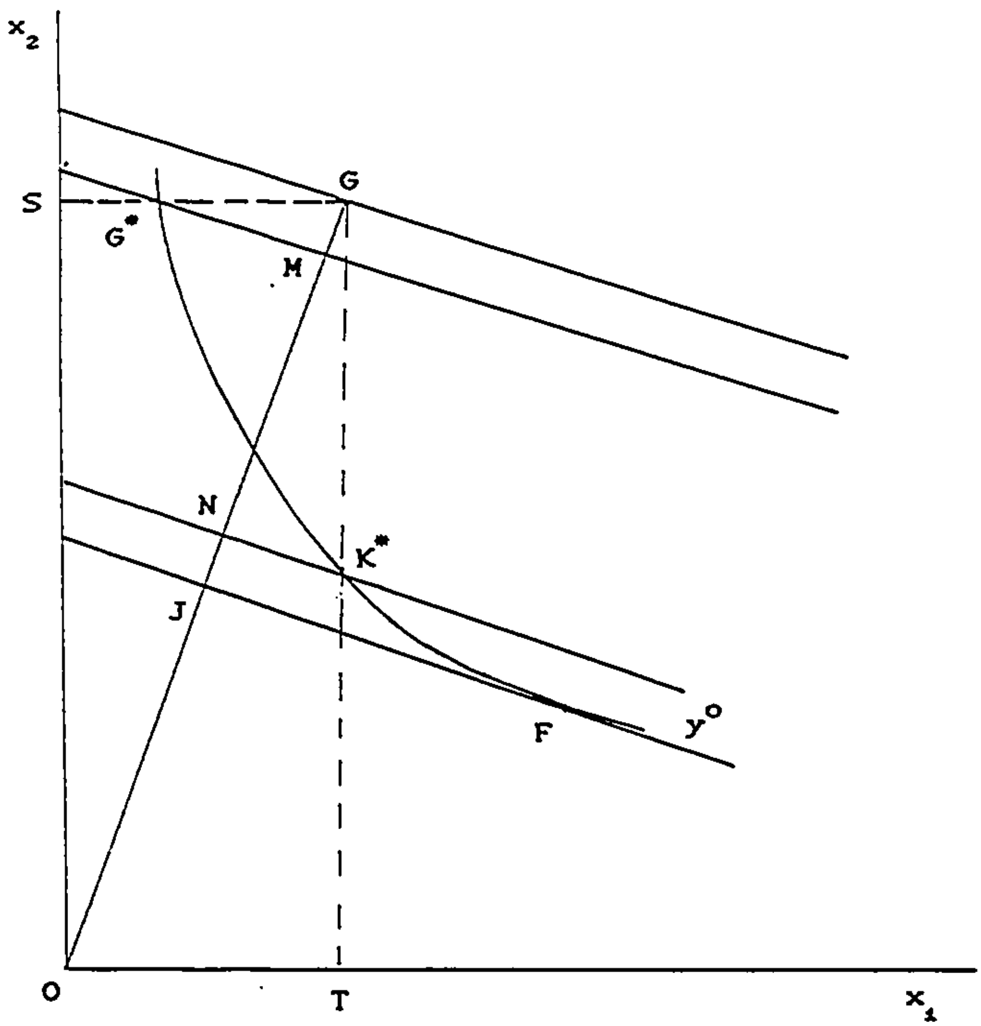
Factor Specific Measures of Efficiency

Our discussion of technical efficiency in the foregoing pages deals only with the efficiency of total factor employment. In other words, neither the generalized input-based Farrell measure nor the output-based frontier measure tells us anything about the contribution of specific factors to technical inefficiency. However, as the studies by Kopp (1981), Lovell and Sickles (1983) and Kumbhakar (1988) show, it is possible to construct input-specific indices of technical inefficiency and to determine the addition to cost resulting from each of these types of inefficiency. Factor-specific indices are useful from the policy point of view, to the extent that they point to the factors upon which managerial effort could be concentrated to achieve the greatest improvement in efficiency.

The idea behind the Kopp indices of single-factor inefficiency can be illustrated with the help of Figure 4, in which G is the actual factor combination, and y^o is the actual output produced. The distance SG^* is the minimum amount of factor 1 required to produce the given output, when factor 2 is fixed at OS units, while the distance TK^* is the minimum amount of factor 2 required to produce that output when factor 1 is fixed at OT units. Thus, part of the inefficiency of G is due to the excessive use of factor 1 by an amount equal to G^*G units, the remainder being due the the excessive use of factor 2 by the amount K^*G. We can thus measure the technical efficiency of factor 1 by the ratio SG^*/SG, and similarly measure factor 2's efficiency by the ratio TK^*/TG. The cost to the firm resulting from single factor inefficiency can be gauged by bringing in factor prices, for which the various isocost lines shown can be drawn. It is clear then that we can measure the technical cost efficiency of factors 1 and 2 by the ratios OM/OG and ON/OG, respectively, since they indicate the cost saving that could be realized by eliminating the inefficiency associated with each factor. The major drawback in giving these indices a cost interpretation is that, unlike the multi-factor index discussed earlier, they are not independent of factor prices. As a result, the efficiency ranking of factors can change for a sufficiently large change in relative factor prices.

It is also possible to measure the allocative efficiency of each factor. Thus, for factor 1 this measure is OJ/OM while for factor 2 it is OJ/ON. Each

FIGURE 4



measure indicates the cost saving that could be had by moving from either of the technically efficient combinations G^* and K^* to the economically efficient combination F. Note that the product of the technical and allocative efficiency indices for each factor is the index of (multi-factor) economic efficiency developed earlier. The question of factor-specific technical inefficiency has been tackled differently by Kumbhakar (1988), in that that efficiency is explicitly modeled. In particular, using the Cobb-Douglas functional from, he postulates the following stochastic production frontier:

$$y = A \Pi \tilde{x}_i^{\alpha_i} \Pi z_i^{\beta_i} e^v \tag{26}$$

where v represents statistical noise, and $\tilde{x}_i$ represents the technically efficient level of each factor relative to the fixed factors (z_i). Factor-specific inefficiency is then introduced by assuming that the technically efficient levels of the factors are related to actual levels according to

$$\tilde{x}_i = x_i \exp(\xi_i) \quad , \quad i = 1, 2, \ldots, n. \tag{27}$$

where $\xi_i \leq 0$ is the factor-specific measure of technical inefficiency. This implies that the production function (after taking logs) can be written as

$$\ln y = \alpha_0 + \sum_i^n \alpha_i \ln x_i + \sum_i^n \alpha_i \xi_i + \sum_i^m \beta_i z_i + v \tag{28}$$

Further, the first-order conditions for cost minimization, written to allow for allocative inefficiency, can be expressed as

$$\ln x_j - \ln x_1 = \ln r_1 - \ln r_j + \ln(\alpha_j / \alpha_1) + \delta_i \tag{29}$$

where the δ_i measure allocative inefficiency. The system of equations represented by (28) and (29) is almost identical to the Schmidt-Lovell model, the only difference being that technical inefficiency is now factor-specific. It is possible to estimate the parameters of this system and obtain estimates of allocative inefficiency (the vector δ) as well as factor-specific technical inefficiency (the vector ξ). The extra proportionate cost that can be attributed to the i^{th} factor is then given by

$$-(1/r)\alpha_i\xi_i \tag{30}$$

and the extra cost attributable to the technical inefficiency of total factor usage is $-(1/r)\Sigma\alpha_i\xi_i$. In comparison, the latter extra cost in the Schmidt-Lovell paper is $(1/r)u$, where u measures the technical inefficiency of total factor employment. In a subsequent paper, Kumbhakar (1989) obtained factor-specific technical efficiency indices from a factor demand system based on the flexible, symmetric-generalized-McFadden cost function.

This concludes the discussion of the various approaches to the measurement of economic efficiency and its components. Our discussion has assumed that the relevant frontiers are known. Before turning to the problems of specification and estimation of frontiers, we examine briefly the implications (for efficiency measurement) of a complication that arises when technical efficiency is not foreseen.

Foreseen vs. Unforeseen Technical Inefficiency: A Complication

In the previous section, we saw how the components of economic efficiency could be measured for an individual firm with the help of the generalized Farrell indices, once the firm's actual output y^o, the factor combination used

x^o and the production frontier are known. The implicit assumption has been that actual output y^o is identical to the output the firm expected to produce (say y^*). However, as Schmidt (1986) has pointed out, if y^o and y^* diverge, important implications follow for the measurement of (allocative) efficiency. Yet this issue has been given little attention in the literature [see, however, Kumbhakar (1987)]. Our purpose is to explore briefly the implications of a divergence between y^o and y^*.

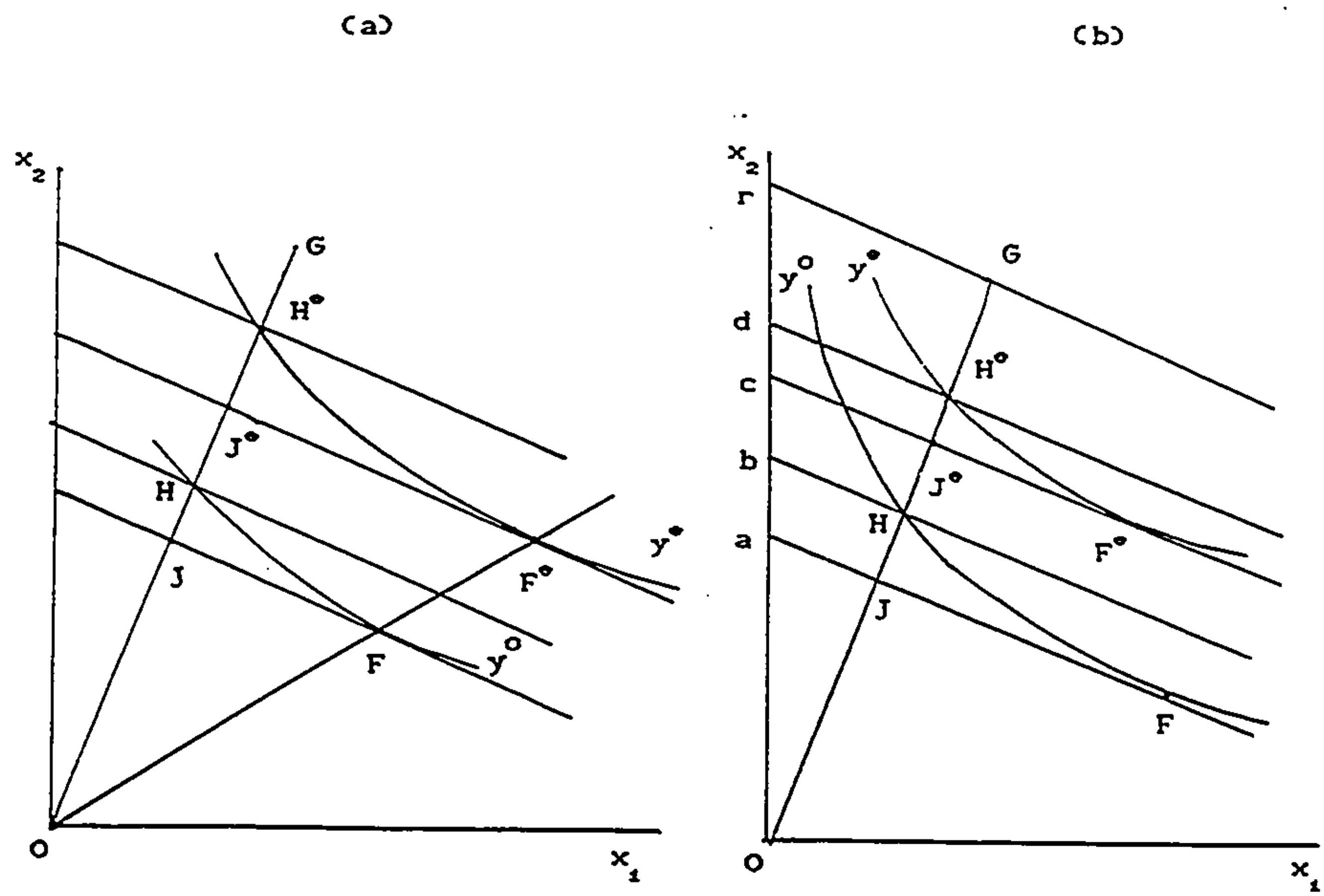
Consider first the case of a deterministic frontier. Here, y^o and y^* would coincide if technical inefficiency were entirely known to the firm, and in general would diverge otherwise.[16] That divergence is of little relevance for efficiency measurement if the technology is homogeneous, since then the measure of allocative efficiency would be the same whether or not there were a divergence.[17] However, if the technology is not homogeneous, the allocatively efficient factor ratio is not independent of output. A divergence between y^o and y^* would mean that allocative efficiency at those two outputs would no longer coincide. It would be correct to evaluate allocative efficency at y^* and not at y^o. However, it is then not possible to attribute the departure from frontier (minimum) cost at y^o to technical and allocative inefficiency alone, so that the generalized Farrell index of economic efficiency cannot be derived as the product of the indices of technical and allocative efficiency. These points are illustrated in Figure 5. Figure 5(a) shows the homogeneous case. Here, the measure of technical efficiency is, as before, OH/OG. Note though that even though y^o and y^* diverge, the allocatively efficient factor ratio is identical at those outputs. Consequently, AE at y^o is OJ/OH, which is equal to AE at y^*, which in turn is given by OJ^*/OH^*. In the non-homogeneous case illustrated in Figure 5(b), on the other hand, the allocatively efficient factor ratios differ at y^o and y^*. Since allocative efficiency should be evaluated at y^* it is clear that the product of the technical efficiency index OH/OG and the appropriate allocative efficiency index OJ^*/ OH^* no longer gives the generalized Farrell index of economic efficiency. Note that the distance ar is the amount by which actual cost exceeds frontier cost at y^o. Of this, br is unambiguously the result of technical inefficiency. However, the cost of allocative inefficiency is cd, and this can be more or less than ab, so that, while (br + cd) does measure the extra cost that can be attributed to the two types of inefficiency, it does not reflect the departure from frontier cost at y^o. It is nevertheless possible to view the divergence of actual cost from frontier cost at actual output (ar) as being made up of the following components:

$$C^a - C(y^o) \equiv ar = br + cd + (ab - cd)$$

where C^a is the actual cost of combination G, and C(.) is the minimum cost of producing y^o. Note that br is the cost of technical inefficiency and cd that of allocative inefficiency. The last bracketed term is the amount by which ab overstates the cost of allocative inefficiency. In other words, it is that part of the additional cost resulting from unforeseen fluctuations in output.

When the frontier itself is stochastic, similar issues are involved, although there is the added complication that output is random so that, independent of whether technical inefficiency is foreseen or not, actual output will almost certainly differ from expected output. The implications of this inherent randomness can be seen by considering first the case with no technical inefficiency. Here, for any given realization of the random variable v (say v^o), the ex post frontier is a simple multiple of the deterministic frontier. Consequently, it can be used to measure allocative efficiency in the

FIGURE 5



usual manner. The problem is that actual output will most likely differ from expected output. For the reasons discussed above, this would not matter as long as the technology were homogeneous, but in the non-homogeneous case allocative efficiency would differ at y^o and y^*. Thus, even without technical inefficiency, the amount by which actual cost exceeds frontier cost at y^o could be more or less than the cost of allocative inefficiency (evaluated at y^*). An additional problem is that expected and actual output are based on different frontiers. Thus, actual output is based on the ex post frontier (that is, a given realization of v), while expected output is likely to be based on the stochastic (random) frontier. As a consequence, this can lead to awkward results. In particular, expected output can be greater than frontier output, given v. One way out of this problem is that instead of dealing with the ex post frontier, we adopt the average (mean or median) frontier as the efficiency standard. In the homogeneous case, the allocative efficiency computations would not differ depending on whether the ex post or average frontier were used. In the non-homogeneous case, one would have to compute allocative efficiency at the expected level of output, which could be taken to be the output implied by the average frontier for the chosen factor combination.

The introduction of technical inefficiency raises no new problems when the technology is homogeneous. Then, whether we use the ex post frontier or the average frontier, and whether technical efficiency is foreseen or not, the measure of allocative efficiency is unaffected. In the non-homogeneous case, the measure of allocative efficiency is affected by unforeseen fluctuations in output, which can arise because of purely random factors as well as unforeseen technical inefficiency. The effect of random factors can be allowed for by dealing with the average frontier. Then, whether technical inefficiency is foreseen or not, the measurement of allocative efficiency raises the same set of issues as the deterministic frontier.

The above discussion suggests that the assumption of a homogeneous technology greatly facilitates the measurement of technical and allocative efficiency. In particular, not only do we not have to make any assumption about whether technical efficiency is foreseen or not, we also do not have to worry about defining and measuring expected output.[18] The cost of the homogeneity assumption is that we impose a prior restriction on the data, one that may not be justified. An alternative approach is to assume that technical inefficiency is foreseen, in which case there are no unforeseen effects upon allocative efficiency except those arising because of random influences when the frontier is stochastic. In this latter case, the effects of random influences can be dealt with by working with the average frontier.[19]

2.4 EFFICIENCY MEASUREMENT: THE PROBLEM OF SPECIFICATION AND ESTIMATION

In this section we look at the problem of specification of models of efficiency measurement as well as the methods that could be used to estimate them.[20] The problem of specification involves not only questions of functional form of the efficiency frontier to be estimated, but also of the assumptions relating to the efficiency variable. These questions play a major role in the methods of estimating the relevant frontiers.

2.4.1 THE PROBLEM OF SPECIFICATION

The question of functional form is an important one, but there is little prior guidance from theory as to the appropriate form of the efficiency frontier. In general, most empirical studies in the realm of production and cost proceed on the premise that the functional form should be as general as possible to capture a wide variety of possible structures. Thus, for example, the translog functional form is generally preferred to the additive CES or Cobb-Douglas models. The cost of adopting more flexible forms, however, is that there is a sharp increase in the number of parameters to be estimated, and a potentially serious collinearity problem. It is, therefore, not uncommon for investigators to adopt more restrictive functional forms.

In the area of frontier estimation, the vast majority of studies have opted for the Cobb-Douglas functional form. One reason for this is that the analytics of frontier estimation are rather complicated even when the relevant frontier takes the relatively simple Cobb-Douglas form. In addition, the self-dual property of the Cobb-Douglas form, not shared by the more flexible forms, makes it particularly useful for identifying technical and allocative inefficiency by estimating a single frontier. Needless to say, the Cobb-Douglas form may be too simple to characterize real world technologies. However, flexible functional forms raise potential collinearity problems, particularly when the production frontier is estimated directly, and as pointed out by Bauer (1990), estimating an overly flexible form may lead to a loss in statistical efficiency. Furthermore, as we have seen in the previous section, a homogeneous function such as the Cobb-Douglas enables one to circumvent the problem of defining and measuring expected output, unless we assume additionally that technical inefficiency is foreseen. This latter assumption, while useful in the non-homogeneous case, leads to other estimation problems, to be discussed shortly. In any event, whatever the chosen functional form, the main drawback of the parametric approach as opposed to the non-parametric approach is that it imposes a particular functional form on the data.

In any study of frontiers, the specification problem of crucial importance is that relating to how the inefficiency variable u is modeled. This is because one's assumptions about the distribution of u across firms (though not necessary in the estimation of deterministic frontiers) can significantly affect the estimates of efficiency. Unfortunately, once again theory is of little assistance here. The only restriction is that the range of u is such that output (cost) is bounded by the relevant frontier. However, there are a number of alternative specifications of the distribution of u that satisfy this criterion, and on a priori grounds there appears to be no compelling reason for choosing one over the other. As Schmidt (1986) points out, the need to make specific assumptions about the distribution of u and v, constitutes the primary weakness of the statistical estimation of frontiers. In what follows, we discuss the common assumptions about u and v. Following that, we discuss estimation methods, and how they enable the measurement of the various types of efficiency discussed above.

We deal with the production frontier, although the analysis can easily be extended, with minor modifications, to the cost (or profit) frontier. As we saw earlier, the production frontier with technical inefficiency can be stated as

$$y = f(x)\ e^{v-u} \tag{31}$$

In the deterministic case, the frontier is simply $f(x)$, while in the stochastic case it is $f(x)e^{v}$. In the latter, since v represents the influence of random factors outside the control of the firm, it is usually assumed to be unbounded. A common assumption is that v is normal with zero mean and constant variance. However, in both the deterministic and stochastic cases, u is assumed to be non-negative, restricting output to lie below or on the frontier. The usual assumption about the one-sided distribution of u is one of the following:

(a) the u are independent normal variates with zero mean and constant variance, truncated at zero. That is, the u are half-normal;

(b) the u are Gamma variates with parameter η;

(c) the u are distributed exponentially with parameter γ.[21]

The Half-Normal Case

When each u follows a normal distribution with zero mean and constant variance σ_u^2, truncated at zero, its probability density can be written as

$$P(u) = 2\ (2\Pi)^{-1/2}\sigma_u^{-1} \exp(-\ u^2/\ 2\ \sigma_u^2) \qquad u \geq 0 \tag{32}$$

Letting $k = e^{-u}$ and making the transformation from u to k, the probability density of k can be shown to be

$$P(k) = A\ k^{-1} \exp\ \{\ -\ (\ln k)^2/\ 2\sigma_u^2\ \} \tag{33}$$

where $A = 2\ (2\Pi)^{-1/2}\sigma_u^{-1}$ and $0 \leq k \leq 1$.

The first moment of k measures the average level of technical efficiency, and can be shown to be

$$E(k) = E(e^{-u}) = \ 2\ [1 - \Phi(\sigma_u)]\ \exp\ (\sigma_u^2) \tag{34}$$

where Φ (.) is the standard normal distribution function. The mode of the distribution of k, which is the point at which P(k) is maximized, can be shown to be

$$M_o(k) = \exp(-\sigma_u^2) \qquad (35)$$

while the median is

$$M_d(k) = \exp(-2\sigma_u^2/3) \qquad (36)$$

It is clear that the distribution of technical inefficiency depends critically upon the variance of u. In particular, the half-normal assumption for u is flexible in that it permits a large number of possible configurations for the distribution of firms according to technical efficiency, and this is perhaps one reason for its popularity in frontier studies. Panel A in Figure 6 below depicts the approximate shapes of the distribution of k (technical inefficiency) for various values of the variance of u.

The Gamma Case

If u follows a (one-parameter) Gamma distribution, its probability density can be written as

$$P(u) = \frac{e^{-u} \; u^{\eta-1}}{\Gamma(\eta)} \;, \qquad u \geq 0 \;, \; \eta > 0 \qquad (37)$$

where $\Gamma(\eta) = \int e^{-u} u^{\eta-1} du$ for $-\infty < u < 0$, is the Gamma integral. Making the transformation from u to k, where $k = e^{-u}$, the density of k is:

$$P(u) = \frac{[\ln(1/k)]^{\eta-1}}{\Gamma(\eta)}, \qquad 0 \leq k < 1 \tag{38}$$

The average level of technical inefficiency, as measured by the expected value of k, can be shown to be

$$E(k) = \int_0^1 \frac{k[\ln k(1/k)]^{\eta-1}}{\Gamma(\eta)} dk = 2^{-\eta} \tag{39}$$

The mode of k is as follows:

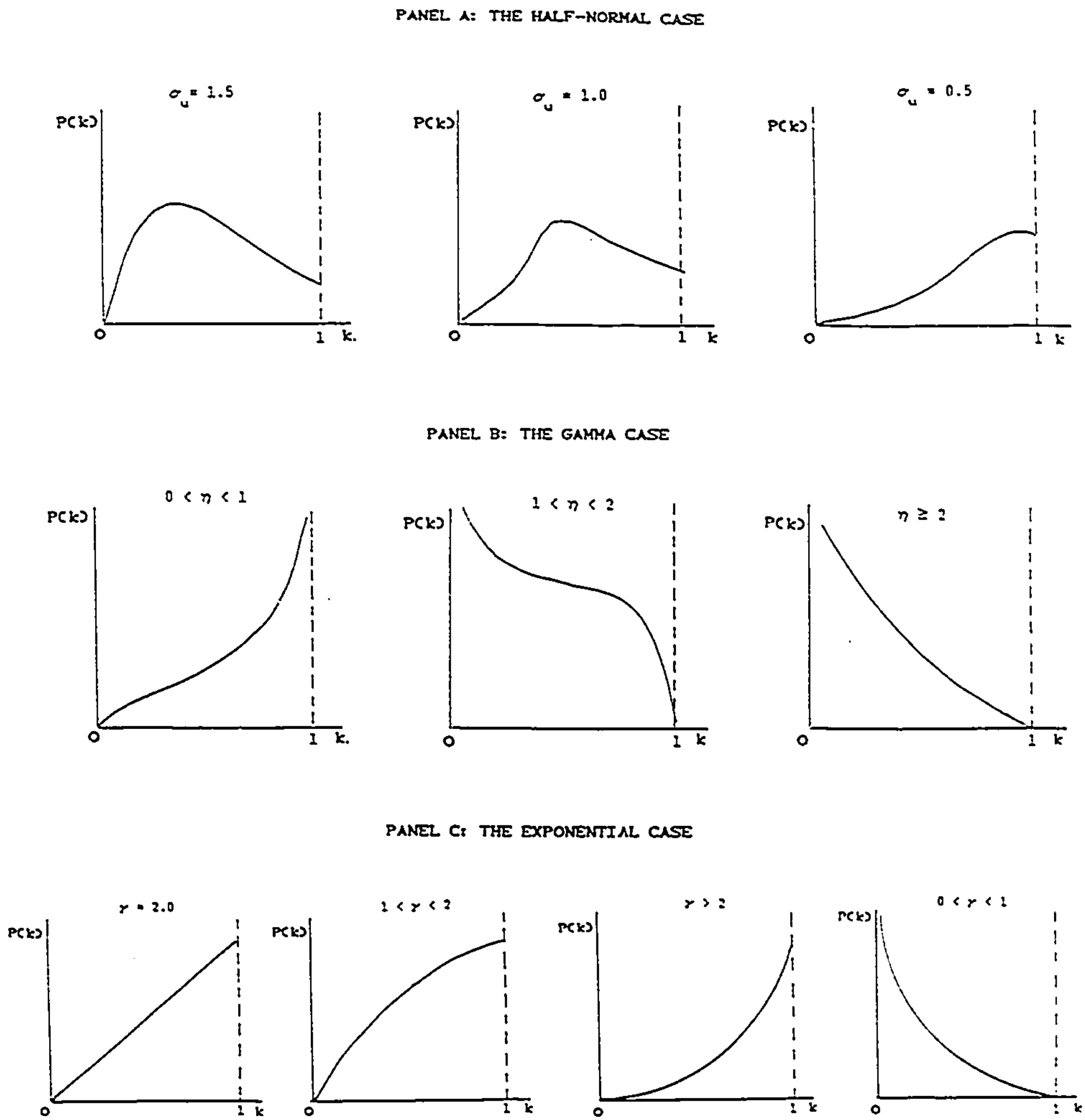
$$M_0(k) = \begin{cases} 1 \text{ if } 0 < \eta < 1 \\ \text{indeterminate if } \eta = 1 \\ e^{-(\eta - 1)} \text{ if } \eta > 1 \end{cases} \tag{40}$$

There is no analytical expression for the median of k when $(\eta-1)$ is not a positive integer. When $n \geq 1$, the median is that value of k for which

$$\sum_{j=0}^{n} \frac{e^{-k} k^j}{k!} = 1/2 \tag{41}$$

The Gamma assumption for u results in a somewhat peculiar distribution of technical inefficiency for plausible values of η. Panel B in Figure 6 shows various shapes of the Gamma density. It is clear that this particular specification would force the majority of firms to be relatively inefficient for $\eta \geq 1$. Only the case where $0 < \eta < 1$ would allow most firms to be relatively efficient. This drawback of the Gamma density can be overcome by adopting the two-parameter Gamma or the exponential distribution. We

FIGURE 6


PANEL A: THE HALF-NORMAL CASE
$\sigma_u = 1.5$
$\sigma_u = 1.0$
$\sigma_u = 0.5$
P(k)
0
1 k
PANEL B: THE GAMMA CASE
$0 < \eta < 1$
$1 < \eta < 2$
$\eta \geq 2$
PANEL C: THE EXPONENTIAL CASE
$\gamma = 2.0$
$1 < \gamma < 2$
$\gamma > 2$
$0 < \gamma < 1$

confine our attention to the latter.

The Exponential Case

If u is exponential, its probability density is

$$P(u) = \gamma\, e^{-\gamma u} \quad , \qquad \gamma \geq 0 \tag{42}$$

Thus the probability density of k can be written as follows

$$P(k) = \gamma\, k^{\gamma-1} \quad , \qquad 0 < k \leq 1 \tag{43}$$

The mean of k is

$$E(k) = \int_0^1 k\, \gamma\, k^{\gamma-1}\, dk = \left[\frac{\gamma}{1+\gamma} \right] \tag{44}$$

The median can be shown to be

$$M_d(k) = (1/2)^{1/\gamma} \tag{45}$$

The mode depends on γ. In particular,

$$M_0(k) = \begin{cases} \text{unity if } \gamma > 1 \\ \text{indeterminate if } \gamma = 1 \\ \text{zero if } 0 < \gamma < 1 \end{cases} \tag{46}$$

The shapes of the distributions of technical inefficiency implied by the exponential density are illustrated in Panel C of Figure 6. It is clear that, in contrast to the Gamma density, a large majority of firms would be relatively inefficient only if γ were positive but less than unity. However, should γ be greater than unity, a majority of firms can be expected to be relatively efficient. Since a Gamma distribution permits a majority of firms to be relatively efficient only for a rather restricted range of its parameter η, while both the half-normal and exponential cases are much more flexible in this context, the latter distributions have most commonly been adopted in the literature.

It might be noted that the specification of the distribution of the technical inefficiency variable u is not necessary for estimating deterministic frontiers, since they can be estimated by non-statistical methods. In general, however, and particularly when the frontier is stochastic, the distributions of both v and u need to be specified.[22] Using appropriate methods, it is possible to estimate both the average level of technical/allocative inefficiency by obtaining point estimates of the mean of u, as well as the technical/allocative inefficiency of each firm in the sample. While estimating average inefficiency is relatively straightforward, once the relevant parameters are known, the estimation of each firm's inefficiency requires some further elaboration.

When the frontier is deterministic, the measurement of each firm's inefficiency presents no special difficulties, since that inefficiency can easily be measured in terms of departures from the estimated frontier. However, when the frontier is stochastic, the estimation of each firm's inefficiency requires separating the departures from the deterministic kernel into those reflecting statistical noise (v) and those reflecting technical inefficiency (u). In the early frontier literature, it was thought that this could not be done. Consequently, earlier studies were simply able to estimate the average level of inefficiency E(u) given that E(v-u)= -E(u). This was viewed as a major drawback of the stochastic frontier vis-a-vis the deterministic frontier. However, in an important paper, Jondrow et al. (1982) were able to demonstrate that it was possible to estimate inefficiency at the firm level in a stochastic frontier framework. We briefly discuss their approach.

Jondrow et al. argue that since $\varepsilon = v - u$ can be estimated, and since ε contains information on u, it should be possible to estimate u from the conditional distribution of u given ε. In keeping with common practice we assume v to be a normal variate with zero mean and constant variance. Let us first consider the case where u is half-normal. Under the assumption that v and u are independent, their joint density takes the form

$$f(u,v) = \frac{2}{\Pi \sigma_u \sigma_v} e^{-1/2 \left[v^2/\sigma_v^2 + u^2/\sigma_u^2 \right]} \quad (47)$$

$u \geq 0$ and $-\infty < v < +\infty$. Then making the transformation from v to ε, we get $f(u,\varepsilon) = f(u,v) \; |dv/d\varepsilon|$, which can be shown to be

$$f(u,\varepsilon) = \frac{1}{\Pi \sigma_u \sigma_v} e^{-1/2 \left[u^2/\sigma_u^2 - (\varepsilon + u)^2/ \sigma_v^2 \right]} \quad (48)$$

It can also be demonstrated [see, for instance, Aigner et al.(1977)] that the density of ε reduces to

$$f(\varepsilon) = \frac{2}{\sqrt{2\Pi}\ \sigma} e^{-\varepsilon^2/2\sigma^2} [1 - \Phi(\varepsilon\lambda/\sigma)] \tag{49}$$

where $\Phi(.)$ is the standard normal cumulative distribution function and $\sigma^2 = \sigma_u^2 + \sigma_v^2$, $\lambda = \sigma_u/\sigma_v$. Then the conditional density of u given ε, $f(u|\varepsilon)$, which is simply $f(u,\varepsilon)/f(\varepsilon)$ can be shown to be

$$f(u|\varepsilon) = \frac{1}{\sqrt{2\Pi}\quad \sigma_* [1 - \Phi(\mu^* /\sigma_*)]} e^{-1/2 \left[(u - \mu^*)/\sigma_*\right]^2} \tag{50}$$

for $u \geq 0$. $\mu^* = - [\sigma_u/\sigma]^2\varepsilon$ and $\sigma_* = (\sigma_u\sigma_v/\sigma)^2$. Thus, given ε, u follows a normal distribution truncated at zero, with mean μ^* and variance σ_*^2.

In order to estimate the inefficiency at each sample point, an estimate of u at each point is needed. As Jondrow et al. point out, a point estimate of either the mean or mode of the conditional distribution of u can be used. It is easy to show that the mode is

$$M_o(u|\varepsilon) = \mu^* \text{ if } \varepsilon \leq 0$$
$$= 0 \text{ if } \varepsilon \geq 0$$

while the mean is

$$E(u|\varepsilon) = \sigma_* \left[\frac{\phi(\varepsilon\lambda/\sigma)}{[1 - \Phi(\varepsilon\lambda/\sigma)]} - \frac{\varepsilon\lambda}{\sigma} \right] \tag{51}$$

With the appropriate estimation techniques, it is possible to estimate ε as well as the other parameters, λ and σ. These then provide the necessary information for computing firm-specific estimates of u from either the mean or mode of that variable.

It can also be demonstrated that if u follows an exponential distribution with parameter γ, the density of u given ε is

$$f(u|\varepsilon) = \frac{1}{\sqrt{2\Pi}\ \sigma_v\,[1 - \Phi(\Omega)]}\, e^{-1/2\sigma_v^2\,(u + \sigma_v\,\Omega)^2} \qquad (52)$$

for $u \geq 0$. Note $\Omega = (\varepsilon + \sigma_v^2\gamma)/\ \sigma_v$. Thus, the conditional distribution of u is that of a normal variable with mean $-\sigma_v\Omega$ and variance σ_v^2, truncated at zero. It is easy to show that the mode of u given ε is

$$\begin{aligned} M_o(u|\varepsilon) &= -\sigma\,\Omega \quad \text{if } -\sigma\,\Omega > 0 \\ &= \quad 0 \quad\ \ \text{if } -\sigma\,\Omega < 0 \end{aligned} \qquad (53)$$

while it can be shown that the mean of u given ε is

$$E(u|\varepsilon) = \sigma_v \left[\frac{f(\Omega)}{1 - \phi(\Omega)} - \Omega\right] \qquad (54)$$

where $\phi(.)$ is the standard normal density.[23]

This ends our discussion of specification issues involved in the estimation of frontiers. We turn next to the problems of estimation.

2.4.2 ESTIMATION METHODS

While the estimation of stochastic frontiers must proceed along statistical lines, that is not necessarily so in the case of deterministic frontiers. Earlier studies of frontiers applied programming techniques to estimate deterministic production frontiers [see for instance Aigner and Chu (1968)]. However, most studies since then have used the more powerful tools of statistical estimation theory. We briefly discuss the non-statistical approach, and then move to the statistical approaches.

The Non-Statistical Approach

Consider the deterministic production frontier $f(x,\theta)$, where θ is the vector of parameters. The problem is to estimate θ such that

$$y \leq f(x,\hat{\theta}) \tag{55}$$

where y is actual output. Since any number of estimates of the parameters can be consistent with this requirement, some criterion for obtaining unique estimates is needed. Aigner and Chu (1968) suggested two alternatives, both of which force the estimated production surface to lie as close to the observations as possible. This is done by imposing a minimizing constraint on the estimated residuals. Thus, they suggested minimizing the sum of squared residuals or the sum of residuals , each subject to the constraint (55). If f(.) is linear, there is a linear programming problem; if it is quadratic, a quadratic programming problem is implied. One difficulty with this approach is that it is very sensitive to outliers, particularly when the quadratic programming specification is used. In order to deal with the outlier problem Timmer (1971) suggested that the frontier be estimated, and then some pre-determined percentage of observations be deleted. Alternatively, efficient observations could be discarded one at a time until the estimates stabilize. As Forsund et al. (1980) point out, this would be a useful procedure provided the estimates stabilized fairly quickly. The greater problem with the programming approach is that, since it is non-statistical, the estimates have no identifiable properties. Therefore, no statistical inference is possible.

The Statistical Estimation of Deterministic Frontiers

Deterministic frontiers can also be estimated statistically, by modifying the ordinary least squares (OLS) approach, or by the maximum likelihood (ML) method. As is well known, under the classical assumptions, the OLS estimators are consistent and efficient.[24] However, the estimation of frontiers by OLS raises two major problems. First, given the one-sided distribution of u, the classical assumption of zero mean is violated. This means that even though the slope parameters are consistently estimated, the intercept is not. Second, a frontier estimated by OLS is not a frontier at all, in that observations can and will lie above it. This makes the measurement of efficiency at the level of the firm awkward. Both difficulties, however, can be addressed by modifying the OLS method as follows.

Consider the estimation of the production frontier (with technical inefficiency), which is assumed (without loss of generality) to be of the Cobb-Douglas form:

$$\ln y = \alpha_o + \sum \alpha_j \ln x_j - u \tag{56}$$

With a minor modification, (56) can be written as

$$\ln y = (\alpha_o - \mu) + \sum a_j \ln x_j - (u - \mu)$$

or

$$\ln y = \beta_o + \sum \alpha_j \ln x_j - w \tag{57}$$

where $\beta_o = (\alpha_o - \mu)$, $E(u) = \mu$, and $w = -(u - \mu)$. Note that since $E(w) = 0$, OLS estimation of the frontier gives consistent estimates of the slope parameters and of β_o (though not of α_o, since it is not identified). If a specific distribution is assumed for u, the OLS residuals can be used to obtain consistent estimates of E(u) from the estimated moments of u. It is then possible to "correct" the OLS intercept $\hat{\beta}_o$ to obtain a consistent estimate of α_o

$$\hat{\alpha}_o = \hat{\beta}_o + \hat{\mu} \tag{58}$$

The "corrected" OLS method (COLS) was first suggested by Richmond (1974), who examined efficiency measurement using this approach under the assumption of a one parameter Gamma distribution for u. This assumption implies that the mean and variance of u are both equal to η. Thus, a consistent estimator of η can be obtained from the OLS residuals as follows:

$$\hat{\eta} = \sum_{1}^{T} e_t^2 \; / \; (T-n-1) \tag{59}$$

where the e_t are the OLS residuals, T is the number of observations, and n is the number of slope parameters. Then a consistent estimator of the intercept can be formed as $\hat{\beta}_o + \hat{\eta}$; that is, by shifting the estimated equation up by $\hat{\eta}$.

While COLS is a relatively simple method of estimating the frontier, it does not guarantee that all observations will lie on or below the frontier, thereby making it difficult for measuring firm-specific technical efficiency in a meaningful manner. Another potential problem is that the correction term in COLS (the mean of u) is dependent upon the distribution assumed for u, and different distributions can lead to quite dissimilar estimates of efficiency. For instance, if u is assumed to follow an exponential distribution instead of a Gamma, the mean and variance of u are $(1/\gamma)$ and $(1/\gamma)^2$ respectively. The correction term is consequently + $(1/\gamma)^{1/2}$. That this may result in large differences in the estimate of average efficiency is seen by noting that when Richmond's mean efficiency for Norwegian manufacturing (based on the Gamma) is recomputed under the exponential assumption, it falls from 87% to only 69% [Forsund et al. (1980)]. Both of these difficulties with the COLS method can be dealt with if, after estimating the model by OLS, the frontier is shifted upward (that is, the intercept adjusted) until no residual is positive. As Greene (1980) has shown, this yields a consistent estimator of the intercept term. Apart from being a simple method of estimation, it imposes no distributional assumptions on the data.

The deterministic frontier can also be estimated using the maximum likelihood (ML) method. This method requires a specific assumption about the distribution of the disturbance u. The popularity of the ML method arises not only because it is based on the appealing criterion of finding those values of the parameters most likely to have generated the sample, but also because, under general conditions, ML estimators are consistent and asymptotically efficient. Their main difficulty is that they tend to be computationally burdensome and impose specific distributional assumptions on the data. The ML principle in a frontier context can be demonstrated as follows.

On the assumption that the u_i are independent and identical random variables, each with density function $P(u_i|\theta)$, where θ is the parameter vector, the log likelihood function L of the sample observations y_i is simply

$$L(y|\theta) = \sum_{i}^{T} \ln P(y_i|\theta) \qquad (60)$$

since the Jacobian of the transformation from u to y is unity. The ML estimators of the parameters are then simply those that maximize L. In the deterministic frontier context, the ML estimators are really programming estimators, since optimization is subject to the inequality constraints $y \leq f(x)$. In fact, Schmidt (1976) has shown that the ML estimators of the Cobb-Douglas frontier function parameters are the linear and quadratic programming estimators of Aigner and Chu (1968), if u is exponential and half-normal, respectively. Thus, for instance, when u is half-normal, the log likelihood function of the sample is

$$L = (T/2)\ln(2/\Pi) - (T/2)\ln\sigma_u^2 - \frac{1}{2\sigma_u^2}\sum_i^T [\ln y_i - \alpha_o - \sum_{j=1}^n \alpha_j \ln x_{ij}]^2 \quad (61)$$

Maximizing L with respect to σ_u^2 yields the ML estimator

$$\sigma_u^2 = \sum_i^T \{\ln y_i - \alpha_o - \sum_j \alpha_i \ln x_{ij}\}^2 / T \quad (62)$$

Substituting this in (61) and ignoring the constant term, we get the concentrated log likelihood function L_c

$$L_c = (T/2) \ln [\sum_i^T \{ \ln y_i - \alpha_o - \sum_j \alpha_i \ln x_{ij}\}^2 / T] - (T/2) \quad (63)$$

The maximization of L_c requires the minimization of the sum of squares of residuals subject to the constraint $y \leq f(x)$. This is clearly a quadratic programming problem. Similarly it can be shown that if u is exponential, ML estimation involves minimizing the sum of residuals subject to the same constraint, and this is a linear programming exercise[see Schmidt (1976)].

A major shortcoming of the ML approach here is that since u is restricted to be non negative, lny ranges from minus infinity to $f(x, \theta)$ and is hence not independent of the parameters. This violates one of the regularity conditions of the ML method [Schmidt (1976)]. In particular, the variances and covariances of the estimators are not known, so that the usual properties of ML estimators are not known and no statistical inference is possible. However, Greene (1980) has shown that while the range problem exists irrespective of the distribution of u, it is possible to obtain the variance-covariance matrix of the estimators and to prove the usual asymptotic properties under certain conditions. In particular, Greene argues that the regularity condition is only a sufficient condition, and that provided the other regularity conditions are satisfied, the usual ML results follow for a certain class of distributions. Thus, Greene shows that if the density of u is zero at u = 0, and the first derivative of the density of u with respect to its parameters approaches zero as u tends to zero, the usual ML results follow. The half-normal and exponential distributions do not satisfy these conditions, but a number of other distributions do (for example the Gamma and log-normal).

The major drawback of a deterministic frontier is that it does not allow for statistical noise which characterizes all data. One important consequence is that estimates of inefficiency are contaminated with statistical noise. Deterministic frontiers then can be expected to understate the degree of efficiency. We turn, thus, to the estimation of stochastic frontiers which explicitly allow for statistical noise.

The Estimation of Stochastic Frontiers

The stochastic frontier can be estimated by COLS or by the ML method. Both methods give consistent estimates, although the latter is likely to be more efficient asymptotically. In either case, specific distributional assumptions about v and u are needed. The most common approach is to assume that the v are identically and independently distributed normal variates with zero mean and constant variance, while the u follow either the half-normal or exponential distribution. These assumptions play a major role not only in estimating the parameters, but also in enabling the separation of the statistical noise from technical inefficiency, a prerequisite for generating firm-specific estimates of technical efficiency. The COLS method involves estimating the frontier by OLS and then, as in the deterministic case, adjusting the constant term by an estimate of $E(\varepsilon)=-E(u)$. A consistent estimator of the latter can be obtained from the moments of u, themselves obtained from the OLS residuals. Thus, for example, if u is half-normal,

$$E(u) = \left[2 / \Pi \right]^{1/2} \sigma_u \qquad (64)$$

This requires an estimate of σ_u which, as shown by Schmidt and Lovell (1979), can be obtained as follows. The OLS residuals can be used to obtain consistent estimates of the third central moment of ε, μ_3, which is given by

$$\mu_3 = \sqrt{\frac{2}{\Pi}} \left[\frac{\Pi - 4}{\Pi} \right] \sigma_u^3 \qquad (65)$$

This yields

$$\hat{\sigma}_u^2 = \left[\sqrt{\frac{\Pi}{2}} \left(\frac{\Pi}{\Pi - 4}\right) \hat{\mu}_3 \right]^{2/3} \qquad (66)$$

where $\hat{\mu}_3$ is the consistent estimate of μ_3 obtained from the OLS residuals. With this estimate, we can obtain an estimate of $E(\varepsilon)$, which is then used to adjust the constant term in the production frontier in order to obtain a consistent estimate of that parameter.

In order to estimate the technical inefficiency for each firm, we need to estimate the mean (or mode) of the conditional distribution of u given ε. As is clear from equation (51) this requires estimates of ε as well as of σ_u and σ_v. An estimate of σ_u is given by equation (66), while an estimate of σ_v can similarly be obtained from the second central moment of ε estimated from the OLS residuals. In particular, it can be shown that

$$\mu_2 = \left[\sigma_v^2 + \frac{\Pi - 2}{\Pi} \sigma_u^2 \right] \qquad (67)$$

Substituting the consistent estimates of μ_2 and σ_u in this equation, we can solve for a consistent estimate of σ_v. This then enables the estimation of u from the mean of the conditional distribution of u given ε, as in equation (51). Note that the estimates of σ_u^2 and σ_v^2 are also indicators of whether statistical noise or technical inefficiency is the relatively more important cause of departures from the deterministic portion of the stochastic frontier. The foregoing approach can be applied to estimate the stochastic frontier and firm level technical inefficiency for alternative specifications of the distribution of u.

A relatively more efficient alternative to COLS is the ML approach, even though the COLS estimates are easier to compute.[25] The ML approach in the present context does not provide analytical expressions for the estimators, so these have to be obtained through numerical optimization. This is because of the more complicated likelihood function, which now involves the probability density of the sum of a symmetrical and a one-sided disturbance. Consider, for instance, the case where u is half-normal and the production function is Cobb-Douglas. The probability density of ε is then given by equation (49). The log likelihood function L of the sample $\ln y$ (ignoring the term involving Π) can be written as

$$L(y/\alpha,\lambda,\sigma) = -(T/2)\ln\sigma^2 - (1/2\sigma^2)\sum_{1}^{T}\varepsilon_i^2 + \sum_{1}^{T}\ln\left[1 - \Phi(\varepsilon_i\lambda/\sigma)\right] \quad (68)$$

where $\Phi(.)$ is the standard normal distribution function, $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\lambda = \sigma_u/\sigma_v$. The first order conditions for maximizing L are:

$$\frac{\partial L}{\partial\sigma^2} = -\frac{T}{2\sigma^2} + \frac{1}{2\sigma^4}\sum_{1}^{T}\varepsilon_i^2 + \frac{\lambda}{2\sigma^3}\sum_{1}^{T}\frac{\phi_i\varepsilon_i}{(1-\Phi_i)} = 0 \quad (69)$$

$$\frac{\partial L}{\partial\lambda} = -\frac{1}{\sigma}\sum_{1}^{T}\frac{\phi_i\varepsilon_i}{(1-\Phi_i)} = 0 \quad (70)$$

$$\frac{\partial L}{\partial\alpha_j} = \frac{1}{\sigma^2}\sum_{1}^{T}\varepsilon_i\ln x_{ij} + \frac{\lambda}{\sigma}\sum_{1}^{T}\frac{\phi_i\ln x_{ij}}{(1-\Phi_i)} = 0 \quad (71)$$

for $j = 0,1,2,\ldots,n$. Further, $\ln x_{ij} = 1$ for $j = 0$, and ϕ is the standard normal density evaluated at the same point as Φ.

It is clear from these (n + 3) equations that analytical solutions for the parameters cannot be obtained, and numerical methods have to be used. Note though that equations (69) and (70) imply that the ML estimator of σ^2 is

$$\hat{\sigma}^2 = (1/T) \sum \varepsilon_i^2 \tag{72}$$

However, note further that the estimation of σ^2 is not independent of the α_i, since the ε_i are functions of the latter. Nevertheless, (72) can serve as a starting point for generating an iterative solution [see Lovell and Schmidt (1979)].

The foregoing discussion deals with the estimation of production frontiers. With minor modifications, it applies equally to the estimation of cost frontiers. Whether one estimates a cost frontier or a production frontier depends upon what assumptions about the input and output variables appear to be appropriate. Thus, the direct estimation of the production function is appropriate if, as we have assumed, input quantities are uncorrelated with the disturbances. As shown by Zellner, Kmenta and Dreze (1966), this condition is met if firms maximize expected profits.[26] On the other hand, the estimation of the cost frontier would be appropriate if input quantities were endogenous but output exogenous. In practice, however, which approach is taken is often determined by data availability. Thus, the estimation of a cost frontier requires data on output as well as factor prices, while a production frontier can be estimated with data on output and input quantities. In cross-sectional studies, particularly at the micro level (such as the one in this thesis) the estimation of cost frontiers is ruled out because of the general absence of factor price variation across units.

It is also possible to estimate the production frontier with technical inefficiency jointly with the first order conditions for cost minimization with allocative inefficiency [equations (22) and (23)]. As pointed out earlier, the primary purpose of joint estimation is that by taking into account cross-equation error correlations and restrictions on parameters, more precisely estimated parameters can be obtained. Schmidt and Lovell (1979) have applied the ML method to such a system on the assumptions that the production function is Cobb-Douglas, the v are normally distributed with zero mean and constant variance, the u are half-normal, and the (n-1) allocative inefficiency vectors $\tau_2, \tau_3, \ldots, \tau_n$ are each normally distributed with mean μ and variance-covariance matrix Σ.[27] As Schmidt (1986) has pointed out, while joint estimation might lead to efficiency gains, the consistency property of the estimators depends upon whether the entire system is correctly specified - that is, not only in terms of the functional form but also the distributional assumptions. The system can be estimated alternatively by a non-linear three-stage least squares procedure, which requires no distributional assumptions. However, these assumptions are eventually needed to separate the statistical noise from technical inefficiency.

2.5 SUMMARY AND CONCLUSIONS

In this chapter, we have discussed the concepts of technical and allocative efficiency, and the approaches to modeling and estimating them. At the heart of the issue is the notion of a frontier, which depicts the optimum value of production or cost, and serves as the efficiency standard. We have focused on the problems of specification and estimation of parametric frontiers, both deterministic and stochastic, from cross-sectional data on a sample of firms. Knowledge of either the cost or production frontier is sufficient to enable the computation of both technical and allocative efficiency. Frontiers that assume that all departures from the deterministic production or cost function represent inefficiency are deterministic, while for stochastic frontiers these departures are seen as reflecting both inefficiency and statistical noise. Deterministic frontiers can be estimated either by non-statistical or statistical methods. The former do not involve distributional assumptions, and hence have no statistical properties. Such frontiers can also be estimated statistically by the COLS or ML method. The former would, under certain conditions, give consistent estimates, but the properties of the latter method cannot be evaluated except in certain cases since one of the regularity properties required to establish the properties of ML estimators is violated. In any event, both methods require specific distributional assumptions about technical or economic inefficiency. The main drawback of the deterministic frontier is that by not allowing for statistical noise, which all economic relationships exhibit, it may lead to a significant overestimation of the degree of efficiency. The problem of statistical noise is taken into account by the stochastic frontier whose estimation depends on distributional assumptions in a more fundamental way. In particular, those assumptions are required not only to estimate the frontier by either the COLS or ML method, but also to separate, at the level of the firm, inefficiency from statistical noise. We have examined some of the common assumptions about the distribution of inefficiency and statistical noise. However, there are no a priori grounds that establish what the correct assumption is.

As Schmidt (1986) has pointed out, while the theoretical basis of efficiency measurement is sound, the empirical study of frontiers is beset with difficulties. Empirically, inefficiency is measured in an essentially residual manner, and can be sensitive to specification not only in terms of functional form, but also in terms of the list of included inputs and distributional assumptions.[28] In addition, the desirable properties that we attribute to our estimators are dependent on whether the model is correctly specified in the broad sense. Specification issues are, however, largely an empirical question since there are few prior guidelines as to the correct specification. In our study, we attempt to address some of the specification issues that have been raised.

FOOTNOTES TO CHAPTER 2

1. The analysis can be extended to deal with multiple outputs. This we do not do here, as our study deals with an essentially single-output firm.

2. Note that the difference between the frontier and non-frontier approaches is largely empirical, not theoretical. In the frontier approach the objective is to characterize and measure inefficiency as deviations below or above the relevant frontier.

3. There is now an extensive literature on the subject. See the survey papers by Forsund et al. (1980) and Schmidt (1986). For more recent and other parallel developments see Journal of Econometrics (1990), Vol.46, Numbers 1/2.

4. See, for instance, Farrell and Fieldhouse (1962) and Seitz (1971).

5. Similar efficiency measures were also suggested by Forsund and Hjalmarsson (1974). Kopp, however, nicely integrates the non-parametric, Farrell approach with the parametric approach.

6. In this section, we assume that the relevant frontier is known and concentrate on how the various types of efficiency can be measured. Section 2.3 deals with specification and estimation issues.

7. Indeed, the efficiency standard adopted by Farrell was deterministic.

8. See, for instance, Forsund and Hjalmarsson (1974), Aigner et al. (1977), Schmidt and Lovell (1979), Lee and Tyler (1978), Kalirajan (1981), Pitt and Lee (1981), Huang and Bagi (1984), and Kumbhakar (1987, 1988) as a representative sample. For a more complete listing see the survey papers mentioned in footnote 3.

9. Kopp developed his measures for the deterministic case. However, his approach can be applied to a stochastic frontier since, ex post, a stochastic frontier differs from a deterministic one only by a multiplicative factor (the realized value of v). Alternatively, since a stochastic frontier is random, one can consider the average of that frontier for the purpose of efficiency measurement. Some of the difficulties of measuring efficiency with a stochastic frontier are discussed later in this chapter.

10. The relationship between the two measures, as expressed by (13), is straightforward for homogeneous technologies. When the technology is not homogeneous, the RTS are no longer a parametric constant, but depend upon scale. However, for the given factor ratios, since frontier and actual output are known, the RTS in that range can be estimated and (13) applied to give the approximate relationship between the output-based and input-based measures.

11. Notice though that, given the radial nature of the Farrell index, the TE index can be computed by taking the ratio of the technically efficient to actual quantity of any one factor input.

12. See footnote 9.

13. Equation (19) follows from the fact that (18) implies

$$x_1^J = (x_1^a/x_2^a)\ x_2^J$$

which after substitution into (17) yields (after some manipulation)

$$x_1^F = C^F/\ [r_1 + r_2(x_2^a/x_1^a)]$$

This can be seen to be identical to (19). Note that in (19) all the variables on the right-hand-side are known.

14. See Schmidt and Lovell (1979). The model represented by (22) and (23) can be extended to accommodate flexible functional forms as well as panel data. See, for example, Kumbhakar (1989, 1990) and Schmidt and Sickles (1984).

15. This is because, according to the Taylor series expansion, $\ln(y^*/y^o)$ is approximately equal to $[(y^* - y^o)/y^o]$.

16. If technical inefficiency is known (foreseen), it is like another input (e.g. management), although unlike other inputs it is unobservable. See Kumbhakar (1987).

17. A divergence between actual and expected output is relevant only for the measurement of allocative efficiency, and that too only when the function is not homogeneous. Technical efficiency can continue to be measured as indicated earlier, whether or not divergence exists.

18. Of course, in the deterministic case, we would not face the problem of defining expected output if technical inefficiency were foreseen. In the stochastic case, this would be necessary even if technical inefficiency were foreseen because output is inherently random.

19. Clearly, the assumption that technical inefficiency is known is a simplification. But as Schmidt (1986) points out, the opposite assumption is no less a simplification, since the truth probably lies in between.

20. We are concerned in this section with estimation issues when the sample constitutes a pure cross-section of firms. Estimation from panel data is thus ignored. See Schmidt and Sickles (1984), Schmidt (1986) and Kumbhakar (1987) for issues arising in that context.

21. Other distributions have also been considered. Thus, Stevenson (1980) considered a normal distribution with a non-zero mean, truncated at zero, Lee (1983) dealt with the flexible four-parameter Pearson family of distributions, and Greene (1990) proposed a two-parameter Gamma distribution.

22. Note that a stochastic frontier can also be estimated without making distributional assumptions. However, those assumptions are eventually needed to separate statistical noise from inefficiency. This issue is discussed shortly.

23. See Jondrow et al. (1982). Note that (50) or (53), and (51) or (54) are not entirely free of statistical noise. They also do not provide consistent estimates of u in that some variability in v is inherent and remains whatever the sample size. Waldman (1984) considered estimators of u and found the Jondrow et al. estimator to be optimal.

24. These assumptions are that the elements of the disturbance vector are independently and identically normally distributed with zero mean and constant variance, and that the explanatory variables are independent of the disturbance term.

25. On the other hand, a Monte Carlo study by Olsen et al. (1980) found that when u is half-normal, COLS performs as well as the ML method.

26. An alternative to expected profit maximization is median profit maximization [Kumbhakar (1987)]. However, as Kumbhakar argues, neither of these behavioural assumptions guarantees that the inputs would be independent of the disturbance term. In particular, if technical inefficiency (u) is known, it can hardly be assumed to be independent of the inputs. Thus, independence between u and the inputs requires the additional assumption that technical inefficiency is unknown to the firm. The independence assumption is a strong one, but one that is commonly employed (often implicitly) in studies that involve the direct estimation of production frontiers.

27. This model allows for systematic as well as unsystematic allocative inefficiency by permitting $E(\tau)$ to be non-zero and zero, respectively. See Schmidt and Lovell (1979) and Kumbhakar (1987).

28. One also needs to address the problems that arise when actual output differs from the output the firm expected to produce.

CHAPTER 3

THE NATURE OF THE SAMPLE ECONOMY, MODELS AND ESTIMATION METHODS

3.1 INTRODUCTION

Our sample economy is the village of Khilghati, lying some 95 miles north of the capital city of Dhaka. Data for a 100 households, out of a total 410, were collected through three interviews of the household heads during the June, 1981 - April, 1982 time interval, these interviews corresponding to the three cropping seasons. Households included in the sample were selected according to two criteria: one, the household head was or had been married, and two, the household cultivated some of its own land.[1] The purpose of this chapter is primarily two-fold. First, in Section 3.2, we outline the broad features and important structural and institutional characteristics of the village of Khilghati. This section provides the background for the specification and estimation of the models used to measure the different types of efficiency. The specification of the models, the estimation strategy and the computation of the various efficiency indices are covered in Section 3.3. Section 3.4 is a summary of the chapter.

3.2 THE NATURE OF THE SAMPLE ECONOMY: THE VILLAGE OF KHILGHATI

In terms of economic and social organization, Khilghati is quite typical of villages in Bangladesh and other densely populated countries of the Indian sub-continent. In 1981-82, it covered an area of 2.9 square miles with a population density of over 900 persons per square mile and a literacy rate of 54 percent, both of which are above the corresponding national averages.

Agriculture is the primary source of livelihood, with crop cultivation based on family farms being the dominant economic activity. Thus, almost 84 percent of total monthly income is derived from agriculture, while crop income itself accounts for about 66 percent of total income and almost 81 percent of agricultural income. Farm size is typically small, reflecting the pressure of population and the fragmentation of holdings. Methods of production are largely unmechanised, with animal power being the primary capital input. However, government irrigation projects and the greater availability of chemical fertilizer have combined to enable some reorganisation of older production techniques and the adoption of newer, high-yielding seed varieties (HYV). Thus, by 1980-82, more than 26 percent of the area under foodgrains was under HYV, compared to an average of just 2 percent during the 1967-69 period, while irrigated area increased by about 13 percent and the quantity of chemical fertilizer, in terms of nutrients per acre, almost quadrupled between those two periods [Alauddin and Tisdell (1988)].

3.2.1 THE NATURE OF ECONOMIC ACTIVITY IN KHILGHATI: AN OVERVIEW

The bulk of economic activity in Khilghati revolves around the cultivation of various food and non-food crops. In the latter category, jute is grown, but the village is overwhelmingly a rice-based economy, as almost 90 percent of total cropped area is devoted to that crop. By contrast, at the national level rice occupied about 80 percent of the total cropped area during the 1981-82 period [Alauddin and Tisdell (1988)]. The dominance of rice in Khilghati relative to other crops is clearly seen in Table 3.1 below, which shows the percent distribution of total cropped area by type of crop, as well as the associated cropping seasons.

The availability of irrigation water in the Khilghati region during the dry winter months has enabled farmers to grow and harvest three paddy crops during the year. As a consequence, Khilghati farmers grow rice throughout the year. Broadcast "Aus" paddy is planted in the spring months of March and April and the crop is harvested in July/August. At that time, transplantation of "Aman" paddy is undertaken and the crop is ready for harvesting by November/December. During the following winter months the fertilizer-intensive high-yielding "Boro" paddy is grown. The increased importance of the winter

TABLE 3.1

The Cropping Pattern

Crop	Cropped area (percent)	Cropping season
Rice	89.6	Whole year
of which		
Broadcast paddy	17.2	March/April - July/August
Transplant paddy	44.8	July/August - Nov./Dec.
HYV paddy	27.5	Nov./Dec. - March/April
Jute	7.4	March/April - July/August
Wheat	2.3	Nov./Dec. - March/April
Oilseeds	0.6	Nov./Dec. - March/April

Source: Adapted from Khandker (1982), Table 4.13, p. 130.

HYV rice crop is evidenced by the fact that it now occupies almost 27 percent of cropped area. Though Khilghati grows only the HYV winter rice, the local non-HYV winter rice is also grown in other parts of the country. However, for the nation as a whole, upwards of 70 percent of all winter rice is now of the high yielding variety [Alauddin and Tisdell (1988)].

Of the other crops grown in Khilghati, wheat and jute are the only ones of any significance, with oilseeds accounting for under one percent of cultivated area. Wheat, of the high-yielding variety, competes with the HYV winter rice, and has begun, in recent years, to compete more vigorously with rice in the diet in rural areas. However, it is of small importance in Khilghati during the period of our sample, occupying only 2-3 percent of total cropped area. Jute appears to be relatively more important and represents the only cash crop grown by the village. Its growing season coincides with that of broadcast Aus paddy. Consequently, it competes with that crop for productive resources. The relative importance of different crops is also reflected by the fact that while all 100 households in the sample grow Aman, 92 grow Aus, 95 grow Boro and 86 grow jute, only 29 households grow wheat and 6 grow oilseeds.

Overall, it appears that Khilghati is essentially a single crop economy from the perspective of the entire crop year. But if the period of analysis is the crop season, this assumption is largely valid only for the summer and winter crop seasons, in which the respective rice crops are dominant. In the spring season, jute appears to compete with rice for land and other productive resources. Thus, in that season, Khilghati can be viewed as a two-crop economy. From the point of view of efficiency measurement in a two-crop framework, we can measure technical and allocative efficiency for each crop as discussed in Chapter 2. However, it is also possible to measure output-mix efficiency to gauge the extent to which households are efficient in choosing the correct output proportions. In this study, however, we do not look into the question of output-mix efficiency. Instead, we treat the village of Khilghati as though it were a single crop economy, and thus confine our attention to the three rice crops grown during the crop year.[2]

3.2.2 TENANCY, FACTOR MARKETS AND EMPLOYMENT

Tenancy arrangements in the sample economy are essentially of two kinds. Households are either strictly owners, or both owners and tenants. The former group does not participate in the market for land services, while the latter group consists of farmers who are either net suppliers or net buyers of land services. In the sample, there are no farmers who are either pure tenants or pure manager-owners. Owners and owner-tenants are about evenly balanced in the sample, with some 52 percent of the households being owner-cultivators, and the remaining 48 percent being owner-tenants. These figures suggest that households in Khilghati participate rather actively in the local land market, although the amounts transacted are relatively small, given that owner-tenants cultivate only about 29 percent of all land in the sample. Of the 279 acres of land owned by the 100 households in the sample, about 20 percent (57 acres) was put on the rental market in the period under study. There are two types of rental arrangements - share tenancy and fixed-rent tenancy. Under the former, the tenant pays as rent a fixed share of the produce from the land, while under the latter the rental is a lump-sum cash payment. Both types of rental arrangements exist in Khilghati, with about 48 percent of rented land being subject to share tenancy.[3]

In an absolute sense, the size of the household farm in Khilghati is small. By Bangladeshi standards, however, our sample shows much variation in farm size. Table 3.2 below shows the distribution of households according to size and the average productivity of land for each size group. It is clear that the bulk of household production takes place on relatively small holdings. In particular, about 70 percent of the households cultivate holdings of 3 acres or less, with the average sample holding being 2.72 acres. Further, the same 70 percent of households account for only 45 percent of the total land cultivated. There does not appear to be any systematic relationship between farm size and productivity, though the data do suggest that productivity is lowest on farms of four acres or more.

TABLE 3.2

The Distribution of Households by Farm Size and Land Productivity

Farm size (acres)	Percent of households	Percent of land cultivated	Land productivity (Taka per acre)
0.1 - 1.0	10	3.0	5,292
1.0 - 2.0	34	19.2	4,603
2.0 - 3.0	26	22.4	4,077
3.0 - 4.0	13	15.1	5,053
4.0 +	17	40.3	3,895

Source: Compiled from Khandker (1982), Table 4.14, p. 130 and Table IV, p. 320. Note that each class interval above contains all farm households with farm size equal to and less than the upper limit of that interval.

Apart from land, which is the principal income-earning asset in Khilghati, and whose ownership is the major determinant of the socio-economic status of a household, labour power is the most important source of income for households. Within the farm household, labour is provided by adult males and females, as well as by minors (those under the age of 15). This labour is allocated among different types of activities. Table 3.3 below depicts the distribution of family labour among activities. It is clear that Khilghati households allocate the bulk of their labour services to crop cultivation. Apart from the cultivation of crops, non-crop activity also appears to be important, with about 24 percent of total family labour input being devoted to that activity. On the other hand, a very small proportion of family labour is supplied in the form of agricultural wage employment. Note also that, in spite of the dominance of crop cultivation, a substantial proportion of family labour is supplied to non-agricultural activities. Of course, there is variation among households in the extent to which these activities are undertaken. Thus, marginal farmers would typically engage much more in agricultural wage employment to supplement their crop income, while farmers higher up on the

TABLE 3.3

Total Family Labour Input by Type of Activity

Type of activity	Percent of households
1. Crop cultivation	41.9
2. Agricultural wage employment	4.6
3. Non-crop production	23.7
4. Non-agricultural activity	29.7

Source: Calculated from Khandker (1982), Table 4.17, p. 140.

socio-economic scale would engage much more in non-agricultural employment by virtue of their greater accessibility to such employment.[4] The sex and age of family members is also important here. Thus, typically women and minors are limited in terms of their off-farm employment opportunities because of social restrictions, although these restrictions are likely to be weaker in the case of marginal farmers. In addition, given the nature of crop cultivation, females and minors typically engage in other non-crop productive activities. While a substantial 42 percent of family labour is allocated to crop cultivation, the reliance on hired labour is also quite significant. Thus, of the total amount of labour input used in crop cultivation in the sample economy, as much as 42 percent represented hired labour.[5] Coupled with the fact that a rather significant amount of family labour seeks employment outside of agriculture, this suggests that there is significant labour market participation by Khilghati households, although women do not appear to participate to the extent that men do. Hired workers are either permanent workers attached to the household or casual workers whose services are purchased when needed. Typically, in Khilghati (as in other villages in Bangladesh and South Asia) a significant proportion of attached workers are minors; however, attached workers constitute a relatively small proportion of the total hired labour force. Only 28 percent of our households reported attached workers.

The degree of mechanization in Bangladeshi agriculture is low, as is to be expected given that cultivation is predominantly based on small, fragmented holdings. Thus, the dominant form of capital input in Khilghati (as elsewhere) is animal (bullock) power, and this input is usually owner-supplied. Some renting of bullock power exists, but this is quite limited. Khilghati agriculture is therefore largely traditional. An important exception to this is the use of high-yielding seed varieties. These seed varieties are fertilizer-intensive and require timely and adequate water supplies. Through various programmes initiated in the early sixties, the government has promoted the spread of modern irrigation and developed a system for the wider application of chemical fertilizer. In Khilghati, this has enabled not only the adoption of a high-yielding spring rice variety, but also of a high-yielding dry season rice variety. Thus, in addition to the traditional practice of using manures, high yielding seed varieties and the use of chemical fertilizers also appear to be an integral part of farming practices in our sample economy.[6]

3.3 THE MODELS AND THE ESTIMATION STRATEGY

In this section, we first specify the models used for the measurement of technical and allocative efficiency of Khilghati farmers, and then outline the estimation strategy. Khandker (1982) and Khandker et al. (1987) have examined the allocative efficiency of the farmers in our sample in terms of departures from the first-order conditions for profit maximization. Our study, however, differs in important respects from theirs. First, their studies are more aggregative in that the efficiency question is not examined from the point of view of individual crops. Rather, on the implicit assumption that the decision-making period of households is the entire crop year, they consider an aggregate of different crops and the inputs associated with their production. The present study, in contrast, involves disaggregation to the level of the individual crop, with the decision-making period being consequently assumed to be the relevant cropping season. The second, more important difference is that the aforementioned studies do not adopt the frontier approach. In those studies, the estimated production function, thus, does not correspond to the theoretical concept of a production function, and cannot therefore be used for obtaining meaningful farm-specific measures of technical efficiency. Furthermore, while their approach enables them to examine how serious departures from the profit-maximizing conditions are for each factor, the extra cost (that is, foregone profit) of those departures cannot be obtained. In our study, not only are we able to estimate the cost saving attainable through the elimination of technical and allocative inefficiency separately, we are able to do so by household and major crop. We also attempt to explain empirically the inter-farm, inter-crop differences in efficiency of both types.

3.3.1 THE FUNCTIONAL FORM

Our measures of technical and allocative efficiency are obtained by estimating both deterministic and stochastic production frontiers. Each type of frontier is estimated for each of the three rice crops grown in Khilghati over the crop year - Aus broadcast paddy, Aman transplant paddy, and Boro HYV paddy. Our choice of the production frontier as the basis of efficiency measurement is predicated on the absence of sufficient factor price variation needed to estimate a cost or profit frontier. In estimating the production frontier, the first major problem is that of specifying the functional form of the deterministic part of the frontier. While flexible functional forms are preferred a priori, the main practical problem with them is that they may introduce a high degree of multicollinearity. Thus, for example, in the case of the translog model, five extra parameters have to be estimated if a fifth factor is included. With simpler functional forms, like the CES or Cobb-Douglas model, on the other hand, the number of extra parameters would be only one. In line with the common approach in frontier studies, we adopt the homogeneous Cobb-Douglas functional form to represent the underlying technology. A significant empirical advantage of adopting a homogeneous function such as the Cobb-Douglas is that we do not have to worry about divergences between actual and expected output in the context of efficiency measurement. As we saw in Chapter 2, such divergences may raise significant difficulties for the measurement of allocative efficiency.[7]

One of the questions that arises in estimating a frontier production function from cross-sectional data is whether one can, a priori, assume that all farmers face the same technology. This is undoubtedly an important issue, and the approximate legitimacy of the assumption (common in the empirical literature) would depend upon the nature of the cross-sectional units being examined and the level of aggregation adopted. In our study, the analysis is conducted at the level of the individual farm household. In addition, the production frontiers we deal with are crop-specific. Coupled with the fact that we are concerned with farmers from the same village, these factors suggest that the adoption of a common frontier to represent the underlying technology in Khilghati is a reasonable assumption. Further support for that assumption comes from the studies by Khandker (1982) and Khandker et al. (1986) who, working with the same group of farmers, examined the question of whether the production function is the same for (i) small and large farmers, and (ii) owner-cultivators and owner-tenant cultivators. These questions have attracted a great deal of attention in the literature on agriculture in less developed countries. For instance, numerous findings suggest that small farms are more productive (per acre) than large farms. However, the tests conducted by Khandker and Khandker et al. with Khilghati data showed that technology does not appear to vary significantly according to either farm size or tenancy status. Even though these studies are aggregative, in that all crops are aggregated into a single output, while this study is crop-specific, their results put our assumption of a common technology for all farmers on a firmer footing.

3.3.2 THE INPUT SET AND FACTOR PRICES

The next question pertains to the choice of inputs to be included. This question acquires added significance in a frontier context for the following reason. In general, the random disturbance reflects the influence of omitted factors, and the exclusion of relevant variables biases the results. But in frontier estimation, there is an additional dimension to the problem. In particular, estimates of efficiency are likely to be sensitive to the number of factors included, given the way efficiency is measured. By allowing for statistical noise, the stochastic frontier is less likely to suffer from this difficulty than the deterministic frontier.[8] On the other hand, the inclusion of a very large set of inputs is not only too demanding from the data point of view, but would lead to a sharp reduction in the degrees of freedom and a severe collinearity problem. Consequently, we adopt an approach that attempts to strike a balance between the largest input set that we could consider for inclusion, given the data, and the set dictated by manageability and estimation considerations.

For Khilghati, we can identify four major inputs - land, labour, animal power, and chemical fertilizer. Fertilizer is a modern input, and its usage is important particularly for the dry season rice crop. It is easily measured, and its inclusion in the production function is clearly warranted. Farmers in the sample also use pesticides, but on a very limited scale. Hence, they can be excluded without any significant effects. However, since we lump together different types of fertilizer, we are assuming that they are perfect substitutes for each other. The land input should reflect the total amount of land (owned plus net land rented) used in the production of each crop. Ideally, it should also be quality-adjusted. However, the absence of the appropriate data rules this out.[9] In any event, the assumption that all land is of approximately the same quality may not be an unduly restrictive assumption for Khilghati. Thus, our land input is the total operational holding of the household. We argued in the previous section that, like much of peasant agriculture in Bangladesh, physical capital in Khilghati is quite rudimentary. The primary capital asset, other than land, is represented by bullocks that are used to plough the land. This greatly facilitates measurement, since otherwise we would face the difficult task of having to aggregate a number of heterogeneous capital assets. Thus, our capital input is the services of a pair of bullocks, measured in animal days, used to produce each rice crop.

The labour input is the most troublesome one, primarily because of its evident heterogeneity. A typical household's total labour input is differentiated not only by sex and age, but also by source (family vs. hired labour). Thus, corresponding to each source, there is a further classification according to sex and age (adults and minors). There are, as a result, potentially eight labour variables to be considered. The simple aggregation of all eight into a single labour input variable would appear to be too restrictive a procedure, implying as it does that all labour inputs are perfect substitutes. Nevertheless, some aggregation is needed to avoid a collinearity problem. Much of the empirical literature on the production functions of farmers in less developed countries tends to ignore the problem of labour heterogeneity, while the studies that address the issue deal primarily with the heterogeneity of family vs. hired labour [see, for instance, Bardhan (1973), Huang (1971), Brown and Salkin (1974), Deolalikar and Vijverberg (1983), and Nath (1974)]. However, heterogeneity with respect to age and/or sex is also potentially important. Khandker (1982) and Khandker et al. (1986) have examined the question of the heterogeneity of labour by both source (hired vs. family labour) and age and sex for the village of Khilghati. Their findings support the use of an aggregate of the labour inputs obtained by taking a weighted sum of the services of adult males, adult females and minors. The weights are the wage rates of the categories relative to the wage rate for adult males. In particular, they find that the disaggregation of the labour input, either by source or by age and sex, does not lead to results that are significantly different from those resulting from such aggregation. However, these findings are not entirely conclusive, in view of the fact that their testing procedure involves using the F ratio to test specifications that are not nested, a procedure that is incorrect. Nevertheless, it could be argued, a priori, that given that adult female labour and minors are involved in crop production on a very limited scale in Khilghati, the disaggragation by age and sex may not be important. In this study, the labour input is a simple aggregate of family and hired labour. In light of the limited role of adult females and minors, we consider only adult, male labour (hired plus family).

There have been numerous nonfrontier studies which suggest that education and other similar attributes (such as membership of co-operative societies or exposure to extension services) have a favourable impact on the technical efficiency of farmers in less developed countries [see the survey paper by Lockheed et al. (1980)]. Studies of this type estimate a nonfrontier production function with education as an explicit "management-input" variable. The results, in general, appear to support the inclusion of such a variable in the production function. However, in a frontier setting, technical efficiency is explicitly modeled by the variable e^{-u}, and inter-farm variations in that variable would likely reflect, amongst other things, the variations in farmer education. In other words, if education is relevant, its effect is represented by e^{-u}, so that including education separately is not necessary. One alternative to the inclusion of education as an input variable in the frontier function is to argue that educated and uneducated farmers do not share a common production frontier. If a separate frontier is estimated for educated and uneducated farmers one can then test whether educated farmers are, on average, more technically efficient. However, there are no compelling reasons, at least for our sample, for assuming that the frontier technology differs for educated and uneducated farmers, and therefore we take a different approach. If education does indeed have a favourable impact on technical efficiency, then one would expect any of the technical efficiency indices proposed to be positively correlated with an appropriately defined education variable. A similar argument could be made for the relationship between allocative efficiency and education. This question can be addressed once the technical (and allocative) efficiency indices have been obtained for each farmer in the sample. The approach can also be extended to deal with other "management-input" variables. Thus, for instance, agricultural co-operatives in less developed countries serve as a conduit for information about more productive farming practices, particularly those pertaining to HYV cultivation. Since HYV cultivation is risky, agricultural co-operatives play an important role in disseminating technical knowledge required for successful HYV cultivation.[10] To the extent that membership enhances management ability, one would expect members to be more efficient than non-members. The same argument could be made for exposure to agricultural extension services. Thus, we do not include an education variable, nor one reflecting membership or nonmembership in an agricultural cooperative explicitly in the production function. Instead, we examine their role in explaining inter-farm variations in efficiency, after the construction of the efficiency indices discussed in the previous chapter.[11]

In addition to factor quantities, we need factor prices in order to compute the allocative efficiency indices, and the costs associated with factor-specific technical inefficiency. The measurement of the relevant factor prices is a relatively straightforward matter when markets are well developed and the appropriate prices can be readily identified. Difficulties arise for identifying the appropriate prices when markets are fragmented and undeveloped, and transactions are governed by kinship and other social and institutional factors. In addition, as is true for the rural areas of less developed countries of the region, large landholding households in Bangladesh dominate the social, political and economic life, and exercise economic and political power. One implication of this is that large farmers are not price takers in the factor markets, an assumption implicit in the measurement of allocative efficiency in Chapter 2. However, for the sample at hand, we can, by and large, identify and measure prices of the factors included in the production function. And, while there is variation in farm size, there do not appear to be households in the sample that could be regarded as being truly large. In any event, the number of the relatively larger farmers is quite small. As a consequence, we feel our assumption that all farmers are price takers in factor markets to be reasonable. We briefly discuss our factor price measurement procedure below.

We have seen that Khilghati households rely quite significantly on casual hired labour in crop production, and that this labour is again dominated by adult males, since social custom inhibits the participation of both adult females and minors in the labour market. As Hossain (1977) and Khandker (1982) argue, the market-determined wage of casual hired labour could serve as an approximate indicator of the opportunity cost of adult family labour devoted to crop production.

The measurement of the price of the services of land raises significant difficulties. This is because the rental market for land is not well developed, and matters are further complicated by the existence of different types of tenancy arrangements. Land rental also happens to be dominated by kinship and patronage. Thus, a significant portion of the land rental arrangements under share tenancy were between relatives, and there is therefore no guarantee that rentals reflect the true scarcity value of the land. In general, rental arrangements under either type of tenancy system are historically determined, with only infrequent recontracting, and may not reflect the current opportunity cost of land services. On the other hand, the sheer pressure of population suggests that, under both types of tenancy, land rentals would probably not diverge significantly from their opportunity costs. Following Khandker (1982), the rental per acre, as determined under the fixed-cash tenancy system, is used in our study to represent the rental price of owned or rented land.

The rental market for bullock power is limited in Khilghati, as most farmers utilize the services of owned bullocks. There is nevertheless some buying and selling of the services of bullocks, and the rental for bullock power quoted by the farmers in the sample appears to be quite uniform over the sample. That rental price is taken to represent the opportunity cost of using owned bullock power. Much of the chemical fertilizer used by farmers comes through government agencies, and is sold at government-determined prices, which thus are very similar for all farmers. However, it is well known that larger farmers typically have better access to inputs such as these, and often the small farmers (usually pure tenants) have to purchase their supplies in the black market, where prices are significantly higher. On the other hand, in our sample the variation in fertilizer prices is quite limited, pointing perhaps to the fact that all farmers have reasonably equal access to government supplies. Table 3.4 below summarizes the definitions of all the output and input variables used in this study .

In conclusion, it might be noted that, like farmers in other developing countries, those in Bangladesh have unequal access to technical knowledge, factor markets, and public services in general.[12] The position of the farmer on the socio-economic scale is an an important factor in determining access. Thus, small farmers with little or no land of their own have limited access to technical knowledge because they lack education and/or because they are unable to become members of co-operatives or to benefit from public services such as those offered by government extension service workers.[13] They also typically have only limited access to factor markets and bank credit. As a result they are often unable to acquire subsidized inputs, such as chemical fertilizer, sold through government agencies, as large farmers are able to pre-empt a large proportion of existing supplies for themselves. It seems likely, therefore, that the degree of access to technical information, to public services, and to factor markets has an important influence on farmer efficiency. For example, the lack of access to technical knowledge will likely

TABLE 3.4

Variable Definitions

Variable symbol	Definition
y	Crop output (maunds)
x_1	Adult labour-hired plus family (man-days)
x_2	Cropped area (acres)
x_3	Bullock power (animal-days)
x_4	Chemical fertilizer (kilograms)
r_1	Wage rate of hired adult males (Tk. per man-day)
r_2	Rental on land (Tk. per acre)
r_3	Rental on bullock power (Tk. per animal-day)
r_4	Unit price of fertilizer (Tk. per maund)

Notes: 1 maund = 37.3261 Kg.

result in lower technical efficiency. In a similar vein, if a farmer is unable to acquire inputs (such as fertilizer) because of limited access to factor markets, this may lead to an even more inappropriate choice of factor combinations, thereby lowering allocative efficiency. The relative importance of these factors in determining the degree of farmer efficiency is difficult to examine empirically.

3.3.4 THE ESTIMATION APPROACH

In this sub-section, we outline the complete frontier models, the estimation strategy, and the assumptions underlying it. We estimate both deterministic and stochastic frontiers for each of the three rice crops. The deterministic kernel of these frontiers is assumed to take the Cobb-Douglas form, in the four factors of production defined in Table 3.4.

Estimating the Deterministic Frontier

For each of the three crops, the deterministic frontier with technical inefficiency is given by

$$\ln y_i = \alpha_o + \sum_j \alpha_j \ln x_{ij} - u_i \tag{1}$$

with $u_i \geq 0$ for all $i = 1, 2, .., T$. Here i indexes the farms in the sample, and $j = 1, 2, 3, 4$ indexes the four factors of production.

As indicated in Chapter 2, the deterministic frontier can be estimated by non-statistical or statistical methods. Under the former approach, we compute the frontier, as suggested by Aigner and Chu (1968), by minimizing either the expression given by (2) or that given by (3), each subject to the constraints given by (4) below:

$$\sum_i^T \left[\hat{\alpha}_o + \sum_j^4 \hat{\alpha}_j \ln x_{ij} - \ln y_i \right] \tag{2}$$

$$\sum_i^T \left[\hat{\alpha}_o + \sum_j^4 \hat{\alpha}_j \ln x_{ij} - \ln y_i \right]^2 \tag{3}$$

$$\ln y_i \leq \hat{\alpha}_o + \Sigma \hat{\alpha}_j \ln x_{ij}, \ \hat{\alpha}_j \geq 0 \text{ for } j = 1, 2, 3, 4 \text{ and } i = 1, 2, ..., T. \tag{4}$$

The ^ symbol specifies a computed value. The former is a linear programming problem, while the latter is a quadratic programming problem. Thus, our first set of estimates is obtained by the application of linear and quadratic programming techniques. Of course, these estimates possess no statistical properties and are sensitive to outliers in the data.

We also estimate the deterministic frontier by statistical methods, and these are based on certain assumptions. In particular, we assume that the u_i are identically and independently distributed with mean μ and variance σ_u^2, and that the explanatory variables are uncorrelated with the u_i. This latter assumption is satisfied if farmers maximize expected or median profit, and technical inefficiency is unknown. As we saw in Chapter 2, under these assumptions, OLS estimation yields consistent estimates of the slope coefficients, but not of the intercept.[14] However, the OLS method does not estimate a frontier, since with this estimation method the estimated function will not be the upper bound to all observations. A solution to these difficulties is to "correct" the OLS intercept estimate. Two types of correction are possible. The first involves adjusting the intercept term until no residual is positive. We call this estimator COLS1. The second involves adjusting the intercept by μ, the mean of the distribution of the u_i. We label this method COLS2. Either one is a consistent estimator of the intercept, though COLS2 does not guarantee that actual output will not exceed frontier output. In addition, while COLS1 does not impose a specific distributional assumption (about the u_i) on the data, such an assumption is required to implement the COLS2 approach. In the latter case, we consider two alternative possibilities, in order to determine whether the results are sensitive to distributional assumptions. In the first, we let the u_i follow a half-normal distribution, in which case the estimate of μ can be shown to be

$$\hat{\mu} = \hat{E}(u) = (2/\Pi)^{1/2} \hat{\sigma}_u \qquad (5)$$

where $\hat{\sigma}_u$ is obtained from the OLS residuals as follows:[15]

$$\hat{\sigma}_u = \left[\sum_1^T \hat{u}_i^2 / (T - 5) \right]^{1/2} \qquad (6)$$

where the $\hat{u}_i$ are the estimated OLS residuals, and (T-5) represents the degrees of freedom. Our alternative assumption is that the u_i follow an exponential distribution. As is well known, the mean of that distribution is simply equal to its standard deviation. Consequently, in this case, the estimate of μ would be given by the expression on the right-hand side of (6). In other words, under COLS2, the OLS estimate of the intercept is adjusted by (5) if the u_i are half normal, and by (6) if they are exponential.[16]

The production frontier can also be estimated by maximum likelihood (ML). Of course, this requires specific assumptions about the distribution of the u_i. As we saw in Chapter 2, given the Cobb-Douglas functional form, the ML estimators are simply the linear and quadratic programming estimators discussed above, according as the distribution of the u_i is exponential or half-normal respectively. However, as we noted in that chapter, these estimators possess unknown statistical properties. Thus, since we obtain the linear and quadratic programming estimators, there is no reason for applying the ML method.

Once the production frontier has been estimated by the different methods outlined above, the various efficiency indices can be computed. In particular, the output-based farm-specific technical efficiency index, $TE_i(y)$, is

$$TE_i(y) = Y_i^o / Y_i^* \qquad (7)$$

where the y in parentheses indicates that this is an output-based measure, Y_i^o

is the actual output of the i^{th} farm household, and y_i^* is that household's frontier output and is given by

$$y_i^* = \hat{A} \prod_{j=1}^{4} x_{ij}^{\hat{\alpha}_j} \tag{8}$$

where $\hat{A}$ = antilog $\hat{\alpha}_o$, $\hat{\alpha}_o$ being the consistent estimator of α_o.

Similarly, we also compute the input-based, multi-factor generalized Farrell technical efficiency index for the i^{th} firm, $TE_i(x)$, as follows:

$$TE_i(x) = x_{ij}^* / x_{ij}^o \qquad j = 1, 2, 3, 4 \tag{9}$$

Here, x_{ij}^o is the actual quantity of factor j used by the i^{th} household, while x_{ij}^* is the technically efficient quantity of that factor required to produce that household's actual output.[17] Note that the x_{ij}^* satisfy the requirement

$$\left[x_{ij}^* / x_{ik}^* \right] = \left[x_{ij}^o / x_{ik}^o \right] \quad \text{for all } j \neq k \tag{10}$$

It can also be shown that an identical index of technical efficiency can be formed by taking the ratio of the cost of the technically efficient input vector x^* to the cost of the actual input vector x^o. That is,

$$r' x_i^* / r' x_i^o \tag{11}$$

where r is the vector of factor prices. Either (10) or (11) can be used to compute the input-based technical efficiency index. Note that $[1 - TE_i(x)]$ gives the proportionate cost savings attainable through the elimination of technical inefficiency.

The estimated production frontier can also be used to obtain factor-specific indices of technical efficiency. Thus, we solve for the technically efficient quantity of factor j for the i^{th} firm ($\hat{x}_{ij}$), given actual output and the actual quantities of all other factors x_{ik} ($k \neq j$).[18] The technical efficiency index for the j^{th} factor of the i^{th} firm, $TE_i(x_j)$, is then given by

$$TE_i(x_j) = \hat{x}_{ij} / x^o_{ij} \qquad \text{for } j = 1, 2, 3, 4 \quad i = 1, 2, \ldots, T \tag{12}$$

Note that this index is not radial in nature. Therefore, it itself cannot be given the cost interpretation of the multi-factor index (10). A cost interpretation becomes possible if we compute the technical cost efficiency index, TCE (x_j), for each factor. For the i^{th} household and the j^{th} factor, this index is

$$TCE_i(x_j) = \left[r_j \hat{x}_{ij} + \sum_{k \neq j} r_k x^o_{ik} \right] / r' x^o_i \tag{13}$$

Here, the numerator is simply the cost of the technically efficient level of the j^{th} factor plus the actual cost of all other factors, while the denominator is actual cost of all factors.It can be seen that one minus the index (13) indicates the cost reduction possible by eliminating the technical inefficiency associated with factor j.

We can also compute the multi-factor allocative efficiency index, AE(x), for each household. This requires finding the allocatively efficient factor vector for the i^{th} household , x^+_i. given actual output y^o_i. This vector is obtained as the solution to the following system of five equations - the frontier isoquant equation for actual output, and the first-order conditions for cost minimization:

$$Y_i^o = \hat{A} \prod_{j=1}^{4} x_{ij}^{\alpha_j} \tag{14}$$

$$\left[\hat{\alpha}_k r_j / \hat{\alpha}_j r_k \right] = \left[x_{ij}^o / x_{ik}^o \right] \quad \text{for } j \neq k \tag{15}$$

We then find the factor vector $x^{\oplus}$ that costs the same as the allocatively efficient vector x^{+} by solving (16) below

$$r' x_i^{\oplus} = r' \; x_i^{+} \tag{16}$$

subject to the restriction

$$x_{ij}^{\oplus} / x_{ik}^{\oplus} = x_{ij}^{o} / x_{ik}^{o} \quad \text{for all } j \neq k. \tag{17}$$

The allocative efficiency index for the i^{th} household is then given by

$$AE_i(x) = x_{ij}^{\oplus} / x_{ij}^{*} \quad \text{for } j = 1, 2, 3, 4 \tag{18}$$

We can easily show that one minus this index measures the cost reduction possible through the elimination of allocative inefficiency. The overall index of economic efficiency for the i^{th} firm, $EE_i(x)$, is then

$$EE_i(x) = TE_i(x) . AE_i(x) \tag{19}$$

Again, one minus this index measures the cost reduction possible through the elimination of both technical and allocative inefficiency.[19]

This leads us to our final firm-specific efficiency index - the index that measures factor-specific allocative efficiency. Thus, the j^{th} factor's allocative efficiency index, $AE_i(x_j)$, can be shown to be [20]

$$AE_i(x_j) = TE_i(x) \cdot AE_i(x) \,/\, TCE_i(x_j) \tag{20}$$

While (13) can be used to determine the cost saving possible by eliminating the technical efficiency of factor j, the index (20) points to the additional cost saving possible if all factors are subsequently adjusted to their allocatively efficient levels. This concludes the discussion on the computation of various efficiency indices.

Estimating the Stochastic Frontier

The stochastic frontier with technical inefficiency can be written as

$$\ln y_i = \alpha_0 + \sum_{j=1}^{4} \alpha_j \ln x_{ij} + \varepsilon_i \tag{21}$$

where $\varepsilon_i = v_i - u_i$, and the v_i represent statistical noise. The stochastic production frontier itself is the deterministic part of (21) plus the v_i. Our objective is to first estimate (21), and then to separate statistical noise from technical inefficiency in order to obtain the frontier.

The model (21) can be estimated by the COLS2 method or by the ML method. In either case, we need to make specific distributional assumptions. While retaining the assumptions underlying the estimation of the deterministic frontier, we assume additionally that the v_i are independently, identically and normally distributed with zero mean and constant variance σ_v^2, and that they are independent of both the explanatory variables and the u_i. As before, we consider two alternative distributional assumptions about the u_i - first, that the u_i follow a half-normal distribution, and second that they are exponentially distributed.

Under the COLS2 method, we first estimate (21) by OLS, and adjust the estimated intercept by the mean of the u_i estimated from the OLS residuals. This adjustment differs from the ones in the deterministic case because now the disturbance term is a composite of both statistical noise and technical inefficiency.[21] When the u_i are half-normal, their mean is

$$E(u_i) = \left[2 / \Pi \right]^{1/2} \sigma_u \tag{22}$$

In order to estimate E(u), we need an estimate of σ_u. The latter can be obtained by first obtaining a consistent estimate of the third moment of the ε_i (from the OLS residuals), and then equating the sample third moment to the corresponding population moment [see the discussion in Chapter 2, Section 2.4.2 for the expressions involved].

When the u_i follow an exponential distribution, the adjustment term, the mean of the u_i, is given by

$$E\ (u_i) = 1/\gamma \tag{23}$$

In order to estimate γ, we once again use the third moment of the ε_i, which can be shown to be

$$\mu_3 = -\ 2\ (1/\gamma)^3 \tag{24}$$

Again, the OLS residuals provide a consistent estimate of μ_3, which can be equated to the population third moment given by (24). The latter equation can then be solved to obtain an estimate of γ.

While the COLS2 method has the advantage of being relatively simple, the ML approach is more efficient asymptotically. Of course, since the ε_i are unbounded, the range problem which precluded the derivation of the statistical properties in the deterministic case no longer exists. As we showed in Chapter 2, the ML method requires numerical optimization techniques in order to estimate the relevant parameters, since maximizing the likelihood function does not lead to explicit solutions for the estimators. Both estimation methods provide consistent estimates of the production parameters and of the variances of the u_i and the ε_i. However, in order to estimate the production frontier, statistical noise has to be separated from technical inefficiency. As we saw in Chapter 2, Section 2.4.1, this can be done by forming the conditional density of the u_i given ε_i, and then estimating either the mean or the mode of the conditional distribution. In this study, we consider only the mean. When the u_i are half-normal, their conditional mean is

$$E\,(u_i/\varepsilon_i) \;=\; (\sigma_u\,\sigma_v\,/\,\sigma)^2 \left[\frac{\phi_i(\varepsilon_i\lambda\,/\sigma)}{[1 - \Phi_i(\varepsilon_i\lambda/\sigma)]} - \frac{\varepsilon_i\lambda}{\sigma}\right] \tag{25}$$

where $\sigma = (\sigma_u^2 + \sigma_v^2)^{1/2}$, $\lambda = \sigma_u/\sigma_v$, and ϕ and Φ are the standard normal density and distribution functions respectively. Both the COLS2 and ML methods yield consistent estimates of the parameters σ_u, σ_v, σ and λ, which along with the estimates of the composite disturbance ε_i provide all the information required to estimate the u_i using (25). Of course, with these estimates it is easy to obtain estimates of the v_i. As a consequence, we are able to estimate the stochastic frontier itself.

If the u_i are assumed to follow an exponential distribution, it can be shown that the mean of the conditional distribution is given by

$$E\,(u_i/\epsilon_i) \;=\; \sigma_v \left[\frac{\phi(\Omega_i)}{1 - \phi(\Omega_i)} - \Omega_i \right] \tag{26}$$

where $\Omega_i = (\epsilon_i + \sigma_v^2 \gamma)/\sigma_v$. Again, the application of either of our estimation methods provides an estimate of each of the elements on the right hand side, so that the u_i and hence the v_i can be obtained.[22]

Once the stochastic frontier has been estimated, efficiency measurement can proceed in the manner outlined for the deterministic frontier above since the estimated stochastic frontier will differ from the deterministic frontier only by a multiplicative factor - namely $\hat{v}_i$, the estimate of v_i. Note that alternatively we can define a mean or median frontier, and use it as the efficiency standard. We do not adopt this latter approach in the present study.[23] Note though that our choice of the homogeneous, Cobb-Douglas function means not only that either approach would give the same estimates of efficiency, but also that we avoid the problems for efficiency measurement arising out of unforeseen fluctuations in output (particularly in the stochastic case). In particular, unforeseen technical inefficiency and/or inherent randomness in output have no impact on the allocatively efficient factor ratios when the function is homogeneous. Table 3.6 presents a summary of our estimation strategy and the efficiency indices computed.

TABLE 3.6

Summary of Estimation Methods and Efficiency Indices

Estimation method	Efficiency indices	Crops
Deterministic frontier	1a. Output-based TE index	Aus Paddy
1. COLS1	b. Multi-factor TE index	T = 78
2. COLS2	2. Multi-factor AE index	
3. LP	3. Multi-factor EE index	Aman Paddy
4. QP	4. Factor-specific TE index	T = 90
	5. Factor-specific TE cost index	
Stochastic frontier	6. Factor-specific AE index	Boro" Paddy
1. COLS2		T = 83
2. ML		

Notes: (i) COLS, ML, LP, and QP stand for the corrected least squares, maximum likelihood, linear and quadratic programming estimators, respectively, and T stands for the sample size.

(ii) TE, AE, and EE stand for technical, allocative and economic efficiency, respectively.

3.4 SUMMARY AND CONCLUSIONS

In this chapter, we have outlined the broad features and discussed the nature of economic activity in our sample economy, the Bangladeshi village of Khilghati. Survey data for a sample of 100 households from this village are used for the purpose of measuring farmer technical and allocative efficiency. Crop cultivation is the major form of economic activity, with rice being, by far, the dominant crop grown. Khilghati grows and harvests three rice crops, each corresponding to the three crop seasons. Production techniques are largely traditional, although the availability of water during the dry season, and the gradual spread of the "Green Revolution" have enabled farmers to adopt high-yielding seed varieties and to use other modern inputs such as chemical fertilizer. We compute both multi-factor and single-factor indices of farmer efficiency. The steps involved in the computation of the various efficiency indices have been discussed at some length in this chapter. Our efficiency indices are derived for each of the three crops on the basis of both deterministic and stochastic production frontiers which are estimated from output-input data for the crops, under the assumption that households are price takers in factor markets. While the production function is assumed to be of the Cobb-Douglas form in four inputs - land, adult labour, bullock-power and chemical fertilizer - the production frontiers are estimated under alternative assumptions, in order to determine the sensitivity of the efficiency indices to estimation methods and to assumptions regarding the distribution of technical inefficiency across households.

We consider not only both the deterministic and stochastic versions of the production frontier, but also the half-normal and exponential distributions to represent the technical inefficiency term. In addition, we estimate the deterministic and stochastic frontiers by two modifications of the OLS method, as well as by the maximum likelihood approach. In the deterministic case, the ML estimators are in fact programming estimators, but their statistical properties are not known. This problem with maximum likelihood is not encountered in the stochastic case, which allows departures from the production function to reflect statistical noise and technical inefficiency. This complicates the estimation procedure, particularly since one now needs to separately estimate these departures in order to obtain indices of technical efficiency for each household. Following Jondrow et al. (1982), we achieve this by estimating the technical inefficiency variable by the mean of its conditional distribution.

FOOTNOTES TO CHAPTER 3

1. See Khandker (1982), Chapter 3 for details on survey design and for a more elaborate description of the data. Our discussion in this section draws selectively from that material.

2. Thus, we do not examine the extent to which Khilghati farmers are efficient in their choice of output proportions.

3. The land market in rural Bangladesh is dominated by large landholders and patron-client relationships. Furthermore, kinship factors are important as well. Thus, in our sample a significant portion of the land that was rented on a share basis reflected transactions between relatives.

4. In general, marginal farmers, particularly those that are pure tenants (of which there are none in our sample), are likely to have limited access to employment off the farms of large landholders. As Ahmed and Freedman (1982) point out, the general existence of surplus labour, and the absence of written contractual agreements, give these landlords the power to appropriate the labour not only of the tenant, but also of his family.

5. The study by Ahmed and Freedman suggests that in rural Bangladesh it is primarily the larger landholding classes that employ hired labour to any extent.

6. Chemical fertilizers are distributed at subsidized rates through government-appointed retailers at the village level or through agricultural co-operatives.

7. Only a small number of frontier studies employ flexible functional forms. Those of more recent vintage that do adopt a translog model. However, those studies deal with the measurement of technical efficiency [see, for instance, Kalirajan (1986), Kalirajan and Flinn (1983) and Kopp and Smith (1980)]. They, therefore, are not confronted with the problems that arise in the measurement of allocative efficiency when more general nonhomogeneous technologies are considered.

8. This is because in a deterministic context, variations in output not explained by variations in inputs is assumed to reflect differences in technical inefficiency.

9. One way of allowing for land quality is to consider two types of land, irrigated and non-irrigated. However, we do not have the requisite data.

10. According to Ahmed and Freedman (1982), while membership in agricultural co-operatives and other similar organizations in Bangladesh has grown, participation is largely confined to large farmers and owner-tenants. Pure tenants' participation is generally limited, and their channels for information tend to be of the informal type (namely, relatives and friends).

11. This approach has been adopted by Kalirajan and Flinn (1983) in their study of technical efficiency of rice farmers in the Philippines.

12. See, for instance, Ahmed and Freedman (1982) and Islam (1978).

13. The study by Ahmed and Freedman shows that the inability or unwillingness of small farmers to participate in co-operatives reflects, respectively, the fact that these farmers often cannot meet the requirements for membership, modest though those might be, and the fear of unequal partnership since such organizations are often dominated by large landholders. The dominance of large farmers in credit co-operatives, for instance, has been documented in the studies by Blair (1978) and IBRD (1974).

14. The assumption that technical inefficiency is completely unknown is probably incorrect, but no more so than the assumption that it is completely known. As Schmidt (1986) points out, the truth is likely to lies somewhere in between.

15. Note that since the u_i are half-normal, σ_u^2 is not the variance, but rather the second moment about zero. The second moment about the mean (the variance of the u_i), on the other hand, is given by:

$$v(u_i) = \left[\frac{\Pi - 2}{\Pi}\right] \sigma_u^2$$

16. Under COLS1, we have $\hat{\alpha}_o = \bar{\alpha}_o + e(max)$, where $e(max)$ is the largest OLS residual, while in the case of COLS2, $\hat{\alpha}_o = \bar{\alpha}_o + \hat{\mu}$. Note that $\bar{\alpha}_o$ is the OLS estimator of α_o.

17. Notice that (9) holds for all j, given the radial nature of the index. Thus, it is necessary merely to compute this index for any one factor.

18. Of course, this makes $\hat{x}_{ij}$ and the actual quantities of all other factors a technically efficient combination for the actual output y^o.

19. This is because we can alternatively express $[1 - EE_i(x)]$ as follows:

$$[1 - TE_i(x)][1 - AE_i(x)]$$

20. Equation (20) follows from the fact that the product of factor-specific allocative efficiency and the index of technical cost efficiency is identical for all factors, and is equal to the multi-factor index of economic efficiency. See Kopp (1980).

21. Since $\varepsilon_i = v_i - u_i$, $E(\varepsilon_i) = - E(u_i)$, as $E(v_i) = 0$ by assumption.

22. Under the COLS2 approach, we first adjust the intercept by adding the mean of the estimated OLS residuals. After the adjustment we recompute the residuals. It is this latter set of residuals that is used to separate technical inefficiency from statistical noise in both (25) and (26).

23. Either frontier would give the same estimates of technical and allocative efficiency. It is important to note though that, if the average frontier is used as the efficiency standard, we cannot use actual output in the process of computing our efficiency measures. This is because actual output reflects both statistical noise and technical inefficiency, while the average frontier is deterministic. Consequently, it is not actual but the average output that would be produced as a result of technical inefficiency alone that is relevant. This requires adjusting actual output y_i^o as follows

$$\bar{y}_i = (y_i^o / e^{\hat{v}_i})$$

when we are looking at the median frontier, and as

$$\bar{y}_i = (y_i^o / e^{\hat{v}_i}) \, e^{\hat{\sigma}_u^2}$$

when we are dealing with the mean frontier. In both expressions, $\bar{y}$ refers to adjusted output. Note that the use of the average frontier is equivalent to a deterministic frontier approach, since the population mean of a stochastic frontier is a deterministic frontier. In other words, we can rationalize a deterministic frontier as the mean stochastic frontier. The crucial difference, however, is that with a deterministic frontier efficiency is computed with respect to actual output, while with the average frontier this is done with respect to average output. Computations of the latter type are clearly more meaningful in that they adjust for statistical noise which the computations of purely deterministic frontiers do not.

CHAPTER 4

DETERMINISTIC FRONTIERS: ESTIMATION AND RESULTS

4.1 INTRODUCTION

In this chapter, we present and discuss our estimates of technical, allocative and economic efficiency of Khilghati farmers in the production of the three rice crops - Aus rice, Boro rice and Aman rice. These estimates are all obtained by estimating a deterministic Cobb-Douglas production frontier in four inputs - land, fertilizer, bullock power, and adult, male labour. The results from the stochastic frontier, our primary interest in this study, are dealt with in the subsequent chapter. In order to enable an orderly treatment of the large body of results, this chapter is organized as follows. Section 4.2 deals with the crop-wise estimates of technical efficiency. It begins, however, with a brief discussion of the ordinary least squares estimates of the production function, since those estimates are required for applying the various corrected least squares (COLS) approaches for estimating the production frontier. In Section 4.3, we present and analyze the allocative and economic efficiency indices by crop. We conclude the chapter with a summary of our findings in Section 4.4.

4.2. A CROP-WISE ANALYSIS OF TECHNICAL EFFICIENCY IN KHILGHATI

We first briefly discuss the OLS estimates of the Cobb-Douglas function applied to each of the three rice crops cultivated in Khilghati. Those estimates are presented in Table 4.1. The Cobb-Douglas function appears to fit the data for each rice crop rather well and each estimated function is highly significant at even the one percent level of significance. The slope coefficients of the estimated function are the input elasticities of output. With a few exceptions, all are statistically significant.[1] With the exception of the labour elasticity and possibly the bullock-power elasticity in the Aus equations, the estimated input elasticities are quite plausible.[2] The importance of fertilizer is indicated by its highly significant elasticity. Somewhat surprising is the finding that that elasticity is larger in the Aman equation than it is in the Boro equation considering that the latter is a fertilizer-intensive, high-yeilding variety (HYV) of rice. The estimates also indicate that the departures from constant returns to scale are slight, with both Aman and Aus depicting mildly decreasing returns and Boro showing slightly increasing returns.

The production function estimated by OLS does not constitute a frontier since observations lie above it. Furthermore, since the production frontier is deterministic, the disturbance term will not have zero mean so that the OLS estimator of the intercept will not be a consistent estimator.[3] One can attempt to address both these problems by appropriately "correcting" the OLS estimator. As we saw in chapter 3, there can be several corrected OLS estimators, since the required correction depends upon the assumptions that one makes. The first version of corrected least squares that we adopt (COLS1) involves adjusting the OLS intercept upward by an amount equal to the largest OLS residual. This leads not only to a consistent estimator of the intercept [Greene (1980)], but also estimates a frontier in that actual output cannot exceed frontier output. The second method we use (COLS2) involves two alternate assumptions about the distribution of the one-sided disturbance term - one that it follows a half-normal distribution, and two, that it follows an exponential distribution. In each case, the OLS intercept is adjusted upward by the mean of the disturbance term which can be estimated from the OLS residuals.[4] Both these versions of COLS2 are consistent estimators of the intercept term. Their major drawback is that they do not guarantee (like COLS1) that actual output will not exceed frontier output. This problem does not arise if the mean adjustments of the intercept are at least as large as the largest OLS residual. We applied COLS1 and both versions of COLS2 to each of the three rice crops.

We also estimate the frontier by two non-statistical methods. Under the first approach, we minimize the sum of residuals (departures from the frontier) subject to the constraint that actual output is less than or equal to fitted output at each observation. This is a linear programming problem, and is equivalent to maximizing the likelihood function under the assumption that the disturbance term is exponentially distributed and the aforementioned constraints hold. The second method involves minimizing the sum of squared residuals under the same constraints; this is a quadratic programming problem and is equivalent to maximum likelihood estimation under the assumption that the disturbance term is distributed half-normally [see Schmidt (1976) and Chapter 2 for details]. Thus, we have five different estimates of the production frontier for each crop - three from applying corrected least squares and two from using the linear and quadratic programming estimators. The main drawback with the programming estimators is that their statistical properties are not known. The estimates of the frontier based on these different estimation methods are presented separately for each crop in Tables 4.2, 4.3 and 4.4. These and other tables containing our results appear at the end of the chapter.

4.2.1 THE ESTIMATES OF THE PRODUCTION FRONTIER

The three COLS estimates for each crop differ from the OLS estimates only in terms of the intercept term.[5] Looking first at the results for Aman rice, note that while the linear programming (LP) and quadratic programming (QP) estimates are similar, they differ quite substantially from the COLS estimates in certain respects. In particular, while the labour and fertilizer elasticities are not very different, the bullock-power and land elasticities are. There is a sizable increase in the bullock-power elasticity in moving from the COLS to the programming estimators and this is largely at the expense of the land elasticity. This could reflect the greater sensitivity of programming estimators to outliers in the data.

Turning next to the estimated frontiers for Boro rice (Table 4.3), note first that the linear and quadratic programming estimates are identical. Second, as in the case of the Aman frontier, the land elasticity decreases and the bullock-power elasticity increases, both changes being large; again, this is likely due to outliers in the data.

The same general sensitivity of estimates is observed when we consider the results for Aus rice. One notable feature is that the labour elasticity, which was very small under COLS, increases substantially under the programming method and appears to be at the expense of both the land and bullock-power elasticities. It seems, therefore, that the Aus frontier estimated by the programming estimators differs from the COLS frontiers in a more fundamental way than was the case with the Aman and Boro frontiers. The question of how significantly differences in the estimates of the parameters of the deterministic production frontier affect measured technical and allocative efficiency is a question we explore in the remainder of this chapter.

4.2.2 THE ESTIMATES OF TECHNICAL EFFICIENCY

Having discussed the various estimates of the production frontier, we turn now to presenting and discussing our estimates of technical efficiency. As we indicated in Chapters 2 and 3, the index of technical efficiency can be an input-based radial measure (the generalized Farrell, multi-factor index) or an output-based index reflecting the farm household's actual output relative to the frontier output.[6] We have summarized our results in Tables 4.5 through 4.7 (the input-based estimates) and Tables 4.8 through 4.10 (the output-based measure), which show (for each crop) the distribution of farm households by technical efficiency as well as by estimation method. While the tables present the results for both the input-based and output-based technical efficiency indices, we confine our attention to the former, primarily because the two are almost perfectly correlated. This is not surprising since, as we indicated in Chapter 2, under conditions of constant returns to scale the two measures are identical.

Table 4.5 depicts the results for Aman rice. Note first that irrespective of the estimation method, no farm household has a technical efficiency index under 50 percent. Note further that the COLS2 estimates are, in general higher than those obtained by any of the other methods. Indeed, several farm households were estimated by COLS2 to have a technical efficiency index in excess of 100. As we have argued before, the correction required by COLS2 does not guarantee that actual output will not exceed the estimated frontier output. For this reason, we find that average degree of efficiency is estimated to be higher under COLS2. Indeed, since the COLS1 adjustment is just sufficient to make at least one household 100 percent efficient, COLS2 would necessarily lead to some households with a technical efficiency index in excess of 100 if the correction term (the estimated mean of the disturbance term) is smaller than the largest OLS residual; this can be seen to be the case for all crops by comparing the COLS1 and COLS intercepts. Thus while the two COLS2 estimates are very similar, it is not surprising that the average level of technical efficiency, which is around the 90 percent level, is nearly 10 percentage points higher than the corresponding average obtained from the COLS1, LP and QP estimates.

The results based on COLS1, LP and QP are very similar, with more than 60 percent of all farmers lying in the 70-80 percent technical efficiency range. While definitely lower than the COLS2 estimates, the COLS1, LP and QP estimates suggest a high degree of technical efficiency in the cultivation of Aman rice. The estimated average level of technical efficiency under these methods is in the 80-82 percent range, suggesting that the elimination of technical inefficiency would lower costs by about 18-20 percent on average, while for the most inefficient farmers, this cost saving could be as much as 40 percent.[7] In summary, it seems that Khilghati households are highly efficient (technically speaking) in the cultivation of Aman rice, with only a handful of farmers with technical efficiency below 70 percent. Since in general technical efficiency tends to be understated in a deterministic context, this finding would likely be supported further in the next chapter where we consider a stochastic production frontier.

The technical efficiency results for Boro are given in Table 4.6. One major difference from the Aman results is that farmers are relatively more evenly distributed along the technical efficiency spectrum, whatever the estimation method used. For instance, the COLS1, LP and QP estimates suggest that more than 15 percent of farm households have a technical efficiency index under 50 percent. The corresponding figure is much smaller for the COLS2 estimates which are again much higher, with the most efficient farmers displaying technical efficiency well in excess of 100. The average level of technical efficiency according to the COLS2 estimates is in the 85-88 percent range and this is lower than the corresponding figures for Aman. But as was the case for Aman rice, the two COLS2 frequency distributions are very similar with similar characteristics.

The COLS1, LP and QP estimates also show similarity. The LP and QP frequency distributions are identical, reflecting the fact that the LP and QP estimates of the production function were virtually the same. The average level of efficiency according to these estimates is in the 70-73 percent range and thus almost 10 percentage points lower than the corresponding figure for Aman rice. These estimates suggest that farm households could realize a cost saving in excess of 25 percent on average by eliminating technical inefficiency, and for the most inefficient farmers, that saving could be as much as 60 percent. CLearly, the results for Boro point to a more uneven and variable performance as compared to Aman.

Turning next to Table 4.7 which contains the results for Aus rice, notice that they are quite different in several respects from those for Aman and Boro. First of all, not only is the average level of technical efficiency much lower in Aus farming but it also varies considerably more across farm households; and this is true whichever set of estimates one looks at. Second, the similarity between the two COLS2 estimates and between the COLS1, LP and QP estimates is no longer that marked. Third, one major difference from previous results that stands out is that the COLS1, LP and QP frequency distributions of technical efficiency are fundamentally different from those for COLS2. For instance, it can be seen that the COLS1 frequency distribution implies that the vast majority of farm households (in excess of 60 percent) have a technical efficiency index under 60 percent; indeed, almost 40 percent of the farmers lie below the 50 percent efficiency level. In contrast, the COLS2 distributions remain markedly skewed to the left, implying that the bulk of the farmers are concentrated in the high efficiency ranges. These differences are also found when the programming and COLS2 results are compared, though the differences are not that dramatic. Overall, these differences in the frequency distributions lead to an average technical efficiency level in the 78-83 percent range under COLS2, and in the 55-65 percent range under COLS1, LP and QP. The latter average implies a substantial average cost saving through the elimination of technical inefficiency, that saving being in the neighborhood of 70 percent for the most inefficient farmers.

From the foregoing discussion it seems that in spite of substantial differences in the COLS1 and LP/QP estimates of the production frontier, the differences in the average level of technical efficiency are not dramatically different for the Aman and Boro crops. The more significant differences in that average arise when we look at the COLS2 estimates which, in the case of each crop, lead to estimates of technical efficiency in excess of 100 percent. The COLS2 estimates, therefore, cannot really be compared meaningfully with those obtained from COLS1, LP and QP. The latter methods suggest that technical efficiency is highest in Aman cultivation and lowest in Aus cultivation, and the estimates themselves appear to be quite plausible.

While we have an interest in estimating technical efficiency levels, an equally relevant approach is to look at the efficiency in an ordinal sense, particularly in light of the fact that we observe efficiency levels to vary by estimation method and crop.[8] In particular, we would like to determine, first, whether a farm household's relative ranking along the technical efficiency spectrum is sensitive to the estimation method and, second, whether that ranking is independent of the crop grown. We examine both these questions next.

4.2.3 AN ANALYSIS OF TECHNICAL EFFICIENCY VARIATIONS BY ESTIMATION METHOD AND CROP

We examine first the sensitivity of a farmer's ranking along the technical efficiency spectrum to the estimation method for each crop. This is done by computing Spearman's rank correlation coefficient between the technical efficiency indices obtained from the COLS1 and programming estimates of the production frontier.[9] There is no need to consider each of the COLS estimates. Since they differ from each other only in terms of the intercept, each will necessarily rank farm households identically. Of course, they could (and do) lead to different estimates of the level of technical efficiency. The LP and QP estimates differ in terms of both the intercept and input elasticities and thus imply fundamentally different estimated frontiers. They could, therefore, lead not only to different estimates of the average level of technical efficiency, but also to a different ranking of farm households. Again, we confine our discussion to the input-based indices since the Pearson as well as rank correlation between each output-based index and its corresponding input-based index was found to be unity. The rank correlations for each crop are shown in Table 4.11. They show that there is a very strong correlation between the ranks of the technical efficiency indices derived from the COLS1, LP and QP estimates of the production frontier. All correlations are in excess of .90 for all crops, suggesting that the relative efficiency ranking of farm households is, by and large, insensitive to the method used to estimate the production frontier, even though that property is not shared by estimates of the average level of efficiency.[10]

We saw above (Tables 4.7, 4.8 and 4.9) that the average technical efficiency varies across crops. We now make an inter-crop comparison to determine whether a farm household's relative efficiency ranking along the technical efficiency spectrum is independent of the crop grown. One might expect a priori that farm households higher up along the technical efficiency scale for one crop would maintain that relative superiority in other crops as well. A strong version of this hypothesis would require that the relative ranking of each farm household is the same over all crops cultivated. A weaker version would require only that the crop-specific technical efficiency indices themselves bear a strong, positive relationship to each other.[11] To examine both these types of correlations, we compute Spearman's rank as well as Pearson's correlation coefficients between the technical efficiency indices for each of the three crops. Those correlations are presented in Table 4.12. We report only the results for the COLS1 and the LP technical efficiency input-based indices. This is because the COLS1 and COLS2 indices are perfectly correlated and the QP index is almost perfectly correlated with LP index. Note also that the correlations reported are based on a sub-sample of 62 farmers; this group represents those farm households that cultivated all three rice crops. The results for both the LP and COLS1 estimates are very similar, and somewhat surprising. For instance, they suggest that a farmer's ranking in the cultivation of Aman is entirely independent of of his/her ranking in the cultivation of Boro, while the Aus ranking appears to be negatively related to the Aman ranking. However, that negative rank correlation is small in value and highly insignificant statistically. On the other hand, there does appear to be a positive, albeit weak, relationship between the the ranking of farmers in Aus and Boro. In fact, the rank correlation coefficient is on the borderline of statistical significance at the 5 percent level. The same general pattern of results is observed if we examine Pearson's correlation coefficients between the technical efficiency indices across crops. It seems, therefore, that there is only mild support for the view that a farm household's technical efficiency is correlated across crops. This suggests that success in one crop need not imply success in others. In turn, this may reflect the possibility that the knowledge and skills required for efficient cultivation are crop-specific. These and other related issues are taken up further in the concluding section of the chapter.

4.3 A CROP-WISE ANALYSIS OF ALLOCATIVE AND ECONOMIC EFFICIENCY IN KHILGHATI

In this section we examine our estimates of allocative and economic efficiency by estimation method for each of the three rice crops. Our allocative efficiency index is the generalized Farrell, multi-factor index discussed in Chapters 2 and 3. It measures the extent to which a farm household is efficient in choosing inputs in the "correct" proportions - that is, the proportions that equalize the ratio of their marginal products to the ratio of their prices. The index is an indicator of the efficiency of total factor usage and does not, therefore, tell us anything about the relative contributions of different factors to overall inefficiency. The index measures the proportionate reduction in cost that can be achieved through the elimination of allocative inefficiency. The index of economic efficiency, also a multi-factor index, is a measure of the extent to which a farm household is successful in minimizing costs. It is obtained as the product of the input-based technical efficiency index of the previous section and the allocative efficiency index. Like those two indices, it can be given a straightforward cost interpretation. In particular, it shows the total cost saving attainable through the elimination of both technical and allocative inefficiency. Both these indices are computed for the deterministic, Cobb-Douglas frontier in the manner described in Chapter 3.[12] Our crop-wise estimates of allocative and economic efficiency are presented in Tables 4.13, 4.14 and 4.15.

Before we evaluate the estimates, it may be noted that unlike the estimates of technical efficiency, the estimates of allocative efficiency based on the three COLS estimators are identical. This is not surprising since the COLS estimators differ only in the manner in which the intercept term is adjusted. This obviously leads to different estimates of technical efficiency, but changes in the intercept (though not in the input-output elasticities) have no effect on the allocatively efficient factor proportions; hence the invariance of the allocative efficiency indices to the COLS estimators. Of course, the COLS estimators of the production frontier are different from the programming estimators. Thus, the allocative efficiency estimates based on the COLS estimators are different form those obtained from the programming estimators. The economic efficiency indices, on the other hand, are not independent of the intercept adjustment (since they depend crucially on technical efficiency), and hence each COLS-based index of economic efficiency is different.

4.3.1 ESTIMATES OF ALLOCATIVE EFFICIENCY[13]

Consider first the efficiency indices for Aman rice in Table 4.13. The allocative efficiency index, which is identical for the three COLS estimators, suggests that over 90 percent of farm households are 60-100 percent allocatively efficient; over half the farmers are 70-80 percent efficient while about 40 percent are 60-70 percent efficient. No farm household is less than 50 percent efficient, and only just under 6 percent of farmers have an allocative efficiency index in excess of 80 percent. The average farmer is about 70 percent efficient. These estimates indicate that an average cost saving of nearly 30 percent could be achieved through the elimination of allocative inefficiency; that saving could be as low as about 17 percent for the most allocatively efficient farmer and about 45 percent for the most inefficient. In contrast to the distribution of technical efficiency, there are no farmers in the sample that are even 85 percent (much less 100 percent) allocatively efficient.

The distribution of allocative efficiency according to the LP and QP estimates differs quite substantially from the COLS distributions; indeed the LP and QP distributions themselves are quite different from each other. Thus, according to the LP estimates, almost all farmers have an allocative index lying in the 40-60 percent range; only a little over 3 percent of farmers lie in the 60-70 percent range, and none above it. This translates into an average allocative efficiency level of only 52 percent, compared with the 71 percent average implied by the COLS estimators. The LP estimates indicate that even the most efficient farmer in the sample could realize a substantial cost saving of 30 percent through the elimination of allocative inefficiency, while that saving would be almost 60 percent for the most inefficient farm household. The LP estimates thus imply a far greater degree of allocative inefficiency among farmers than the COLS estimates.

The QP results lie in between the LP and COLS results. Thus, over 95 percent of farmers lie in the 50-70 percent range, and only 2.2 percent lie in the 70-80 percent range. This translates into an average allocative efficiency level of about 60 percent, which lies between the LP and COLs averages. Further, the most efficient farm household's allocative efficiency index is about 75 percent while the most inefficient farmer has an index of 48 percent. This again lies within the corresponding intervals for the COLS and LP estimates. Thus, the estimates of the level of allocative efficiency and its distribution by farm household are sensitive to estimation method and the average level of allocative efficiency is lower than the average level of technical efficiency in Aman cultivation.

We turn next to the estimates of allocative efficiency in the cultivation of Boro rice. These are presented in Table 4.14. Looking first at the COLS estimates, about 75 percent of farm households lie in the 70-100 percent efficiency interval. As a result, the average level of allocative efficiency is somewhat higher than that found for Aman, with the most efficient farm household clearly being more efficient than the most efficient farm household in the cultivation of Aman. However, the least efficient farmer has about the same level of allocative efficiency in both cases. The Boro estimates obtained from the COLS method point to a 25 percent cost saving through the elimination of allocative inefficiency; the corresponding figure for Aman is about 30 percent.

Turning to the programming estimates of allocative efficiency, we note that while these are very different from the corresponding COLS estimates, the LP and QP estimates are identical. However, this follows only because, as we pointed out earlier in the chapter, the LP and QP estimates of the frontier production function were identical. Notice that the QP/LP estimates of allocative efficiency are not only much lower than those obtained from the COLS method, but are lower than the QP and LP estimates for Aman rice. Thus, for Boro it is seen that more than 80 percent of farm households have an allocative efficiency index lower than 50 percent. Unlike the frequency distributions for COLS, the LP/QP distributions are clearly skewed to the right, and this translates into an average level of allocative efficiency of only 45 percent. Thus, the allocative efficiency indices as measured by the QP/LP and COLS methods are far more different in Boro cultivation than in Aman cultivation. The higher average level of allocative efficiency in Boro as compared to Aman cultivation, as indicated by the COLS estimates, would suggest that Khilghati farmers have been successful in adapting the newer HYV technology embodied in Boro cultivation. The LP/QP estimates however, seem to contradict that. On the other hand, the QP/LP estimates of the Boro production frontier appear to be quite unrealistic. Both the land and labour elasticities are substantially smaller compared to their COLS values. To some extent, such differences were found for the land elasticity in the QP/LP estimates of the Aman frontier. However, in that case, the differences were not nearly as big. It seems reasonable to conclude that the allocative efficiency indices based on the COLS method are perhaps more reasonable than those obtained under the LP and QP methods.

The allocative efficiency indices for Aus rice, presented in Table 4.16, show that the average level of allocative efficiency, calculated from the COLS estimates of the frontier, is only about 49 percent. This is much lower than the corresponding averages for Aman and Boro rice and points to a significant average cost saving of over 50 percent through the elimination of inefficiency; for the most inefficient farmers that saving could be almost 70 percent, while for the most efficient it is still a sizable 30 percent. About 75 percent of farmers lie in the 40-60 percent range of the allocative efficiency spectrum, and no farmer has an allocative efficiency index above 70 percent.

The QP/LP estimates, on the other hand, are very different form the COLS estimates. In particular, the frequency distribution of allocative efficiency is highly skewed to the left, with more than 70 percent of farmers in the LP case, and 67 percent of farmers in the QP case lying in the 80-100 percent allocative efficiency range. In both cases, this puts the average level of allocative efficiency at a level that is one-and-a-half times the corresponding average obtained under the COLS method. Thus, while the LP and QP results are not only very different from those obtained under the COLS method, they are also quite different from those obtained for the two other crops. Whatever the factors behind the inter-crop differences, the differences between the COLs and LP/QP estimates can be traced to differences in the estimates of the frontier function. It seems that the labour elasticity is much to low, and the capital elasticity somewhat on the high side, under COLS estimation. By the same token, LP/QP estimation appears to lead to an unrealistically high labour elasticity, and a smaller than expected land elasticity. Given the particular configuration of factor prices, this leads to the substantial differences observed. It seems likely that the Aus frontier function is not well estimated by either the COLS or programming approaches, and that true values of the aforementioned elasticities lie in between those obtained. If that were the case, the allocative efficiency indices would likely not display the wide variations observed, and also would be somewhat more in line with those observed for the other rice crops. On balance it would seem that the average level of allocative efficiency in Aus cultivation is much too high, based on the programming method, and perhaps too low based on the COLS method.

Overall, the estimates of technical and allocative efficiency suggest that Khilghati farmers have been successful in the cultivation of the new-technology Boro crop in the sense that, in both technical and allocative terms, the average level of efficiency in that crop compares favourably with the average efficiency levels in the cultivation of the traditional Aman and Aus crops. In particular, average allocative efficiency is highest in Boro while average technical efficiency is not much lower than is the case for Aman.

4.3.2 AN ANALYSIS OF ALLOCATIVE EFFICIENCY VARIATIONS BY METHOD AND CROP

In sub-section 4.2.3, we observed that the average level of technical efficiency showed variation across crops as well as estimation method. We then explored the question of whether the relative ranking of farm households along the efficiency spectrum was sensitive to those variations. The purpose of the present sub-section is examine this issue in the context of allocative efficiency, variations in which appear to be more pronounced (both across crops and estimation method) as compared to those in the case of technical efficiency. This is particularly so in the case of Aus rice. The only difference in the present analysis as compared to the one undertaken for technical efficiency is that the allocative efficiency indices are, by definition, the same for all COLS estimators; the COLS estimates are, however, different from the programming estimates.

We begin by first examining the variations in allocative efficiency by estimation method. For this purpose we computed Spearman's rank correlations between the allocative efficiency indices obtained by using the COLS1, LP and QP estimation methods. Those correlations are shown in Table 4.16 for each rice crop. It can be seen that, as far as the Aman and Boro rice crops are concerned, no rank correlation coefficient is less than 0.90. This suggests that in spite of the large differences between the estimates of average allocative efficiency obtained from the COLS and programming approaches, the relative ranking of farm households is, by and large, preserved. The rank correlations for Aus rice, for which the differences in the COLS and programming estimates of the average level of allocative efficiency were not only much more substantial in comparison with the Aman and Boro crops, but were also in the opposite direction, tell a different tale. With rank correlations of about 0.54, it seems that the COLS ranking is quite different from the LP/QP rankings. Thus, in contrast to the results for the Aman and Boro crops, the more fundamental differences in the COLS and programming estimates of the frontier function are reflected in both substantial differences in the estimates of the average level of allocative efficiency as well as in changes in the relative positions of farmers along the allocative efficiency spectrum. Nevertheless, the rank correlations are statistically significant and their magnitudes point to a moderate, positive relationship between the ranks.

We next turn our attention to the question of whether a farm household's relative allocative efficiency is independent of the rice crop grown, particularly since the average level of allocative efficiency varies substantially across crops (at least between the Aman/Boro and Aus crops). Table 4.17 shows the rank correlations (as well as the Pearson correlations) between the allocative efficiency indices across crops. The correlations shown are based on the COLS1 and LP estimates of the production frontier. The rank correlations show that the relative ranking of a farm household in Aman cultivation is independent of its ranking in Boro cultivation, irrespective of the estimation method. That independence extends to Aman and Aus as well if we consider the LP-based indices. On the other hand, there does appear to be a positive relationship between a farm household's rank in the cultivation of Boro and in the cultivation of Aus though that relationship appears to be only moderately strong (but statistically significant) in the COLS case, and on the weak side in the LP case.[14] This pattern of rank correlations is mirrored by Pearson's correlation coefficients. Overall, there is some evidence in the sample that the ability of farmers to choose the "right" input proportions in one crop carries over into other crops. That evidence does not appear to be strong, but it is stronger than that found for technical efficiency. The lack of a strong, positive relationship may well reflect, as we argued in the case of technical efficiency, the possibility that allocative skills are crop-specific. On the other hand, this may well reflect that possibility that while there are many common factors that determine a farmer's ability in choosing technically and/or allocative efficient factor combinations, their relative importance in the cultivation of different crops may differ. For example, farmer contact with government extension agents or with agricultural co-operatives may have a favourable impact on efficiency in general. However, that favourable impact may be stronger in the case of a new-technology crop such as Boro rice as compared with the relatively more traditional crops such as Aus rice. In addition, farmers may differ not only in the technical and allocative information they have, but also in their ability to use that information to their advantage. It is, therefore, quite possible for various efficiency indices to display crop-wise variations.

Having examined our estimates of allocative efficiency, we turn next to the economic efficiency indices.

4.3.3 THE ESTIMATES OF ECONOMIC EFFICIENCY

The index of economic efficiency measures the ability of a farm household to produce a given output at minimum cost. The index used in this study is the generalized Farrell, multi-factor index of economic efficiency and is defined as the product of the input-based index of technical efficiency and allocative efficiency. As defined, every farmer's economic efficiency index can at best be equal to each of its component indices, and in general will be smaller than both. Our estimates of this index for each of the rice crops are contained in Tables 4.13, 4.14 and 4.15. For each of the crops, it is not surprising that the average level of economic efficiency is lower than the average level of either technical or allocative efficiency. Depending upon the estimation method employed, the average value of the index varies from a low of about 42 percent to a high of about 89 percent for Aman, a low of 33 percent to a high of 63 percent for Boro, and a low of 27 percent to a high of 55 percent for Aus. The higher averages, in each case, are associated with the COLS2 estimates which led to technical efficiency indices in excess of 100 for several households. Overall, the results suggest that allocative mistakes contribute proportionately more to economic inefficiency than technical errors in the case of Aman and Boro, though their relative contribution to economic efficiency varies with the estimation method used. For the Aus crop there does not appear to be much of a difference in the relative contributions of technical and allocative inefficiency if we look at the COLS1 estimates. But the LP/QP estimates imply that technical inefficiency contributes much more to economic inefficiency than allocative inefficiency. However, in light of our earlier argument that the LP/QP estimates of the frontier, more so than the COLS1 estimates, are questionable, it seems that it is reasonable to conclude that allocative inefficiency is at least as important as technical inefficiency in leading to economic inefficiency.

Earlier in the chapter, we examined the question of whether the relative ranking of farmers in terms of technical and allocative efficiency is independent of the method of frontier estimation and the crop grown. With regard to the former issue, we found that irrespective of the particular COLS or programming method used, the ranking of farmers according to technical efficiency remains the same. That ranking is substantially, but not exactly the same, if we compare the programming results with the COLS results. In the case of allocative efficiency, the choice of COLS method cannot influence the ranking since each COLS method must lead to the same estimate of allocative efficiency. However, it turns out that the two programming estimators also do not affect the ranking; and, there is only a slight difference in the way the programming and COLS approaches rank the farmers. Not surprisingly, the economic efficiency ranking displays much the same pattern with high (in excess of 0.92) rank and Pearson's correlation coefficients (not reported here) between the LP/QP and COLS economic efficiency indices for all crops. Thus, even though our estimates of the level of economic efficiency are sensitive to estimation method, the relative position of farmers along the economic efficiency spectrum is not.

We conclude our discussion of the economic efficiency estimates by touching briefly upon the question of whether the economic efficiency of farm households is related across crops. By examining Spearman's rank as well as Pearson's correlation coefficients (not reported here), we again find little evidence to suggest that economic efficiency is highly correlated across crops either in terms of ranks or levels. This is not surprising given our previous findings for technical and allocative efficiency and the fact that the product of those two indices define the economic efficiency index. There is, nevertheless, some evidence that points to the existence of a positive, statistically significant but weak relationship between the economic efficiency indices for the Aus and Boro crops.

4.4 THE RELATIONSHIP BETWEEN TECHNICAL AND ALLOCATIVE EFFICIENCY

The technical and allocative efficiency indices estimated in this study are defined to be independent of each other. In other words, a farm household could be allocatively efficient even though it is technically inefficient; or, it could be technically efficient yet allocatively inefficient. However, the two types of efficiency need not be independent in the behavioral sense. It seems highly probable that efficient farmers are more likely to lie closer to their production frontiers <u>and</u> to their least-cost expansion paths than inefficient ones. Thus, one would expect that technical and allocative efficiency are positively related. Whether this prior expectation is borne out in practice is essentially an empirical question, particularly since, as some have argued, there need be no reason for <u>static</u> efficiency indices to be positively correlated given that the goal of efficiency is essentially a dynamic problem.[15] In other words, while allocative and technical efficiency can quite reasonably be expected to be positively related over time, the nature of that relationship in any given period is unpredictable [see Schmidt and Lovell (1980)]. Schmidt and Lovell (1980) proposed a model in which allocative and technical inefficiency are correlated. This model is an extension of the model proposed by the same authors in an earlier paper which we discussed in Chapter 2. Unfortunately, their approach cannot be implemented here since it requires variations in factor prices across the units, and that is something that we do not have. Nevertheless, we can examine whether the allocative and technical efficiency of Khilghati farmers is correlated in each of the three crops. We do this by computing Spearman's rank and the Pearson correlation coefficients between the technical and allocative efficiency indices for each rice crop. Those correlations are reported in Table 4.18 for the COLS1, LP and QP estimation methods. They do not support the existence of a strong, positive relationship between technical and allocative correlations. Indeed, at the 5 percent level, all correlations are statistically insignificant.

This concludes our discussion of the estimates of technical, allocative and economic efficiency of Khilghati farmers on the assumption that the production frontier is deterministic. In the concluding section of the chapter, we summarize our findings and draw some implications.

4.5 SUMMARY AND CONCLUSIONS

We estimated a deterministic Cobb-Douglas production frontier by statistical and programming methods for the three rice crops - Aman, Boro and Aus - cultivated in our sample economy of Khilghati. The frontiers were used to generate estimates of the technical, allocative and economic efficiency of farm households. Those estimates were found to be sensitive to the choice of estimation method. In particular, the linear and quadratic programming estimates were quite different from those obtained by applying three versions of the corrected least squares method. This likely reflects the sensitivity of the programming method to outliers in the data. It is possible that the programming estimates are less reliable than those obtained by applying corrected least squares.[16]

In general, we found that the estimates of technical, allocative and economic efficiency vary by estimation method and crop. Farm households appear to be more efficient in Aman and Boro cultivation than in Aus cultivation. Thus, average technical efficiency is estimated to be above 80 percent in Aman and below 65 percent in Aus. These figures point to an average cost saving of about 20 percent in Aman and 35 percent (or more) in Aus cultivation through the elimination of technical inefficiency. The average level of allocative efficiency was found to be generally lower than the level of technical efficiency and it was highest in Boro cultivation and lowest in Aus cultivation. Thus, allocative inefficiency appeared to be the relatively greater contributor to economic inefficiency. Average allocative efficiency is estimated to be around 75 percent in Boro and 50 percent in Aus.

In spite of the variation of both technical and allocative efficiency by estimation method, the ranking of farm households is, for the most part, unaffected.[17] The average level of efficiency varies across crops and we found little evidence to support a strong, positive relationship between efficiency indices across crops. A statistically significant, but weak relationship between the technical (and allocative) efficiency indices for Aus and Boro was found. We also examined whether farmers that are relatively more technically efficient are also relatively more allocatively efficient. The results did not support this. Interestingly, we found evidence to indicate that Khilghati households have adapted quite well to the new-technology, HYV Boro rice in that the average level of technical and allocative efficiency in Boro cultivation compares very favourably with the corresponding averages for the traditional Aman and Aus rices.

We found that there are crop-wise variations of average efficiency and that farmer efficiency levels/ranks across crops correlate rather weakly. Nevertheless, it is not inconceivable that there are genuine inter-crop differences in efficiency for the same group of farmers. Thus, for instance, given that efficient cultivation practices could vary across crops, a farm household's ability to implement those practices could also vary across crops, perhaps because of differences in the information available to it and/or in its growing experience with those crops. It may also well be the case that farmers are at different stages in the "learning by doing" process across crops, although it is likely that this may partly reflect differences in growing experience. These arguments suggest that managerial ability could vary across crops and result in low correlations between efficiency ranks/levels and in differences in the average level of efficiency across crops. This may be especially true when we are considering crops that are radically different, as for example, the new-technology Boro rice and the traditional Aman and Aus rices.

While the above argument could be advanced to support our findings, some caution is warranted. All our results are based on the assumption that the production frontier is deterministic. This is a drawback in that such a frontier implies that all departures from it are the result of inefficiency, even though it is more than likely that those departures partly reflect measurement error as well as purely random influences. Both measurement error and random effects can be expected to vary across individual households as well as across crops. As a result, the differences in measured technical efficiency across individuals and crops need not reflect genuine differences in efficiency. Under these circumstances, the differences in average efficiency and the absence of strong correlations in efficiency across crops that we have observed could reflect those effects. A major potential source of measurement error is the land input. Quality differences in the land input can be substantial across farm households, more so than in the case of other inputs. Thus, variations in measured technical efficiency could reflect variations in the quality of land rather than in technical efficiency. Of course, it is not clear to what extent measurement error and random influences contaminate our efficiency estimates. It might be noted though that Aman and Aus rice are rain-fed crops that depend crucially on the monsoon and are, therefore, more likely to be subject to random influences (e.g. flooding or drought) than the irrigation-fed Boro rice which is grown in the dry, winter months. This may point to the greater dangers of postulating a deterministic frontier for Aman and Aus than for Boro. In the next chapter, we examine efficiency indices derived from a stochastic frontier that permits deviations from the deterministic function to reflect both inefficiency as well as measurement error and random effects.

FOOTNOTES TO CHAPTER 4

1. The exceptions are the labour elasticities in the Aus and Boro equations.

2. The labour elasticity for Aus rice is too small. It is possible that this reflects labour's low productivity arising perhaps due to underemployment of household family labour during the growing season. However, one would then expect other labour elasticities to also be small, and this is not the case.

3. The non-zero mean follows from the distribution of the disturbance term which must be one-sided in order to meet the definition of a deterministic frontier. We are assuming that input quantities are independent of the disturbance term. This is justified if we assume that farm households maximize expected or median profits and technical inefficiency is unknown to the household. Under these assumptions, OLS estimators of all parameters except the intercept are consistent.

4. For example, if the disturbance term is $-u$, $u \geq 0$, then the mean of u is $E(u) = (2/\Pi)^{1/2}\sigma_u$ when u is half-normal and $E(u) = (1/\gamma)$ when it is exponential. σ_u is the standard deviation of the normal distribution and $(1/\gamma)$ is the mean and standard deviation of the exponential distribution. The OLS residuals are used to estimate E(u) and this is added to the OLS intercept to obtain the COLS2 intercepts.

5. The differences in the intercepts reported in Tables 4.2, 4.3 and 4.4 and the OLS intercept are the estimates of the adjustments indicated in the text and in footnote 4.

6. The individual farm household output-based index of technical efficiency is obtained by computing $\exp(-\hat{u})$ where the $\hat{u}$ are the OLS residuals. The input-based index is given by (LA^*/LA) where LA^* is the minimum amount of land required to produce the actual output and it itself is given by

$$LA^* = \left[y/\exp(\alpha_o^*)Z\right]^{1/\sum \hat{\alpha}_i}$$

α_o^* is the corrected intercept, $\hat{\alpha}_i$ are the estimated input elasticities, and

$$Z = \left[(FT/LA)^{\hat{\alpha}_2} (KA/LA)^{\hat{\alpha}_3} (LAB/LA)^{\hat{\alpha}_4} \right]$$

FT, KA and LAB are the actual quantities of fertilizer, bullock power and labour used by the farm household.

7. Recall from chapter 2 that $[1 - TE(x)]$ measures the proportionate cost saving made possible by eliminating technical inefficiency.

8. This may especially be true for Aus rice for which the average level of technical efficiency, as estimated by COLS1, is only 56 percent.

9. Spearman's rank correlation coefficient r_s is defined as

$$r_s = 1 - [\,6\Sigma d_i^2/n(n^2 - 1)]$$

where the d_i are the differences in the ranks of the two series being compared and n is the size of the sample. For large samples, the standard normal statistic $z = r_s(n - 1)^{1/2}$ can be used to test whether the two series are independent or not.

10. We also computed Pearson's correlation coefficient between the technical efficiency indices. They too confirmed the existence of a strong positive relationship between the technically efficiency indices.

11. Large differences in the ranks of a few observations can substantially lower the rank correlation between two series, though the Pearson's correlation coefficient between them can still be large.

12. Actually, the allocative efficiency index can be obtained in either of two ways. We could follow the method outlined in Chapter 3. Alternatively, we could find the cost-minimizing levels of each factor for the actual output produced. The ratio of the cost of the cost-minimizing factor combination to actual cost is the index of economic efficiency. The allocative efficiency index can then be obtained by dividing the economic efficiency index by the input-based index of technical efficiency.

13. The calculation of allocative efficiency involves factor prices. Our factor price data are all rental/hire prices per unit of factor services. The units in which factor services are measured are explained in the notes to Table 4.1. Other than the rental for land, all factor prices are crop-specific. They vary across farms and crops, but that variation is limited and in some cases absent. The land rental is not crop-specific and is calculated by dividing the cost of land rented on a cash basis by the amount of land rented on a cash basis. The modal value of the land rental series was used to represent the opportunity cost for land services for those households that rented no land. In the case of bullock-power, most households did not rent the services of bullocks. However, a few did and the rental rate they paid was used to represent the opportunity cost of using owned bullock-power.

14. In the COLS case, the correlations also point to a positive relationship between household ranks in Aman and Aus. However, the relationship is weak and barely significant at the 5 percent level.

15. See, for instance, Farrell (1957), Forsund and Hjalmarsson (1974) and Fuss and McFadden (1970).

16. On the other hand, as far as Aus rice is concerned, the labour elasticity appears to be unrealistically low, and the bullock-power elasticity somewhat on the high side in the COLS equations.

17. An exception is the ranking of households according to their allocative efficiency indices in Aus cultivation. We found that the rank correlation

of that index computed by the COLS and programming methods was positive and statistically significant, but it had a value slightly above 0.50, pointing to some significant differences in the ranking of farmers.

TABLE 4.1

OLS Estimates of the Production Function (by crop)

Crop	Constant	ln(LA)	ln(FT)	ln(KA)	ln(LAB)	$\bar{R}^2$	F
		Input Variables					
Aus rice	0.9082 (0.678)	0.3892 (0.184)	0.1357 (0.055)	0.4413 (0.135)	0.0125 (0.137)	0.857	116.5
Aman rice	1.4839 (0.462)	0.3167 (0.130)	0.2900 (0.046)	0.1885 (0.114)	0.1911 (0.092)	0.965	616.5
Boro rice	1.8019 (0.699)	0.4597 (0.618)	0.1731 (0.076)	0.2492 (0.115)	0.1623 (0.137)	0.936	300.5

Notes: i) LA = land input (in acres), FT = fertilizer (in maunds, 1 maund = 82 pounds), KA = bullock power (in bullock-days), LAB = adult-labour (in man-days). Figures in parentheses are estimated standard errors.

ii) Sample size is 78 for Aus rice, 90 for Aman rice, and 83 for Boro rice.

TABLE 4.2

Estimates of the Derterministic Frontier: Aman Rice

		Input Variables			
Estimation method	Constant	ln(LA)	ln(FT)	ln(KA)	ln(LAB)
COLS1	1.7100	0.3167	0.2900	0.1885	0.1911
COLS2(HN)	1.5822	0.3167	0.2900	0.1885	0.1911
COLS2(E)	1.6072	0.3167	0.2900	0.1885	0.1911
LP	1.0644	0.1282	0.2567	0.4099	0.1682
QP	1.2005	0.1769	0.2600	0.3478	0.1847

Notes:
- i) COLS stands for corrected least squares, HN for the half-normal distribution and E for the exponential distribution.
- ii) LP stands for linear programming and QP for quadratic programming.
- iii) The COLS estimates differ from the OLS estimates only with respect to the intercept.

TABLE 4.3

Estimates of the Deterministic Frontier: Boro Rice

Etimation method	Constant	Input Variables ln(LA)	ln(FT)	ln(KA)	ln(LAB)
COLS1	2.1764	0.4579	0.1731	0.2492	0.1623
COLS2(HN)	1.9529	0.4579	0.1731	0.2492	0.1623
COLS2(E)	1.9912	0.4579	0.1731	0.2492	0.1623
LP	1.6450	0.2096	0.1757	0.5046	0.0667
QP	1.6450	0.2096	0.1757	0.5046	0.0667

Notes: See TABLE 4.1 and TABle 4.2

TABLE 4.4

Estimates of the Deterministic Frontier: Aus Rice

Estimation method	Constant	Input Variables ln(LA)	ln(FT)	ln(KA)	ln(LAB)
COLS1	1.5189	0.3892	0.1357	0.4413	0.0125
COLS2(HN)	1.1244	0.3892	0.1357	0.4413	0.0125
COLS2(E)	1.1793	0.3892	0.1357	0.4413	0.0125
LP	0.3637	0.1945	0.1582	0.2212	0.4368
QP	0.2966	0.1739	0.1593	0.2399	0.4368

Notes: See TABLE 4.1 and TABLE 4.2

TABLE 4.5

The Distribution of the Input-based Technical Efficiency Index: Aman Rice

TE(x) (percent)	Relative Frequency (% of households)				
	COLS1	COLS2(HN)	COLS2(E)	LP	QP
0 - 50	0.0	0.0	0.0	0.0	0.0
50 - 60	1.1	0.0	0.0	1.1	1.1
60 - 70	15.6	3.3	4.4	13.3	13.3
70 - 80	33.3	14.4	14.4	32.2	33.3
80 - 90	31.1	30.0	36.7	31.1	31.1
90 -100	18.9	52.2	44.4	22.2	21.1
Maximum	100.0	113.8	111.0	100.0	100.0
Minimum	58.4	66.5	64.8	58.0	58.7
Mean	80.1	91.2	88.9	81.7	81.7
S.D.	9.7	11.0	10.7	10.3	10.2

Notes: i) TE(x) stands for the input-based technical efficiency index, and S.D. stands for the standard deviation.
ii) Households with TE(x) equal to the upper limits of the efficiency intervals are grouped in the next (higher) efficiency interval.

TABLE 4.6

The Distribution of the Input-based Technical Efficiency Index: Boro Rice

TE(x) (percent)	Relative Frequency (% of households) COLS1	COLS2(HN)	COLS2(E)	LP	QP
0 - 50	3.6	1.2	1.2	6.0	6.0
50 - 60	12.1	1.2	2.4	12.1	12.1
60 - 70	33.7	7.2	9.6	19.3	19.3
70 - 80	30.1	19.3	27.7	32.5	32.5
80 - 90	14.5	28.9	25.3	15.6	15.6
90 - 100	6.0	42.2	33.7	14.6	14.6
Maximum	100.0	123.9	119.4	100.0	100.0
Minimum	34.8	43.1	41.5	37.8	37.8
Mean	70.9	87.8	84.7	73.0	73.0
S.D.	11.9	14.8	14.3	14.4	14.4

Notes: See TABLE 4.5

TABLE 4.7

The Distribution of the Input-based Technical Efficiency Index:
Aus Rice

TE(x) (percent)	Relative Frequency (% of households)				
	COLS1	COLS2(HN)	COLS2(E)	LP	QP
0 - 50	38.5	6.4	6.4	17.9	19.2
50 - 60	28.2	5.1	9.0	24.3	23.1
60 - 70	15.4	19.2	23.1	21.8	21.8
70 - 80	11.5	16.7	21.8	14.1	12.8
80 - 90	3.9	19.2	15.4	11.5	12.8
90 - 100	2.5	33.3	24.4	10.3	10.3
Maximum	100.0	149.6	141.5	100.0	100.0
Minimum	27.5	41.2	38.9	29.7	30.0
Mean	55.5	83.1	78.5	65.3	65.2
S.D.	14.9	22.3	21.1	17.8	17.7

Notes: See TABLE 4.5

TABLE 4.8

The Distribution of the Output-based Technical Efficiency Index: Aman Rice

TE(y) (percent)	Relative Frequency (% of households)				
	COLS1	COLS2(HN)	COLS2(E)	LP	QP
0 - 50	0.0	0.0	0.0	0.0	0.0
50 - 60	1.1	0.0	0.0	1.1	1.1
60 - 70	15.6	2.2	4.4	11.1	11.1
70 - 80	33.3	14.4	14.4	31.1	31.1
80 - 90	31.1	31.1	36.7	31.1	33.3
90 - 100	18.9	52.2	44.4	25.6	23.3
Maximum	100.0	113.6	110.8	100.0	100.0
Minimum	58.8	66.8	65.2	59.2	59.6
Mean	80.3	91.3	89.0	82.3	82.3
S.D.	9.6	10.9	10.6	10.0	9.9

Notes: TE(y) stands for the output-based technical efficiency index.

TABLE 4.9

The Distribution of the Output-based Technical Efficiency Index: Boro rice

	Relative Frequency (% of households)				
TE(y) (percent)	COLS1	COLS2(HN)	COLS2(E)	LP	QP
0 - 50	6.0	1.2	1.2	4.8	4.8
50 - 60	13.3	1.2	3.6	12.1	12.1
60 - 70	32.5	8.4	8.4	18.1	18.1
70 - 80	28.9	21.7	26.5	31.3	31.3
80 - 90	13.3	25.3	25.3	19.3	19.3
90 - 100	6.0	42.2	34.9	14.5	14.5
Maximum	100.0	125.0	120.4	100.0	100.0
Minimum	33.2	41.6	40.0	39.5	39.5
Mean	69.9	87.4	84.1	74.0	74.0
S.D.	12.3	15.3	14.8	14.0	14.0

Notes: See TABLE 4.8

TABLE 4.10

The Distribution of the Output-based Technical Efficiency Index: Aus Rice

TE(y) (percent)	Relative Frequency (% of households)				
	COLS1	COLS2(HN)	COLS2(E)	LP	QP
0 - 50	37.2	6.4	6.4	20.5	20.5
50 - 60	26.9	4.0	8.9	23.1	23.1
60 - 70	17.9	19.2	21.8	21.8	21.8
70 - 80	10.3	17.9	21.8	14.1	14.1
80 - 90	5.1	19.2	16.7	10.2	10.2
90 - 100	2.6	33.3	24.4	10.2	10.2
Maximum	100.0	148.4	140.4	100.0	100.0
Minimum	28.3	42.0	39.7	29.3	29.6
Mean	56.2	83.3	78.9	64.6	64.5
S.D.	14.8	21.9	20.9	17.9	17.9

Notes: See TABLE 4.8

TABLE 4.11

Spearman's Rank Correlations Between Technical Efficiency Indices (by crop)

Aman rice	COLS1	LP	QP
COLS1	1.00		
LP	0.95	1.00	
QP	0.98	0.98	1.00
Boro rice			
COLS1	1.00	1.00	
LP	0.93	0.93	
QP	0.93	0.93	1.00
Aus rice			
COLS1	1.00		
LP	0.92	1.00	
QP	0.93	0.93	1.00

Notes: All correlations reported above are computed from the input-based technical efficiency index.

TABLE 4.12

Inter-crop Rank Correlations of Technical Efficiency

Estimation method	Crop	Aman rice	Boro rice	Aus rice
COLS1	Aman rice	1.00 (1.00)		
	Boro rice	-0.08 (-0.04)	1.00 (1.00)	
	Aus rice	-0.14 (-0.14)	0.22 (0.15)	1.00 (1.00)
LP	Aman rice	1.00 (1.00)		
	Boro rice	-0.09 (-0.06)	1.00 (1.00)	
	Aus rice	-0.12 (-0.10)	0.21 (0.14)	1.00 (1.00)

Notes: The numbers in parentheses are Pearson's correlation coefficients.

TABLE 4.13

The Distribution of Allocative and Economic Efficiency: Aman Rice

AE and EE (percent)	COLS1		COLS2(HN)		COLS2(E)		LP		QP	
	Relative Frequency (% of households)									
	AE	EE	AE	EE	AE	EE	AE	EE	AE	EE
0 - 30	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.2	0.0	0.0
30 - 40	0.0	1.1	0.0	0.0	0.0	0.0	0.0	33.3	0.0	11.1
40 - 50	0.0	16.7	0.0	6.7	0.0	8.9	40.0	53.3	1.1	48.9
50 - 60	1.1	50.0	1.1	24.4	1.1	27.8	56.7	11.1	57.8	30.0
60 - 70	42.2	24.4	42.2	42.2	42.2	41.1	3.3	0.0	38.9	10.0
70 - 80	51.1	7.8	51.1	18.9	51.1	17.8	0.0	0.0	2.2	0.0
80 - 100	5.6	0.0	5.6	7.8	5.6	4.4	0.0	0.0	0.0	0.0
Maximum	83.5	78.0	83.5	88.8	83.5	86.6	68.3	57.2	75.2	66.0
Minimum	55.5	39.9	55.5	45.4	55.5	44.3	41.4	26.2	47.6	31.1
Mean	71.2	57.0	71.2	64.9	71.2	63.3	51.8	42.4	59.6	48.7
S.D.	5.5	8.3	5.5	9.4	5.5	9.2	4.9	6.7	5.2	7.5

Notes: AE and EE stand for allocative and economic efficiency respectively; EE = AE * TE(x).

TABLE 4.14

The Distribution of Allocative and Economic Efficiency: Boro Rice

AE and EE (percent)	Relative Frequency (% of households)									
	COLS1		COLS2(HN)		COLS2(E)		LP		QP	
	AE	EE	AE	EE	AE	EE	AE	EE	AE	EE
0 - 30	0.0	1.2	0.0	0.0	0.0	0.0	2.4	32.5	2.4	32.5
30 - 40	0.0	9.6	0.0	2.4	0.0	2.4	12.0	54.2	12.0	54.2
40 - 50	0.0	27.7	0.0	8.4	0.0	9.6	68.7	12.0	68.7	12.0
50 - 60	1.2	41.0	1.2	26.5	1.2	26.5	14.5	1.2	14.5	1.2
60 - 70	22.9	18.1	22.9	30.1	22.9	37.3	1.2	0.0	1.2	0.0
70 - 80	61.4	1.2	61.4	21.7	61.4	16.9	1.2	0.0	1.2	0.0
80 - 100	14.5	1.2	14.5	10.8	14.5	7.2	0.0	0.0	0.0	0.0
Maximum	92.8	83.2	92.8	103.1	92.8	99.4	72.0	54.0	72.0	54.0
Minimum	53.3	28.1	53.3	34.8	53.3	33.5	26.4	19.0	26.4	19.0
Mean	74.1	52.4	74.1	65.0	74.1	62.6	45.4	33.0	45.4	33.0
S.D.	6.3	9.6	6.3	11.9	6.3	11.5	6.1	7.0	6.1	7.0

Notes: See TABLE 4.13

TABLE 4.15

The Distribution of Allocative and Economic Efficiency: Aus Rice

AE and TE (percent)	Relative Frequency (% of households)									
	COLS1		COLS2(HN)		COLS2(E)		LP		QP	
	AE	EE	AE	EE	AE	EE	AE	EE	AE	EE
0 - 30	1.3	69.2	1.3	17.9	1.3	25.6	0.0	3.8	0.0	6.4
30 - 40	12.8	19.2	2.8	4.6	12.8	34.6	0.0	12.8	0.0	11.5
40 - 50	37.2	9.0	37.2	24.4	37.2	21.8	0.0	21.8	0.0	28.2
50 - 60	39.7	2.6	39.7	11.5	39.7	11.5	0.0	28.2	0.0	23.0
60 - 70	9.0	0.0	9.0	9.0	9.0	3.8	1.3	15.4	1.3	14.1
70 - 80	0.0	0.0	0.0	2.6	0.0	2.6	24.3	9.0	30.8	9.0
80 - 100	0.0	0.0	0.0	0.0	0.0	0.0	74.4	9.0	67.9	7.7
Maximum	69.2	50.4	69.3	75.4	69.3	71.3	92.9	89.0	91.0	86.7
Minimum	28.4	9.7	28.4	14.5	28.4	13.8	67.9	21.8	66.0	21.2
Mean	48.9	27.3	48.8	40.8	48.8	38.6	84.1	55.0	81.9	53.5
S.D.	8.1	9.0	8.1	13.4	8.1	12.7	5.9	15.8	5.9	15.4

Notes: See TABLE 4.13

TABLE 4.16

Spearman's Rank Correlations Between Allocative Efficiency Indices (by crop)

	COLS1	LP	QP
Aman rice			
COLS1	1.00		
LP	0.91	1.00	
QP	0.94	1.00	1.00
Boro rice			
COLS1	1.00		
LP	0.90	1.00	
QP	0.90	0.90	1.00
Aus rice			
COLS1	1.00		
LP	0.53	1.00	
QP	0.54	0.54	1.00

TABLE 4.17

Inter-crop Rank Correlations of Allocative Efficiency

Estimation method	Crop	Aman rice	Boro rice	Aus rice
COLS1	Aman rice	1.00 (1.00)		
	Boro rice	-0.01 (0.05)	1.00 (1.00)	
	Aus rice	0.25 (0.28)	0.40 (0.50)	1.00 (1.00)
LP	Aman rice	1.00 (1.00)		
	Boro rice	0.04 (0.11)	1.00 (1.00)	
	Aus rice	0.05 (0.07)	0.18 (0.13)	1.00 (1.00)

Notes: Numbers in parentheses are Pearson's correlation coefficients.

TABLE 4.18

Spearman's Rank Correlations between Technical and Allocative Efficiency

Estimation method	Aman rice	Boro rice	Aus rice
COLS1	0.04 (0.02)	-0.04 (-0.09)	0.11 (0.11)
LP	0.07 (0.03)	-0.13 (-0.25)	0.06 (0.08)
QP	0.09 (0.06)	-0.13 (-0.25)	0.06 0.08

Notes: Numbers in parentheses are Pearson's correlation coefficients.

CHAPTER 5

STOCHASTIC FRONTIERS: ESTIMATION AND RESULTS

5.1 INTRODUCTION

In this chapter, we present and analyze our estimates of technical, allocative and economic efficiency on the assumption that the production frontier is stochastic. A stochastic frontier allows departures from the deterministic kernel to reflect random influences/measurement error (that is, statistical noise), technical efficiency or both. One of our primary aims is to separate technical inefficiency from statistical noise. This can be expected to lead to more reliable estimates of the frontier and of efficiency. On that expectation, our analysis is carried a step further in this chapter. Thus, we also construct factor-specific indices of technical efficiency, technical cost efficiency and allocative efficiency. These were discussed in Section 2.3.2 (Chapter 2). Unlike the multi-factor indices that have been the focus of our attention, factor-specific indices are indicators of the relative efficiency of various factors. They could, thus, be useful in identifying the factors upon which effort to improve efficiency would have the greatest impact. A second issue examined in this chapter is the relationship between the education of farmers and their efficiency levels. In particular, does education foster efficiency ? Numerous empirical studies of the agricultural sector of developing countries appear to suggest that it does.[1] Education can be viewed as a major determinant of an individual's ability to read and write, or of his/her numeracy skills, factors which are likely to be important in determining his/her managerial ability. Thus, we examine whether the education level of the farm household is an important determinant of its technical and allocative efficiency.

The rest of this chapter is organized as follows. We begin in Section 5.2 with the estimates of the stochastic frontier, and then move on to an analysis of our estimates of technical efficiency. Section 5.3 deals with the allocative and economic efficiency estimates. One of the questions we examine once again is whether allocative and technical efficiency are related. In Section 5.4 we present and analyze the estimates of factor-specific efficiency, while Section 5.5 examines whether our results support the widely-held belief that education promotes farmer efficiency. We conclude the chapter in Section 5.6 with a summary of our findings and the broad conclusions that can be drawn from them.

5.2 A CROP-WISE ANALYSIS OF TECHNICAL EFFICIENCY IN KHILGHATI

We saw in Chapter 2 that the stochastic production function can be written as

$$y = f(x)e^{v-u} \qquad (1)$$

As in the deterministic case, e^{-u} measures technical inefficiency while e^{v} captures the effects of random factors and measurement error. The disturbance u is assumed to follow either a half-normal distribution or an exponential distribution. The random disturbance v, on the other hand, is assumed to be normal with zero mean and constant variance. Under these assumptions, we estimate the above function by two alternative methods - COLS2, which is extended to deal with the stochastic nature of the frontier, and the maximum likelihood (ML) technique. In either case, we get two sets of estimates, each corresponding to the particular assumption we make about the distribution of u. Notice that, since v is unbounded, we do not need to ensure that the estimated residuals are negative. However, the estimation of the above function by either of the methods indicated does not provide an estimate of the (stochastic) frontier. To estimate the stochastic frontier, we need to separately estimate v and u; that is, we need to obtain an estimate of the particular realization of v. This can be done, as shown in Chapter 2, by taking the mean of the conditional distribution of u given (v-u). This enables the estimation of the stochastic frontier, and the estimates of the various efficiency indices can be constructed as before.

Before we discuss the estimates of the production function, a word on the COLS2 and ML estimation methods. The COLS2 method requires adjusting the OLS intercept by the mean of the disturbance u, E(u), which is

$$E(u) = (2/\Pi)^{1/2}\, \sigma_u \qquad (2)$$

when u is distributed half-normally, and

$$E(u) = (1/\gamma) = \sigma_u \qquad (3)$$

when u is distributed exponentially. In the deterministic case, each of these means could be estimated from the standard deviation of the OLS residuals. However, in the stochastic case, the OLS residuals are estimates of (v-u) and not of u alone. Consequently, some additional computations, as indicated in Chapter 3, are needed. In particular, in the half normal case, the third moment of (v-u), μ_3, can be shown to be

$$\mu_3 = (2/\Pi)[(\Pi-4)/\Pi]\sigma_u^3 \tag{4}$$

μ_3 can first be estimated from the OLS residuals to obtain an estimate of σ_u, which then enables the estimation of the mean of u from equation (2). If u follows an exponential distribution, the third moment of (v-u) is

$$\mu_3 = -2/\gamma^3 \tag{5}$$

Again, the third moment is estimated from the OLS residuals and substituted in (5) to obtain an estimate of γ which is then substituted in (3) to obtain an estimate of the mean of u.[2]

The ML method requires the derivation of the log-likelihood function on the assumption that v is normal with zero mean and constant variance while u is either half-normal or exponential. Under the half-normal assumption, the log-likelihood function ca be written as

$$L = T\ln(2) + T\ln(\sigma^{-1}) + \sum_i^T \ln\phi_i(\varepsilon_i\sigma^{-1}) + \sum_i^T \ln\Phi_i(-\varepsilon_i\lambda\sigma^{-1}) \tag{6}$$

where ε = v-u, $\sigma = (\sigma_u^2 + \sigma_v^2)^{1/2}$, $\lambda = \sigma_u/\sigma_v$, $\phi(.)$ is the standard normal density, and $\Phi(.)$ is the standard normal distribution function. Maximizing this function yields ML estimates of the production function parameters, λ and σ^{-1}. In the exponential case, on the other hand, the log-likelihood function is

$$L = T\ln(\gamma) + (T/2)\gamma^2\sigma_v^2 + \gamma\sum_i^T \varepsilon_i + \sum_i^T \ln\Phi_i[-\varepsilon_i/\sigma_v - \gamma\sigma_v] \tag{7}$$

where γ is the reciprocal of the mean and standard deviation of the (one-parameter) exponential distribution. Maximizing (6) yields ML estimates of the production function parameters, γ and σ_v^2. We turn now to a discussion of our results. The tables containing these are presented at the end of the chapter.

5.2.1 ESTIMATES OF THE STOCHASTIC PRODUCTION FUNCTION

Our estimates of the function when f(x) is Cobb-Douglas are presented in Tables 5.1, 5.2 and 5.3. Note that the estimated equations are estimates of the deterministic kernel of the stochastic frontier. Frontier estimates can be generated only when the stochastic term e^v has been estimated. As was the case for the deterministic frontier, the COLS2 estimates differ from the OLS results only in terms of the intercept term, which has been adjusted in the manner described above. In general, it can be observed that the estimates of the input elasticities for each crop are quite similar across equations and are, in fact, close to their OLS counterparts. They are all significant at the 5 percent level except for the labour elasticity in the Aus and Boro equations. Broadly speaking, while the ML and OLS estimates are similar, the estimated standard errors of the coefficients under ML estimation are generally lower, thereby attesting to the greater precision of the ML estimates.

Along with the estimates of the elasticities, we also estimate several other parameters. These are the variance of the normally distributed variable v, and the variance of the half-normally/exponentially distributed variable u.[3] These variances are obtained from the second and third moments of the OLS residuals in the case of the COLS estimates. Under the ML method, these variances are obtained from the ML estimates of the parameters of the half-normal/exponential distributions. From the variances of v and u we can estimate θ, the ratio of the variance of u to the variance of (v-u).[4] This statistic performs a useful function since it is an indicator of the relative importance of technical inefficiency and statistical noise in explaining the variations in output across farm households.

Looking at the results for Aman rice, it can be seen that the inter-farm variations in output do not appear to be dominated by either statistical noise or technical inefficiency. According to the COLS2 and ML estimates under the exponential assumption, only about 20-24 percent of output variations are a result of inefficiency, while the corresponding range under the half-normal assumption is 38-54 percent. Thus, under the half-normal assumption, technical inefficiency variations are the more important, while the opposite holds under the exponential assumption. Note though that under either the COLS or ML method, the variations due to technical inefficiency are lower in the exponential case than in the half-normal case. Nevertheless, in either case, the variations due to statistical noise are large enough to validate the estimation of a stochastic frontier.

For Boro rice, technical inefficiency appears to play a relatively more important role in the variations in output than is the case in the cultivation of Aman rice. This is more so according to the estimates of θ based on the half-normal assumption. But even those estimates imply that statistical noise accounts for at least 20 percent of the observed variations in output. In the exponential case, statistical noise accounts for roughly half of those variations.

The estimates of θ for the Aus crop, on the other hand, clearly suggest that 70 percent or more of the observed variations can be traced to statistical noise. This, in fact, confirms our contention in the previous chapter that the technical efficiency estimates for Aus were more likely to reflect factors other than inefficiency.[5] Overall, while the relative importance of statistical noise in explaining the variations in output varies across crops, in each case statistical noise appears to be important, a result that supports the assumption of a stochastic frontier. The foregoing discussion also indicates that the deterministic estimates of technical efficiency were likely underestimates, particularly in the case of the Aus crop.

Before we turn to the estimates of technical efficiency, we briefly indicate how the stochastic frontier was estimated - that is, how we separated statistical noise from technical inefficiency. The details of the procedure are outlined in Chapters 2 and 3. As we have indicated in those chapters, farm- specific estimates of u can be obtained by estimating the conditional mean of u given (v-u). Our estimates of that mean in the half-normal and exponential cases are respectively

$$E(\hat{u}) = -(\hat{\sigma}_u\hat{\sigma}_v/\hat{\sigma})\left[\phi(\hat{\varepsilon}\hat{\lambda}/\hat{\sigma})/\{1-\Phi(\hat{\varepsilon}\hat{\lambda}/\hat{\sigma})\} - \hat{\varepsilon}(\hat{\lambda}/\hat{\sigma})\right]$$

$$E(\hat{u}) = -\hat{\sigma}_v\left[\phi(A)/[1-\Phi(A)] - A\right]$$

where $\hat{\varepsilon}$ is the estimated residual, $\hat{\sigma}_u$ and $\hat{\sigma}_v$ are the estimated standard deviations of the normal variables u and v respectively, $\hat{\sigma} = \hat{\sigma}_v^2 + \hat{\sigma}_u^2$, $\hat{\lambda} = \hat{\sigma}_u/\hat{\sigma}_v$, $\phi(.)$ and $\Phi(.)$ stand for the standard normal density and the standard normal distribution function, respectively, and $A = (\hat{\varepsilon}/\hat{\sigma}_v) + \hat{\gamma}\hat{\sigma}_v$.[6] In the COLS2 estimation, the estimated OLS residuals are used to estimate the means. Under maximum likelihood estimation, the required estimates can be obtained from the maximum likelihood estimates of λ, σ, γ and σ_v which are parameters in the likelihood function under either of the assumptions about the distribution of u. Once u has been estimated in this fashion, v can easily be estimated. As a consequence, a particular realization of the frontier function, $f(x)e^{\hat{v}}$, becomes known. That function then can be used to obtain all the efficiency indices very much along the lines followed in the deterministic case. We turn next to a discussion of the efficiency indices.

5.2.2 THE ESTIMATES OF TECHNICAL EFFICIENCY

Our estimates of the input-based and output-based technical efficiency indices are presented in Tables 5.4 through 5.9. However, we confine our discussion to the former since the two indices are almost identical because the production function estimates imply near-constant returns to scale. Looking at the results for Aman rice, presented in Table 5.4, it can be seen that the vast majority of farm households are highly efficient in the technical sense. In particular, in contrast to the results for the deterministic frontier, more than 90 percent of the households have a technical efficiency level in excess of 90 percent if we look at the COLS2 and ML results based on the assumption that u follows an exponential distribution. The results for the half-normal case are only slightly different. Of course, the efficiency levels estimated from the COLS2 method in the deterministic case cannot be compared with the estimates obtained in the stochastic case because in the former, the technical efficiency index is not guaranteed to be no greater than 100, and we found this to be the case for several households.[7] It is interesting to note that, in spite of this, the average efficiency levels in the stochastic case are higher than those obtained under the COLS2 estimation method in the deterministic case. On the other hand, the distributions of farm households in both cases are similar in that both imply that the majority of farmers are relatively efficient. The technical efficiency indices do not appear to be very sensitive to the estimation method employed. The average level of technical efficiency is in the 89-95 percent range, with the most efficient farmers being about 96-97 percent efficient while the most inefficient farmers have a technical efficiency level in excess of 70 percent. These numbers suggest an average cost saving in the 5-11 percent range through the elimination of technical inefficiency. In the deterministic case, that cost saving was about 20 percent (looking at the COLS1, LP and QP estimates). It seems, therefore, that as far as the cultivation of Aman rice is concerned, most farm households do not differ much in the level of efficiency, and that level is high. Note that this is also reflected in the small standard deviation relative to mean technical efficiency under each estimation method. Thus, the deterministic frontier appears to have underestimated the technical efficiency of farm households in Aman cultivation.

We saw above that variations in technical inefficiency play a relatively more dominant role, relative to statistical noise, in the variations in output in Boro cultivation as compared to Aman. This is reflected in the frequency distributions of technical efficiency for Boro in Table 5.5. There is greater variation in technical efficiency levels across farm households as compared to the results for Aman. While the bulk of farm households lie in the higher ranges of the technical efficiency spectrum, there is a greater proportion lying in the lower ranges as well. In addition, while there are differences in the frequency distributions of the technical efficiency indices according to estimation method, those differences do not translate into substantial differences in average technical efficiency,which lies in the relatively narrow 81-89 percent range. Compared to the COLS1, LP and QP results obtained in the previous chapter, the level of technical efficiency is definitely higher in the stochastic case, averaging about 10-15 percentage points above the average technical efficiency levels obtained in the deterministic case. There is also less variation in efficiency levels across farm households, as compared to the deterministic case, largely because some of the variation about the deterministic function is accounted for by statistical noise. The estimates of the average level of technical efficiency in Boro cultivation point to an average 10-20 percent cost saving that could be achieved through the elimination of technical inefficiency; for the most inefficient farmers that saving is quite substantial (at least 50 percent).[8] Again we note that average efficiency levels based on the exponential assumption are higher as compared to the half-normal case.

We next consider the results for Aus rice; these are presented in Table 5.6. The results are dramatically different from those obtained in the deterministic case. There is a strong indication that in the latter case, the estimates of technical efficiency are contaminated by statistical noise. In fact, in the previous sub-section we saw that a substantial proportion of departures from the deterministic function for Aus reflect statistical noise, implying that technical inefficiency is not that important a reason for inter-farm variations in output as implied by the deterministic frontier. This point is borne out by examining the frequency distributions involved. Notice that the vast majority of farm households lie in the 70-90 percent range along the technical efficiency spectrum according to the estimates based on the half-normal distribution, and in the 80-100 range according to those based on the exponential distribution. Once again, the exponential results point to generally higher efficiency levels, averaging in the 82-90 percent range. Even the most inefficient farm households have efficiency levels no lower than 62 percent. Under the COLS1, LP and QP estimates in the deterministic case, the efficiency level of the most inefficient farmer was a low 30 percent. The average cost saving achievable through the elimination of technical inefficiency is in the 10-20 percent range according to the stochastic frontier estimates; in the deterministic case, the corresponding range was 35-45 percent. Hence, farm households appear to be far more technologically efficient in the cultivation of Aus than implied by the results of the previous chapter.

Thus, in spite of the fact that the estimates of the deterministic portion of the stochastic production function are only marginally different from those in the previous chapter, the results point clearly to the importance of not attributing all variations in output to technical inefficiency. The need to separate variations due to inefficiency from those reflecting statistical noise is clearly demonstrated by the results for Aus cultivation. Farm households appear to most efficient technically in Aman cultivation, but that superiority is not substantial. Technical efficiency in the cultivation of the new-technology, Boro rice is again found to be in line with the efficiency found in the traditional Aman and Aus crops. However, farm households appear to be more widely distributed across the technical efficiency spectrum in Boro cultivation, with a greater percentage of households lying in the lower ranges, as compared to the other crops. Thus, for instance, the most inefficient farm households in Boro cultivation have a technical efficiency index as low as 43 percent; in contrast, the lowest technical efficiency index stands at 62 percent for Aus and 72 percent for Aman. It seems that the technology for Boro is implemented much less uniformly than is the technology of the traditional crops. The gains from an improvement in technical efficiency are likely to be greater than what is indicated by the average levels of technical efficiency in Boro cultivation.[9]

In Chapter 4 we conducted an analysis of the variations in technical efficiency across farm households. Our aim was to determine whether in the light of differences in the estimates of average efficiency by estimation method and crop, the relative ranking of farm households along the technical efficiency spectrum is sensitive to both estimation method and the crop grown. In the present context, given the relative stability of the distribution of the technical efficiency index by estimation method, it is hardly likely that the ranking of households would show any significant differences. Indeed, we calculated Spearman's rank correlation coefficient between the technical efficiency indices obtained by the COLS2 and ML estimation methods for each crop. In almost all cases, those correlations were virtually perfect, pointing to the high degree of stability of the different technical efficiency indices.

As for the question of whether a household's efficiency ranking is independent of the crop grown, the apparent similarity of technical efficiency estimates across crops does not guarantee that significant differences in household rankings do not occur across crops. To examine the relationship between the technical efficiency of farmers across crops, we computed Spearman's rank correlation as well as Pearson's correlation coefficients. The results are displayed in Table 5.10 for the COLS2 and ML estimation methods based on the assumption that u is half-normal.[10] There is only one positive rank correlation (that between Aus and Boro), the other two being negative. In all cases, however, the rank correlations are not statistically significant at the 5 percent level. The same pattern is displayed by the Pearson correlation coefficients. Thus, we find no evidence to suggest that technical efficiency ranks or levels are positively correlated across crops.

We had reached a similar conclusion in the deterministic case. In that case, we had argued that differences in the effects of random factors and measurement error across individual households and crops may have been the reason. While we cannot rule out these factors in the current context, since there is no assurance that we have been able to completely or accurately remove the effects of those factors, it seems that success in the cultivation of one crop does not guarantee success in the cultivation of others, pointing perhaps to the crop-specificity of skills and/or differences in farmers' experience in growing the different crops. This is quite conceivable if we compare the new-technology, Boro rice with the traditional Aman and Aus rices. We next turn to our estimates of allocative and economic efficiency.

5.3 THE ESTIMATES OF ALLOCATIVE AND ECONOMIC EFFICIENCY

The indices for allocative and economic efficiency are computed in much the same manner as in the deterministic case. In the stochastic case, the only difference is that the frontier used to make the computations is represented by the particular realization, $f(x)e^{\hat{v}}$, of the stochastic frontier. Since the estimate of the particular realization of the random disturbance v is farm-specific so is the production frontier. In the deterministic case, all farm households faced exactly the same production frontier. Of course, this difference between the deterministic and stochastic cases is merely one of scale. We begin first with a discussion of the allocative efficiency indices.

5.3.1 THE ESTIMATES OF ALLOCATIVE EFFICIENCY

The estimates of allocative and economic efficiency are presented in

Tables 5.11, 5.12 and 5.13. In this sub-section we examine only the allocative efficiency indices. As in the deterministic case, note that the two COLS2 estimates of allocative efficiency are identical for each crop. This is because the COLS estimates differ only in terms of the intercept, and this cannot affect the allocatively efficient factor combinations. Note further that the COLS2 economic efficiency indices reported in this chapter are also identical to the COLS2 indices obtained in the deterministic case. This too is to be expected since the only difference between a stochastic frontier and a deterministic frontier estimated by COLS2 is that, apart from the different intercept adjustments, the former additionally involves scaling the deterministic function by e^{v}, and this is also equivalent to an intercept adjustment. We have included the COLS2 estimates in the table in order to enable an easy comparison with the maximum likelihood estimates. The latter involve different estimates of not only the intercept but also of the input elasticities. They, thus, can be expected to lead to different estimates of allocative efficiency. How different the estimates of allocative efficiency are depends on how dramatically the ML estimates of the input elasticities differ from those obtained by applying OLS. Since we have already seen that the ML and COLS estimates of those elasticities are quite similar, the allocative efficiency indices should display a pattern very similar to that displayed by the indices derived from the COLS2 estimates. On the other hand, the LP and QP estimates of the previous chapter are very different from both the ML and COLS2 estimates, and we can expect substantial differences in the corresponding allocative efficiency indices.

For Aman rice, the results for which are presented in Table 5.11, it is evident that the ML estimates lead to only marginally different estimates of allocative efficiency as compared to the COLS2 estimates. The allocative efficiency distributions are very similar; this leads to an estimate of the average level of allocative efficiency of about 70 percent under the ML method in both the half-normal and exponential cases, and this is just under the average of 71 percent implied by the COLS2 estimates. Of course, the ML and COLS2 estimates are very different from those implied by the LP and and QP estimates. It may be recalled that the averages based on the LP and QP methods were 52 and 60 percent respectively. Thus, the ML method in the stochastic case does not change our view of the allocative efficiency of farm households in the cultivation of Aus rice. It seems that, on average, farmers can expect about a 30 percent saving in costs by eliminating allocative inefficiency. In contrast, the LP and QP estimates implied a cost saving of at least 40 percent.

The results for Boro rice display the same general pattern. The allocative efficiency estimates based on the two sets of ML estimates are very similar with the exponential case implying marginally higher allocative efficiency. The ML estimates are also very much in line with the COLS2 estimates, with the former implying an average of 77 percent as compared to an average of 74 percent based on the COLS2 method. These averages are significantly greater than the 45 percent average implied by the LP and QP estimates. The ML estimates imply an average cost saving of about 23 percent through the elimination of allocative efficiency. This is somewhat larger than the corresponding saving implied in the cultivation of Aman. Thus, while farm households appear, on average, to be more efficient technically in Aman cultivation, the opposite is true in the allocative sense.

The general pattern observed for Aman and Boro is seen to hold for Aus. The two sets of estimates of allocative efficiency based on the ML estimation method are very similar with an average allocative efficiency level of about

50 percent. This is only marginally higher than the estimate implied by the COLS2 method. The frequency distributions are also very similar. Again, the ML estimates are very different from those obtained by the LP and QP methods. Thus, while the COLS2 and ML methods imply an average allocative efficiency level of about 50 percent, the corresponding LP/QP average is greater than 80 percent. Indeed, while the LP and QP estimates imply that most farmers are highly efficient in the allocative sense the opposite is implied by the ML and COLS2 estimates. Again, it seems likely that the LP and QP methods overestimate allocative efficiency while the ML/COLS2 methods underestimate it.[11] If this conjecture has validity, the average cost saving attainable through the elimination of allocative inefficiency is perhaps around the 40 percent level. This still implies a high level of allocative inefficiency in an absolute sense, as well as in comparison to the other crops.

On balance, it seems that farm households are relatively most efficient in the allocative sense in Boro cultivation and that for all crops the average level of allocative efficiency is lower than the average level of technical efficiency. In that sense our findings for the stochastic case are not very different from those obtained with the deterministic frontier. This is not surprising given the relatively slight differences in the ML and COLS2 estimates of the input elasticities of the production frontier.

We turn next to the question of whether the relative position of farm households along the allocative efficiency spectrum is affected by the estimation method. In light of the fact that the COLS2 and ML estimates of the frontier differ only slightly, and that the efficiency distributions corresponding to those estimates are very similar, it is not surprising that the rank correlations between the allocative efficiency indices based on different estimation methods were nearly perfect. It will be recalled that in the deterministic case, there were high correlations between the COLS1/COLS2 and LP/QP allocative efficiency indices for Aman and Boro, but those correlations were far from perfect in the case of Aus rice.[12]

The more interesting question is whether allocative efficiency is related across crops. In the previous chapter we did find a positive and statistically significant relationship between the allocative efficiency rankings in Aus and Aman, and between the Aus and Boro rankings, using the COLS1/COLS2 estimates. However, those correlations were relatively moderate (under 0.50). Since the COLS2 estimates of allocative efficiency in the stochastic case are no different, we can expect to get the same correlations. How those correlations are affected by the ML method can be seen by examining the rank correlations presented in Table 5.14. It is clear that the correlations of the indices based on the ML method are very similar to those obtained under the COLS2 method, primarily because the ML frontier estimates vary little from the COLS2 estimates of the frontier.

In concluding our discussion of the allocative efficiency indices, we note that the findings match closely those obtained in the deterministic case under the COLS estimation method. For all crops, there appears to be greater variation in allocative efficiency than in technical efficiency across farm households, and the average level of allocative efficiency is lower than the average level of technical efficiency. Farm households appear to be relatively most efficient in the allocative sense in Boro cultivation, and the least efficient in Aus cultivation. Given that the technical efficiency levels were also relatively high in Boro cultivation, these results further confirm the finding that farmers in Khilghati have been largely successful in adapting to the new technology, Boro rice crop. Of course, the measured allocative efficiency indices suggest that further improvement in efficiency could bring substantial gains, more so in the cultivation of Aus. We also find some evidence pointing to a positive relationship between allocative efficiency in Aus and Boro cultivation, and between Aman and Aus cultivation.

5.3.2 THE ESTIMATES OF ECONOMIC EFFICIENCY

While the ML estimates of allocative efficiency were found to differ only marginally from the COLS estimates, and the latter are themselves identical to the COLS estimates in the deterministic case, the technical efficiency indices based on both methods in the stochastic case are very different from the technical efficiency indices obtained in the deterministic case. This points to substantial differences in the estimates of economic efficiency in the stochastic and deterministic cases; and, since the technical efficiency indices are more reliable under the stochastic frontier assumption because the effects of statistical noise are removed from them, the estimates of economic efficiency based on the stochastic frontier are also likely to be more reliable.

The estimates for Aman rice (Table 5.11) show that the indices of economic efficiency do not vary much according to estimation method. Thus, average economic efficiency varies approximately in the 60-65 percent range, pointing to an overall average cost saving of about 35-40 percent through the elimination of both technical and allocative inefficiency. For the most efficient farmers this saving is just over 20 percent while for the least efficient it could be almost as great as 50 percent. The 60-65 percent economic efficiency level is substantially greater than that implied by either the LP or QP estimates, and somewhat higher than those obtained by the COLS1 method of estimating the deterministic frontier.[13] Thus, overall a considerable cost saving could be achieved in the cultivation of Aman through efforts aimed at reducing technical and allocative efficiency. However, since technical efficiency is at a high level, most gains are to be had by concentrating efforts in improving allocative skills.

The estimates of economic efficiency in Boro cultivation show a little more variation than those for Aman. However, the average economic efficiency index, which varies in the 60-69 percent range, is in line with the Aman index, pointing therefore to similar cost saving through the elimination of technical and allocative errors. However, this range for average economic efficiency is considerably higher than the estimate of average economic efficiency obtained in the deterministic case. In fact, the LP and QP estimates implied an average economic efficiency index of only 33 percent. The roughly similar average economic efficiency levels in Aman and Boro cultivation arise because, while average technical efficiency is higher in Aman cultivation, this is offset by the higher average allocative efficiency in Boro. But, as in the case of Aman cultivation, proportionately greater gains can be achieved in Boro cultivation by correcting allocative errors.

The results for Aus (Table 5.13) are very different not only from those obtained for Aman and Boro, but also from those obtained under the COLS1 method in the deterministic case. On the other hand, the LP and QP estimates point to an average level of economic efficiency that is considerably higher. The average level of economic efficiency is in the 40-50 percent range, and this is well below the corresponding range for Aman and Boro. In addition, that range is about one-and-a-half times the COLS1 average, and somewhat lower than the 53-55 percent average obtained under the LP and QP methods. The difference between the stochastic results and those based on the COLS1 estimates in the deterministic case is predominantly due to the substantially higher estimate of technical efficiency obtained under the stochastic assumption. The difference between the stochastic results and the deterministic LP/QP results reflects the very high allocative efficiency levels implied by the LP and QP estimates. While the stochastic frontier likely provides a much more realistic picture of technical efficiency in Aus cultivation, the poorly estimated labour elasticity in all cases makes the allocative efficiency, and hence economic indices somewhat unreliable. Nevertheless, it seems reasonable, given the more reliable estimates of technical efficiency, to conclude that the elimination of allocative efficiency in Aus cultivation would result in a proportionately larger cost reduction, even though we cannot be very certain about the magnitude of that reduction.

5.3.3 THE RELATIONSHIP BETWEEN TECHNICAL AND ALLOCATIVE EFFICIENCY

We examined the relationship between allocative and technical efficiency in the context of a deterministic frontier, and found little evidence to suggest that the two bear a strong positive relationship to each other. We briefly examine whether the move to a stochastic frontier alters that finding. We have seen above that estimating the stochastic frontier by the ML method leads to materially different estimates of allocative efficiency. However, we found that while technical inefficiency does play an important role in explaining inter-farm variations in output, statistical noise, too, accounts for a substantial proportion of those variations and the relative importance of statistical noise varies across crops. The estimates of technical efficiency under the stochastic approach are, therefore, likely to be more reliable, and the question that we examine now is whether the new estimates of technical efficiency correlate with the estimates of allocative efficiency. Thus, we report Spearman's rank as well as the Pearson correlation coefficients between the two efficiency indices, by estimation method and crop, in Table 5.15. It is apparent that there is virtually no relationship at all between the ranks or levels of technical and allocative efficiency in Aman and Aus cultivation. While there does appear to be a positive, but weak, relationship in the case of Boro, none of the rank correlations are statistically significant at the 5 percent level. We conclude, therefore, that farmers' technical skills are unrelated to their allocative skills. We reached the same conclusion in the deterministic case. This means that adjusting for statistical noise basically provides more reliable estimates of technical efficiency, though it does not appear to make a difference to the ranking of households along the technical efficiency spectrum, so that no relationship between technical and allocative efficiency is found.[14]

5.4 FACTOR-SPECIFIC EFFICIENCY

So far we have dealt with the estimates of multi-factor technical efficiency. These indices measure the inefficiency of total factor usage, and cannot provide information as to the relative importance of different factors in causing inefficiency. Thus, a given level of technical efficiency, as we have measured it thus far, could have been produced by a relatively excessive use of labour and a relatively frugal use of land, or the reverse pattern of input usage. Consequently, the multi-factor indices of technical efficiency, useful as they are, obscure the fact that factors contribute differently to inefficiency. The usefulness of factor-specific indices of efficiency is that they measure the relative efficiency of different factors and can thus indicate the areas where efforts to improve efficiency need to be directed.[15]

In this section we estimate a set of factor-specific efficiency indices for the Aman, Boro and Aus rice crops. These indices were discussed in Chapter 2 and are (a) a factor-specific technical efficiency index (b) a technical cost efficiency index and (c) an allocative efficiency index. The factor-specific technical efficiency index is the ratio of the technically efficient employment of a factor to the actual employment of that factor, given the actual quantities of all other factors, for the level of output actually produced. This index is thus an indicator of the proportionate amount by which the employment of a factor can be reduced without reducing the level of output, holding the quantities of all other factors constant. The definition of this index implies that it cannot be radial in nature as are the multi-factor indices discussed above. Therefore, the index cannot be given the cost interpretation associated with the multi-factor indices. Nevertheless, it is possible to construct a cost-based, factor-specific technical efficiency index. This is index (b) above, and it measures the cost reduction possible through the elimination of factor-specific technical inefficiency, again given the actual levels of all other factors. The technical cost efficiency index is defined as the ratio of the cost of the technically efficient level of a factor plus the cost of all other factors to the cost of the actual employment levels of all factors. The distinction between the indices (a) and (b) is not trivial. (a) measures excessive factor employment in the physical sense, and (b) measures efficiency in a cost sense. It is possible that the most efficient factor in the sense of (a) need not be the most efficient factor in the sense of (b). For example, a farmer's usage of land may be relatively the most excessive. However, if that excessive use of land is eliminated, the proportionate cost saving may be smaller than that achievable through the elimination of the technical inefficiency associated with some other factor whose excessive use is relatively less than that of land. This difference follows from the fact that the factor-specific technical efficiency index is not radial in nature. The cost of the technically efficient level of a factor plus the cost of the actual quantities of all other factors expressed as a percentage of minimum cost (for the actual output produced) is the factor-specific allocative efficiency index (c). It indicates the cost saving possible by adjusting the technical efficient level of a factor and the actual levels of all other factors to their cost minimizing levels. As we showed in Chapter 2, the product of the technical cost efficiency index (b) and the allocative efficiency index (c) is the multi-factor index of economic efficiency.

We estimated each of the aforementioned factor-specific indices for each of the crops. Our results are presented in Tables 5.16, 5.17 and 5.18. Only the results derived from the ML method, based on the assumption that the disturbance u is half-normal, are shown since all other estimation methods lead to very similar results for the stochastic frontier. Instead of presenting the detailed results in the form of frequency distributions, we have shown only the major summary results.

We first examine the results for Aman rice. Looking at the land input, we note that its average technical efficiency index stands at 67.4. This indicates that farm households could produce the same level of output if the inefficiency in the use of land were eliminated - that is, if the employment of the land input were cut by 32.6 percent. It can be seen that the inefficiency in fertilizer usage is about the same, while that of labour is the highest. Labour employment could be reduced by almost 43 percent with no reduction in output. Note though that the most efficient farmers have roughly the same level of efficiency in the employment of all factors; at the lower end of the efficiency spectrum, however, the greatest inefficiency is associated with the labour input, which could be reduced by more than 80 percent without adversely affecting output. This indicates significant overutilization of labour. However, it is possible that the survey data for the labour input overstates the extent to which it is productively employed. The technical efficiency of labour also shows much greater variation than the technical efficiency of the other factors. This is seen by noting that the standard deviation relative to the mean is almost 30 percent for labour, while the corresponding figures for land, fertilizer and bullock-power are 21.2 percent, 21 percent and 26.1 percent, respectively. However, the fact that the factor with the greatest technical inefficiency is not necessarily the factor which would lead to the greatest saving via the elimination of its technical inefficiency, can be seen by considering the average value of the technical cost efficiency index. Thus, while labour's usage is most inefficient in the physical sense, the prevailing factor prices imply that the greatest cost saving (37.1 percent) occurs by eliminating the technical inefficiency of the fertilizer input. Eliminating the physical inefficiency of the labour input would involve a cost saving of only 26 percent. Of course, our discussion is in terms of the average farmer. The factor with the greatest cost saving would in general vary across households. What additional cost saving is potentially possible once a particular factor's technical inefficiency has been eliminated can be determined by looking at the allocative efficiency index. Thus, if fertilizer's technical inefficiency is eliminated, a cost saving of 37.1 percent can be realized; if, in addition, all factor quantities are then adjusted to their allocatively efficient levels, a cost saving of just under 2 percent can additionally be realized. Factor-specific allocative efficiency is the greatest for the fertilizer input, and the lowest for the labour input. In other words, the relatively most technically efficient factor in the cost sense is also the factor with the lowest allocative efficiency index.

The incidence of factor-specific technical inefficiency is generally much higher in the cultivation of Boro rice. For instance, while the average technical efficiency index for land is slightly greater in Boro than in Aman, the corresponding indices for labour, fertilizer and bullock-power are lower, averaging 42 percent, 46 percent and 40 percent respectively. The latter are much lower than the average levels found in Aman cultivation, and suggest that there is significantly more over-utilization of factors in Boro cultivation. Note also the relatively greater variation in the technical efficiency indices for fertilizer, bullock-power and labour as indicated by their standard deviations relative to their respective means. For instance, the technical efficiency index for the most inefficient farmers is under 2 percent for fertilizer and labour and only 3 percent for bullock-power, suggesting that for those farmers much of factor employment is largely unproductive. In the physical sense, therefore, land is the most efficient input with an average technical efficiency index of about 68 percent. Again, while the labour input is the relatively least efficient in the physical sense, it is clearly not the factor on which managerial effort to improve efficiency should be concentrated if the objective is cost saving. The greatest cost saving would be achieved by eliminating technical inefficiency in the employment of bullock-power or fertilizer. Either of these factors would yield a cost saving of more than 30 percent if used in the correct amounts. The land input would yield a cost saving of just under 30 percent, while the cost saving from an efficient use of labour would be a low 8 percent. Note that for the most efficient farm households, the cost saving from greater efficiency in the utilization of the labour input would be virtually zero, while it would be at least 12 percent for the other factors. While the cost saving attainable via the elimination of factor-specific technical inefficiency varies substantially across factors, the additional saving through an adjustment of all factors to their allocatively efficient levels lies within a relatively narrow range for land, fertilizer and bullock-power, varying from a low of about 6 percent in the case of fertilizer and bullock-power to a high of about 9 percent in the case of land. For the labour input, on the other hand, that additional cost saving averages a high 30 percent.

Looking at the technical efficiency indices for the four factors in Aus cultivation, the major difference is that virtually all of labour employment is redundant. This is quite unreasonable, but is to expected, given the very low labour elasticity in the Aus production function. That low elasticity was seen to be partly responsible for the low levels of allocative efficiency found in earlier sections. Factor-specific technical efficiency indices are likely to be even more sensitive to the estimates of the input elasticities, since they are more closely tied to a factor's productivity. Bullock-labour is the relatively most technically efficient factor with an average index of about 65 percent. The efficiency of land is only marginally lower, but fertilizer is substantially inefficient with an average technical efficiency index of only 29 percent. Notice that in spite of some rather different estimates of factor-specific technical efficiency the Aus results fit into a general pattern displayed by the Aman and Boro crops too. In particular, in all cases, labour is the relatively most inefficient, with land and bullock-power appearing to be more efficient than fertilizer (at least, in two of the three crops). The substantial inefficiency of labour usage in the physical sense does not carry over to the technical cost efficiency index. That index shows that the elimination of technical efficiency in labour employment would bring an average cost saving of less than 25 percent, while the elimination of inefficiency in the usage of either one of the other inputs would involve an average cost saving in excess of 50 percent. Of course, there are substantial variations in the factor-specific technical cost efficiency index, with the least efficient farmers being in a position to realize an even greater cost saving through the elimination of technical inefficiency. While we have seen that the greatest cost saving is achieved via the elimination of technical inefficiency in fertilizer usage, the additional cost saving by then adjusting all factors to their cost minimizing proportions would be under 4 percent. In contrast, in the case of labour, that additional cost saving is about 55 percent.

In concluding this section, we take note of several points. Our estimates indicate that, on average, most factors individually display a high level of technical inefficiency in the physical sense. On balance, land and bullock-power appear to be used relatively most efficiently, although in absolute terms the technical efficiency index for land, which is an extremely scarce resource in rural Bangladesh, is below 70 percent. For all crops, technical inefficiency is easily the greatest in the employment of labour, reflecting perhaps the underemployment of its family component. On the cost interpretation, however, the greatest saving comes not from eliminating technical inefficiency of the labour input. In fact, the results point to substantial cost saving via the elimination of technical inefficiency in the usage of either of the other three inputs. Of course, which factor represents the best avenue for realizing the greatest cost saving varies across farm households. Note also that the relative importance of different factors in generating cost reductions via the elimination of technical inefficiency depends on relative factor prices. Changes in those prices could alter the ranking of factors in terms of the relative amount of cost savings they could each potentially generate.[16]

5.5 EDUCATION AND EFFICIENCY: AN ANALYSIS OF THE RESULTS

At the empirical level, the effect of farmer education on efficiency has been given considerable attention in the economic development literature. By and large, most studies suggest that education has a positive effect on farm productivity. The findings also indicate that a minimum of about 3 years of education is required for that positive effect. There can be little doubt that education is an important factor in the overall economic development of agrarian economies such as Bangladesh. It seems reasonable to argue that educated farmers are more likely to be receptive to, and to adopt newer technologies. The level of education of a farm household is likely to be an important determinant of its ability to acquire, understand and implement relevant information required for the efficient cultivation of crops, particularly of the new-technology variety. On the other hand, it is easy to overplay the importance of education relative to experience in general, and experience in the cultivation of specific crops, in particular. Nevertheless, the more radically the production methods differ from traditional ones, the more can education be expected to be an important influence. Our purpose in this section is to examine whether the efficiency (both technical and allocative) of farm households is dependent on farmer education levels.

To begin with, we categorize farm households in our sample into four groups - those with no education at all, those with between 1 and 3 years of education, those with 4 but less than 7 years of education , and those with education in excess of 7 years. For each of these groups we computed the average level of technical and allocative efficiency by estimation method and crop. Our results are reported in Table 5.19.

Looking at the results for Aman rice, there seems to be little indication that education has a positive impact on technical efficiency. If anything, farm households with 1-3 years of education have a slightly higher technical efficiency than farmers with no, or even more education. On the other hand, farm households with more education appear to be more efficient in the allocative sense. This is borne out by each of the allocative efficiency indices presented. These results are somewhat surprising, in that we would expect education to be similar in its impact on technical and allocative efficiency. On the other hand, we found that technical and allocative efficiency in Aman cultivation do not appear to be correlated. This may lead to a correlation between education and allocative efficiency, but none between education and technical efficiency. The results for Boro rice are quite different. Thus, technical efficiency seems to be positively related to the education level of farm households, though the results indicate that education beyond the 6 year level has no impact. This is quite in line with expectations since the beneficial impact of education can be expected to taper off beyond some threshold level of education. Noteworthy is the result, however, that education does not appear to be positively related to allocative efficiency. In fact, it seems that more educated farmers are relatively less efficient in the allocative sense. This is, of course, contrary to expectations, but is in line with our earlier finding that technical and allocative efficiency in Boro cultivation are not related. The figures for Aus are quite similar to those for Boro rice. In particular, technical efficiency appears to be a little higher for households educated up to 3 years, but lower compared to those with more than 3 years of education. Further, as far as allocative efficiency is concerned, better educated farmers appear to be less efficient. This again is contrary to expectations. Thus, the results presented in Table 5.19 show that the better educated farmers appear to be technically more efficient in Boro cultivation, and the same direct relationship is found between allocative efficiency and education in Aman cultivation. We also examined the education-efficiency relationship in a regression context, allowing for the possibility that that relationship might be a non-linear one. We considered two alternative regression equations:

$$Z_i = \beta_0 + \beta_1 E_i + \beta_2 E_i^2 + \zeta_i$$

$$\ln Z_i = \beta_0 + \beta_1 E_i + \beta_2 E_i^2 + \tau_i$$

where Z stands for the technical/allocative efficiency index and E for the education (in years) of the head of the farm household. Either form allows for the impact of education to vary with the level of education. A priori, the expectation is that $\beta_1 > 0$ and $\beta_2 < 0$. We found that all regressions fit the data very poorly, with overall explanation being below 10 percent and with the exception of the technical efficiency regressions for Boro and the allocative efficiency regressions for Aman, all of the equations being statistically insignificant at the 5 percent level. In the insignificant equations, none of the education variables is statistically significant. In spite of the poor fit, the statistical significance of the technical efficiency regressions for

Boro and the allocative efficiency regressions for Aman are noteworthy. In both sets of equations, the education variables have the right signs; education has a positive impact on efficiency, but that effect declines with an increase in the educational level. Thus, these findings are in line with those in Table 5.19. The regression results for Boro and Aman are as follows (standard errors in parentheses):

<u>Boro</u> 1. $$\underset{}{\hat{TE}} = \underset{(1.244)}{83.18} + \underset{(0.694)}{1.3925E} - \underset{(0.068)}{0.0800E^2} \qquad R^2 = 0.08, \quad F(2,80) = 3.58$$

2. $$\ln\hat{TE} = \underset{(0.016)}{4.413} + \underset{(0.009)}{0.0179E} - \underset{(0.001)}{0.001E^2} \qquad R^2 = 0.08, \quad F(2,80) = 3.43$$

<u>Aman</u> 1. $$\hat{AE} = \underset{(0.780)}{69.47} + \underset{(0.524)}{0.8918E} - \underset{(0.059)}{0.0750E^2} \qquad R^2 = 0.04, \quad F(2,87) = 1.90$$

2. $$\ln\hat{AE} = \underset{(0.011)}{4.24} + \underset{(0.008)}{0.0130E} - \underset{(0.005)}{0.0011E^2} \qquad R^2 = 0.04, \quad F(2,87) = 2.00$$

We also considered the role that household membership in co-operative societies might play in fostering farmer efficiency. Such membership provides farmers access to information on improved cultivation practices and could,therefore, have a favourable impact on efficiency. However, the inclusion of a dummy variable to capture that effect did not materially change the results. While membership in co-operatives was found to have a positive impact on efficiency in most regressions, that effect was not statistically significant.

The inability to find any relationship between technical efficiency and education in Aman and Aus may largely be due to the fact that farm households appear to be very similar in terms of technical efficiency. This can be seen from the very low standard deviation of the technical efficiency index relative to the mean for both those crops. It is interesting to note that the allocative efficiency index for Aman shows greater variation and this might perhaps be reflected in the positive relationship between education and allocative efficiency found for that crop. It is not clear why there appears to be no relationship between allocative efficiency and education for Boro and Aus. One possibility is that the estimates of allocative efficiency for Aus are not reliable, as we have pointed out before. It could also be that the variations in allocative efficiency in Boro are perhaps also more closely tied to growing experience (more so than in the traditional crops) than to education alone. Finally, institutional constraints (rather than inefficiency alone), which determine a farmer's access to timely credit or fertilizer inputs supplied by government agencies, may be reflected in the indices of allocative efficiency, thereby weakening any tie that might exist between education and efficiency.

Thus, while we do find that efficiency and education are positively related and, as we might expect, the positive effect of education declines with the level of education, that evidence is not uniform across all crops.

5.6 SUMMARY AND CONCLUSIONS

In this chapter, we estimated a stochastic Cobb-Douglas production frontier and used it to estimate farmer efficiency in the cultivation of rice in the village of Khilghati. A deterministic frontier assumes that all departures from it are due to inefficiency, while a stochastic frontier explicitly recognizes that those departures are also likely to reflect statistical noise. One of the major tasks in this chapter was to separate technical inefficiency from statistical noise so that more reliable estimates of technical efficiency could be obtained. How the stochastic approach affects the estimates of allocative efficiency depends fundamentally on how the estimates of the input elasticities are affected.

The production function was estimated by the COLS2 and ML methods. The former estimates differ from the corresponding deterministic estimates only in terms of the intercept adjustment involved. The ML method, based on the assumption that u is either distributed half-normally or exponentially, can lead to estimates that are different from those obtained by the COLS2 approach. But in our case, the ML estimates are only marginally different from the COLS2 ones. The main benefits from the stochastic approach were two-fold. First, the ML estimators have smaller standard errors pointing to greater precision of the estimates. Second, in estimating a stochastic frontier we also separate inefficiency from statistical noise. Indeed, our estimates indicate that while the importance of statistical noise (relative to technical inefficiency) in explaining the variations in output varies from crop to crop, statistical noise does account for a substantial portion of those variations in all crops. This is particularly true for Aus rice, for which as much as 70 percent or more of output variations can be traced to statistical noise.

We separated statistical noise v from inefficiency u by estimating the conditional mean of u given (v-u), and found that the technical efficiency indices are quite significantly affected. Average technical efficiency in Aman is the highest (approximately 90 percent compared to 80 percent in the deterministic case), but that average is not appreciably lower in both Aus and Boro, pointing to a high level of technical competence in the cultivation of all crops. The high level of technical efficiency in Boro also suggests that Khilghati farmers have successfully adapted to the new-technology crop. However, in comparison to Aman and Aus, the farm households appear to show greater unevenness in technical efficiency.

We also found that the technical efficiency ranking of farmers in one crop is largely independent of their ranking in other crops, suggesting that the skills required for efficient technical management might be crop-specific.On balance, the results show that Khilghati farmers are much more efficient technically than implied by the deterministic frontier, and that the average level of technical efficiency varies less substantially across crops.

The estimates of allocative efficiency based on the COLS2/ML methods were similar, but differed substantially from the LP/QP estimates of the previous chapter. In general, the average level of allocative efficiency was highest in Boro (75 percent) and lowest in Aus (50 percent). Of course, in the case of Aus, the very small estimated labour elasticity accounts for this. It is quite likely that allocative efficiency in Aus cultivation is probably higher. We also find that farm households appear to relatively more inefficient in the allocative sense than they are in the technical sense. This suggests that the elimination of allocative inefficiency would bring greater proportionate cost gains than the elimination of technical efficiency. Thus, for instance, the elimination of technical inefficiency in Aman would result in an average cost saving of 10 percent while the elimination of allocative inefficiency would reduce costs by as much as 30 percent.

We found some evidence to indicate a weak-to-moderate relationship between allocative efficiency across crops. On the other hand, we found very limited evidence to suggest that technical and allocative skills are correlated across crops. The results from the deterministic frontier also implied this.

We also constructed some factor-specific efficiency indices. These indices are useful in that, unlike the multi-factor indices discussed so far, since they measure the inefficiency associated with individual factors, they provide information regarding the sources of inefficiency; that information could be useful in devising a strategy for improving efficiency. Our results indicated that, in the physical sense, the greatest inefficiency is associated with the labour input; this finding is uniform across crops pointing to generally substantial over-utilization of that input. Even though the average technical efficiency levels of land and bullock-power are much higher, in absolute terms, the averages are quite low. For example, the average technical efficiency index for land lies in the 62-68 percent range, suggesting that land utilization could be reduced by more than 30 percent without reducing output. This high level of inefficiency of land use is disturbing in a country like Bangladesh where it is an extremely scarce resource due to the significant population pressure on land. In spite of the significant physical inefficiency of labour, it is not necessarily the input upon which effort to improve efficiency needs to be expended, if cost saving is the objective. Thus, the cost saving (on average) from eliminating the technical inefficiency of labour in Boro cultivation is only 8 percent, while eliminating the inefficiency in land use would lower costs by as much as 30 percent. While the elimination of technical inefficiency in land use lowers costs by about 30 percent, an additional cost saving of 10 percent can be realized by adjusting all factors to their allocatively efficient levels. Our estimates in general suggest that even if there are constraints on a farmer's ability to adjust relative factor proportions, the adjustment of a single factor in the direction of greater efficiency could bring substantial saving in costs, though that factor could differ across both households and crops. It needs to be borne in mind that the estimates of the cost of technical inefficiency are not independent of factor prices. A sufficiently large change in relative factor prices could substantially change the ranking of a factor in terms of the proportionate cost saving that it could generate.

We finally examined whether technical and allocative efficiency are positively related to the education level of farm households, as many studies seem to indicate. We did find some evidence indicating that education does have a favourable impact on efficiency, but that impact declines with the level of education. However, this finding was confined to technical efficiency in Boro cultivation and to allocative efficiency in Aman cultivation.

FOOTNOTES TO CHAPTER 5

1. See page 1, Chapter 1 for references.

2. The COLS2 estimators in the stochastic and deterministic cases are identical except for the manner in which the intercept is adjusted. The input elasticities in both situations are the same.

3. Note that, under the exponential assumption, the variance of u is $(1/\gamma^2)$. However, under the half-normal assumption, that variance is not σ_u^2. Rather, it can be shown to be $[\Pi-2/\Pi]\sigma_u^2$.

4. Since we assume that v and u are independent, the variance of (v-u) is the sum of the variances of v and u.

5. In fact, we had argued earlier that both Aman and Aus, being rain-fed crops, are more dependent on the monsoon and hence more likely to be subject to random influences than the dry-season Boro crop. This seems to be borne out by the estimates of θ.

6. Note that since σ_u^2 is not the variance of u, σ^2 is not the variance of (v-u).

7. In the stochastic case, though, none of the farm households had a technical efficiency index in excess of 100 under the COLS2 estimation method.

8. Of course, in the deterministic case, the average cost saving for the most inefficient farmers was found to be even greater.

9. One reason for the greater variation in technical efficiency levels in Boro cultivation may be that farmers have adapted at different rates as well as with varying degrees of success to the new technology.

10. We do not consider the exponential case since, as we indicated above, the technical efficiency indices obtained by applying different estimation methods were almost perfectly correlated.

11. The reason for this is that, as we indicated in the previous chapter, the labour elasticity is likely overstated in the LP/QP case and understated in the COLS/ML cases.

12. In the deterministic case, the relatively low correlations for Aus reflected the substantially different estimates of the input elasticities. In the stochastic case, on the other hand, the COLS2/ML estimates of those elasticities are very similar. This accounts for the smaller differences in the estimates of average allocative efficiency in the stochastic case.

13. We do not compare the economic efficiency indices obtained by applying COLS2 in the deterministic case to those obtained by applying the same method under the stochastic frontier assumption, because in the former case many farm households were found to be more than 100 percent technically efficient. This makes the economic efficiency index for those farmers quite meaningless.

14. That is, even though the ML method leads to vastly different estimates of technical efficiency, it does not alter the relative ranking of farmers along the efficiency spectrum. We can therefore, expect the same pattern of correlations between technical and allocative efficiency as that found in the deterministic case.

15. These indices were discussed in some detail in Chapter 2 (Section 2.3). For additional details, see Kopp (1981).

16. In general, if relative factor prices remain relatively stable, the results suggest that either land, bullock-power or fertilizer is the greatest potential source of gain (in terms of cost saving) via the elimination of factor-specific technical inefficiency. It is possible though that relative factor prices do change over time. However, given the increasing scarcity of land relative to the population it has to sustain, it is more than likely that the relative rental price of land would rise. In that case, the potential cost saving via the elimination of technical inefficiency in land would be even more substantial when compared to the saving that the elimination of inefficiency in labour use might generate.

TABLE 5.1

Estimates of the Stochastic Production Function: Aman Rice

Estimation method	Const.	ln(LA)	ln(FT)	ln(KA)	ln(LAB)	Var(u)	Var(v)	θ
		Input Variables						
COLS2(HN)	1.59	0.3167 (0.130)	0.2900 (0.046)	0.1855 (0.114)	0.1911 (0.092)	0.006	0.009	0.385
COLS2(E)	1.54	0.3167 (0.130)	0.2900 (0.046)	0.1885 (0.114)	0.1911 (0.092)	0.004	0.012	0.241
ML(HN)	1.48 (0.509)	0.2822 (0.148)	0.2856 (0.033)	0.2225 (0.161)	0.1933 (0.091)	0.008	0.007	0.544
ML(E)	1.55 (0.568)	0.3137 (0.164)	0.2908 (0.036)	0.1988 (0.176)	0.1807 (0.097)	0.003	0.012	0.198

Notes:
i) LA = land input (in acres), FT = fertilizer (in maunds, 1 maund = 82 pounds), LAB = adult labour (in man-days).
ii) Numbers in parentheses are standard errors.
iii) Sample size is 78 for Aus, 90 for Aman, and 83 for Boro.
iv) COLS stands for corrected least squares, ML for maximum likelihood, HN for the half-normal distribution, and E for the exponential distribution.
v) θ = variance(u)/variance(v-u).

TABLE 5.2

Estimates of the Stochastic Production function: Boro Rice

Estimation method	Const.	ln(LA)	ln(FT)	ln(K)	ln(LAB)	Var(u)	Var(v)	θ
		Input Variables						
COLS2(HN)	2.03	0.4579 (0.168)	0.1731 (0.076)	0.2492 (0.115)	0.1623 (0.137)	0.029	0.007	0.810
COLS2(E)	1.94	0.4579 (0.168)	0.1731 (0.076)	0.2492 (0.115)	0.1623 (0.137)	0.018	0.018	0.507
ML(HN)	2.05 (0.653)	0.4591 (0.151)	0.1871 (0.069)	0.2118 (0.111)	0.1763 (0.137)	0.021	0.012	0.622
ML(E)	2.0 (0.618)	0.4825 (0.146)	0.1836 (0.066)	0.2005 (0.103)	0.1821 (0.128)	0.015	0.018	0.458

Notes: See Table 5.1

TABLE 5.3

Estimates of the Stochastic Production Function: Aus Rice

Estimation method	Const.	ln(LA)	ln(FT)	ln(KA)	ln(LAB)	Var(u)	Var(v)	θ
		Input Variables						
COLS2(HN)	1.09	0.3892 (0.184)	0.1357 (0.055)	0.4413 (0.135)	0.0125 (0.137)	0.020	0.054	0.272
COLS2(E)	1.02	0.3892 (0.184)	0.1357 (0.055)	0.4413 (0.135)	0.0125 (0.137)	0.013	0.061	0.171
ML(HN)	1.13 (0.841)	0.3933 (0.221)	0.1391 (0.053)	0.4231 (0.135)	0.0205 (0.158)	0.021	0.048	0.303
ML(E)	1.05 (0.827)	0.3973 (0.217)	0.1369 (0.052)	0.4276 (0.129)	0.0150 (0.154)	0.011	0.058	0.153

Notes: See TABLE 5.1

TABLE 5.4

The Distribution of the Input-based Technical Eficiency Index: Aman Rice

TE(x) (percent)	Relative Frequency (% of households)			
	COLS2(HN)	COLS2(E)	ML(HN)	ML(E)
0 - 50	0.00	0.00	0.00	0.00
50 - 60	0.00	0.00	0.00	0.00
60 - 70	0.00	0.00	0.00	0.00
70 - 80	3.30	0.00	7.80	0.00
80 - 90	35.60	7.80	42.20	5.60
90 - 100	61.10	92.20	50.00	94.40
Maximum	96.00	97.20	96.40	97.40
Minimum	77.10	82.80	71.90	84.60
Mean	90.40	94.10	88.80	94.70
S.D.	4.30	2.80	5.80	2.70

Notes: i) TE(x) stands for the input-based technical efficiency index, and S.D. stands for the standard deviation.
ii) Households with a TE(x) equal to the upper limits of the efficiency intervals are grouped in the next (higher) efficiency interval.

TABLE 5.5

The Distribution of the Input-based Technical Efficiency Index: Boro Rice

	Relative Frequency (% of households)			
TE(x) (percent)	COLS2(HN)	COLS2(E)	ML(HN)	ML(E)
0 - 50	1.20	1.20	1.20	0.00
50 - 60	1.20	0.00	0.00	1.20
60 - 70	12.00	1.20	7.20	1.20
70 - 80	27.70	7.20	19.30	7.20
80 - 90	34.90	38.50	44.60	56.60
90 - 100	22.90	51.80	25.30	33.70
Maximum	97.00	96.30	95.80	96.50
Minimum	43.10	49.60	48.70	50.60
Mean	81.30	88.40	83.80	89.30
S.D.	10.60	7.50	8.80	7.10

Notes: See TABLE 5.4

TABLE 5.6

The Distribution of the Input-based Technical Efficiency Index: Aus Rice

TE(x) (percent)	Relative Frequency (% of households)			
	COLS2(HN)	COLS2(E)	ML(HN)	ML(E)
0 - 50	0.00	0.00	0.00	0.00
50 - 60	0.00	0.00	0.00	0.00
60 - 70	5.10	0.00	6.40	0.00
70 - 80	24.40	5.10	24.40	3.80
80 - 90	62.80	35.90	61.50	33.30
90 - 100	7.70	59.00	7.70	62.80
Maximum	92.40	95.00	92.70	95.40
Minimum	64.60	73.50	62.40	75.20
Mean	82.90	89.40	82.50	90.10
S.D.	6.00	4.20	6.70	3.90

Notes: See TABLE 5.4

TABLE 5.7

The Distribution of the Output-based Technical Efficiency Index: Aman Rice

TE(y) (percent)	Relative Frequency (% of households) COLS2(HN)	COLS2(E)	ML(HN)	ML(E)
0 - 50	0.00	0.00	0.00	0.00
50 - 60	0.00	0.00	0.00	0.00
60 - 70	0.00	0.00	0.00	0.00
70 - 80	3.30	0.00	7.80	0.00
80 - 90	35.60	6.70	41.10	5.60
90 - 100	61.10	93.30	51.10	94.40
Maximum	96.10	97.20	96.50	97.40
Minimum	77.40	83.00	72.30	84.80
Mean	90.50	94.20	89.00	94.80
S.D.	4.20	2.70	5.70	2.40

Notes: See TABLE 5.4. TE(y) stands for the output-based technical efficiency index.

TABLE 5.8

The Distribution of the Output-based Technical Efficiency Index: Boro Rice

TE(y) (percent)	Relative Frequency (% of households)			
	COLS2(HN)	COLS2(E)	ML(HN)	ML(E)
0 - 50	1.20	1.20	1.20	1.20
50 - 60	2.20	0.00	0.00	0.00
60 - 70	10.80	1.20	8.40	1.20
70 - 80	32.50	8.40	19.30	7.20
80 - 90	31.30	39.80	44.60	10.80
90 - 100	21.70	49.40	26.50	79.50
Maximum	96.80	96.10	95.70	96.30
Minimum	41.60	48.10	47.50	48.90
Mean	80.60	88.00	83.30	88.80
S.D.	10.90	7.70	9.00	7.40

Notes: See TABLE 5.7

TABLE 5.9

The Distribution of the Output-based Technical Efficiency Index: Aus Rice

TE(x) (percent)	Relative Frequency (% of households) COLS2(HN)	COLS2(E)	ML(HN)	ML(E)
0 - 50	0.00	0.00	0.00	0.00
50 - 60	0.00	0.00	0.00	0.00
60 - 70	5.10	0.00	6.40	0.00
70 - 80	23.10	5.10	23.10	3.80
80 - 90	62.80	34.60	62.80	33.30
90 - 100	9.00	60.30	7.70	62.80
Maximum	92.60	95.10	92.90	95.50
Minimum	65.20	74.00	63.10	75.70
Mean	83.20	89.60	82.90	90.30
S.D.	5.90	4.10	6.50	3.80

Notes: See TABLE 5.7

TABLE 5.10

Inter-crop Rank Correlations of Technical Efficiency

Estimation Method	Crop	Aman rice	Boro rice	Aus rice
COLS2(HN)	Aman rice	1.00 (1.00)		
	Boro rice	-0.08 (-0.05)	1.00 (1.00)	
	Aus rice	-0.16 (-0.22)	0.20 (0.12)	1.00 (1.00)
ML(HN)	Aman rice	1.00 (1.00)		
	Boro rice	-0.07 (-0.05)	1.00 (1.00)	
	Aus rice	-0.16 (-0.21)	0.18 (0.10)	1.00 (1.00)

Notes: The numbers in parentheses are Pearson's correlation coefficients.

TABLE 5.11

The Distribution of Allocative and Economic Efficiency: Aman Rice

AE and EE (percent)	COLS2(HN)		COLS2(E)		ML(HN)		ML(E)	
	AE	EE	AE	EE	AE	EE	AE	EE
0 - 30	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
30 - 40	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
40 - 50	0.0	0.0	0.0	0.0	0.0	5.6	0.0	0.0
50 - 60	1.1	23.3	1.1	11.1	2.2	36.6	3.3	14.4
60 - 70	42.2	61.1	42.2	58.9	55.5	46.6	47.7	61.1
70 - 80	51.1	4.4	51.1	30.0	38.8	11.1	44.4	24.4
80 - 100	5.6	0.0	5.6	0.0	3.3	0.0	4.4	0.0
Maximum	83.5	77.4	83.5	79.4	81.8	75.5	82.6	78.6
Minimum	55.5	52.1	55.5	54.0	54.4	47.0	54.6	53.2
Mean	71.2	64.2	71.2	67.0	69.4	61.7	70.1	66.4
S.D.	5.6	6.0	5.6	5.7	5.5	6.5	5.6	5.6

Relative Frequency (% of households)

Notes: AE and EE are the allocative and economic efficiency indices respectively; EE = TE(x)*AE.

TABLE 5.12

The Distribution of Allocative and Economic Efficiency: Boro Rice

AE and EE (percent)	COLS2(HN)		COLS2(E)		ML(HN)		ML(E)	
	Relative Frequency (% of households)							
	AE	EE	AE	EE	AE	EE	AE	EE
0 - 30	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
30 - 40	0.0	2.4	0.0	0.0	0.0	0.0	0.0	0.0
40 - 50	0.0	10.8	0.0	2.4	0.0	4.8	0.0	2.4
50 - 60	1.2	30.1	1.2	18.1	1.2	25.3	1.2	8.4
60 - 70	22.9	44.6	22.9	47.0	12.0	44.6	12.0	35.0
70 - 80	61.4	10.8	61.4	31.3	57.8	24.1	53.0	51.8
80 - 100	14.5	1.2	14.5	1.2	28.9	1.2	33.7	2.4
Maximum	92.8	80.6	92.8	80.1	93.2	81.7	93.6	82.8
Minimum	52.3	34.8	53.3	40.0	55.3	40.5	56.7	42.4
Mean	74.0	60.2	74.0	65.5	76.5	64.0	77.2	68.9
S.D.	6.3	9.0	6.3	7.5	6.1	8.1	6.1	7.5

Notes: See TABLE 5.11

TABLE 5.13

The Distribution of Allocative and Economic Efficiency: Aus Rice

AE and EE (percent)	Relative Frequency (% of households)							
	COLS2(HN)		COLS2(E)		ML(HN)		ML(E)	
	AE	EE	AE	EE	AE	EE	AE	EE
0 - 30	1.3	7.7	1.3	3.8	1.3	5.1	1.3	3.8
30 - 40	12.8	38.5	12.8	24.4	10.3	33.3	11.5	20.5
40 - 50	37.2	48.7	37.2	52.6	27.0	47.4	32.1	50.0
50 - 60	39.7	2.6	39.7	18.0	51.2	12.8	44.8	24.4
60 - 70	9.0	0.0	9.0	1.3	8.9	1.3	9.0	1.3
70 - 80	0.0	0.0	0.0	0.0	1.3	0.0	1.3	0.0
80 - 100	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Maximum	69.2	61.7	69.2	64.4	72.0	64.2	70.7	66.1
Minimum	28.4	21.0	28.4	24.2	30.0	21.7	29.1	25.4
Mean	48.8	40.5	48.8	43.7	51.0	42.2	50.1	45.6
S.D.	8.1	7.6	8.1	7.7	8.3	7.9	8.2	7.8

Notes: See TABLE 5.11

TABLE 5.14

Inter-crop Rank Correlations of Allocative Efficiency

Estimation method	Crop	Aman rice	Boro rice	Aus rice
COLS2(HN)	Aman rice	1.00 (1.00)		
	Boro rice	-0.01 (0.05)	1.00 (1.00)	
	Aus rice	0.23 (0.26)	0.43 (0.52)	1.00 (1.00)
ML(HN)	Aman Rice	1.00 (1.00)		
	Boro rice	-0.03 (0.04	1.00 (1.00)	
	Aus rice	0.23 (0.26	0.39 (0.50)	1.00 (1.00)

Notes: Numbers in parentheses are Pearson's correlation coefficients.

TABLE 5.15

Spearman's Rank Correlations between Technical and Allocative Efficiency

Estimation method	Aman rice	Boro rice	Aus rice
COLS2(HN)	0.04 (0.04)	-0.04 (-0.11)	0.11 (0.10)
COLS2(E)	0.04 (0.06)	-0.04 (-0.11)	0.11 (0.09)
ML(HN)	0.06 (0.06)	-0.01 (-0.09)	0.12 (0.11)
ML(E)	0.04 (0.04)	0.01 (-0.09)	0.12 (0.09)

Notes: Numbers in parentheses are Pearson's correlation coefficients.

TABLE 5.16

Factor-specific Efficiency Indices: Aman Rice

	Factors of Production											
	Land			Fertilizer			Bullock-power			Labour		
	TEF	TCE	AEF	TEF	TCE	AEF	TEF	TCE	AEF	TEF	TCE	AEF
Mean	67.4	72.2	85.6	67.7	62.9	98.1	61.1	64.7	95.4	57.1	73.8	83.7
S.D.	14.3	5.7	6.9	14.2	6.6	1.0	16.0	6.3	2.1	16.9	6.3	6.7
Max	88.1	85.5	95.9	88.3	77.2	99.7	85.2	77.9	98.2	83.1	85.0	93.4
Min	31.7	55.5	58.2	32.1	48.8	95.6	23.3	50.9	87.1	18.7	56.1	65.0

Notes: i) TEF stands for the factor-specific, technical efficiency index, TCF for the factor-specific, technical cost efficiency index, AEF for the factor-specific, allocative efficiency index.
ii) Max and Min stand for the maximum and minimum values respectively.

TABLE 5.17

Factor-specific Efficiency Indices: Boro Rice

	Factors of Production											
	Land			Fertlizer			Bullock-power			Labour		
	TEF	TCE	AEF	TEF	TCE	AEF	TEF	TCE	AEF	TEF	TCE	AEF
Mean	68.2	70.5	90.7	42.2	67.7	94.5	46.1	67.8	94.4	40.3	92.4	69.7
S.D.	14.7	7.5	4.6	19.1	8.1	2.3	18.9	8.2	2.5	19.1	6.2	10.2
Max	90.9	87.1	97.4	79.0	83.7	99.1	81.2	83.8	98.6	77.9	99.7	90.4
Min	19.8	53.3	73.9	1.9	45.3	89.0	3.0	45.5	82.6	1.5	66.8	47.0

Notes: See TABLE 5.16

TABLE 5.18

Factor-specific Efficiency Indices: Aus Rice

	Factors of Production											
	Land			Fertilizer			Bullock-power			Labour		
	TEF	TCE	AEF	TEF	TCE	AEF	TEF	TCE	AEF	TEF	TCE	AEF
Mean	62.8	48.6	86.8	29.1	43.9	96.2	64.8	44.2	95.5	0.21	77.8	54.2
S.D.	11.8	8.9	4.5	13.3	8.6	2.3	11.4	8.4	2.1	0.47	7.7	8.6
Max	82.9	72.1	94.9	58.9	68.4	99.2	84.0	67.0	98.1	2.80	93.9	73.5
Min	31.0	25.3	74.1	3.7	22.3	85.9	33.7	22.5	83.5	0.00	55.5	29.4

Notes: See TABLE 5.16

TABLE 5.19

Technical and Allocative Efficiency by Education Level

Education (in years) and Crop	Average Technical Efficiency				Average Allocative Efficiency		
	COLS2(HN)	COLS(E)	ML(HN)	ML(E)	COLS2(HN)	ML(HN)	ML(E)
<u>Aman rice</u>							
0	90.2	94.0	88.6	94.6	69.9	68.3	68.8
1 - 3	91.1	94.6	90.0	95.2	73.3	71.3	72.1
4 - 6	90.1	94.1	88.2	94.7	72.8	71.0	71.6
7 +	90.9	94.2	89.7	94.7	71.5	69.7	70.4
<u>Boro rice</u>							
0	78.5	86.4	81.4	87.5	75.2	77.5	78.2
1 - 3	82.5	89.2	84.6	89.9	72.9	75.6	76.3
4 - 6	84.9	90.8	86.9	91.7	74.3	76.6	77.2
7 +	84.2	90.5	86.2	91.1	70.0	72.7	73.3
<u>Aus rice</u>							
0	82.8	89.4	82.4	90.1	49.8	52.0	50.9
1 - 3	83.8	90.1	83.5	90.8	47.5	49.8	48.7
4 - 6	83.0	89.2	82.6	89.9	48.7	50.9	49.8
7 +	82.0	88.8	81.5	89.6	45.9	47.9	47.0

CHAPTER 6

SUMMARY AND CONCLUSIONS

In this study, we have attempted to measure the efficiency of Bangladeshi farmers in the cultivation of rice by examining a sample of farmers from Khilghati, a village lying about 95 miles north of the capital city of Dhaka. The data used were collected by Khandker (1982) and are for the 1981-82 crop year beginning in March. The question of the efficiency of farmers in less-developed countries is an important one since agriculture is the main source of livelihood for the bulk of the population. Therefore, it is not surprising that this issue has attracted considerable attention in the development literature. Whether farmers are more or less efficient in the static sense (that is, within the framework of a given technology) or in the dynamic sense (that is, in adopting newer, more efficient technologies) has important implications for the standard of living of the population at large. In Bangladesh, the land is highly fertile; yet yields in agriculture in general, and in rice (the dominant food crop) in particular, are among the lowest in the world. Given the scarcity of land, which reflects the high pressure of population, the government has attempted to encourage the more intensive use of land from the cultivation of crops in the dry, winter season and the adoption of new, high-yielding varieties of seeds. Indeed, important strides have been made in the move towards the adoption of "Green Revolution" technologies through various programmes initiated by the government in the early sixties. While the adoption of more productive varieties of seeds and the more intensive use of scarce land resources are undoubtedly steps in the right direction, attention also needs to be paid to improving the efficiency of farmers within the framework of any technology, be it of the traditional or more modern kind. One of the aims of this study was to construct several indices in order to assess the efficiency of Khilghati farmers in the cultivation of traditional and non-traditional rice crops. Our results tell us something about the incidence of different types of inefficiency in general, how those types of inefficiency vary across crops, and the direction government policy might have to take in promoting greater efficiency.

Issues relating to the measurement of efficiency were discussed at length in Chapter 2. We first presented, in Section 2.2, a brief theoretical outline of the well known concepts of static efficiency.These are the concepts of technical, allocative and price efficiency. In this study, we did not deal with the measurement of price efficiency. Instead, we focused our attention on technical and allocative efficiency. As is well known, technical efficiency refers to the efficiency of factor use in the physical sense. It is an attribute of the production function which depicts the maximum output that can be produced given input quantities, or the minimum input quantities required to produce a given level of output. Allocative efficiency is a cost concept; it is associated with the question of whether a firm utilizes inputs in the "right" proportions. If a firm utilizes inputs efficiently in the technical and allocative senses, the firm is said to be economically efficient. Economic efficiency is itself an attribute of the cost function which shows the lowest cost of producing any level of output. These concepts can be extended to deal with firms that produce multiple outputs. However, our study is concerned only with farmers who produce a single output.

At the theoretical level, technical and economic efficiency (which subsumes technical and allocative efficiency) are essentially frontier concepts. A frontier function depicts the optimum value of a variable given the levels of its arguments. Thus, the production frontier (function) defines the maximum output given input levels, or the minimum input levels required for any level of output. Similarly the cost frontier (function) shows the lowest cost of producing a given level of output. At the theoretical level, inefficiency can be represented by departures from the relevant frontier. For instance, departures from the production frontier represent technical inefficiency while departures from the cost frontier indicate technical inefficiency, allocative inefficiency or both. Once the relevant frontier is known, firms can be evaluated to assess their technical and allocative efficiency.

In Section 2.3, we reviewed the various approaches to efficiency measurement starting with the pioneering work of Farrell (1957). We considered alternative models of efficiency measurement on the assumption that the relevant frontier is known. Farrell's approach was non-parametric. He proposed input-based measures of technical, allocative and economic efficiency on the assumption of a constant-returns-to-scale technology. Since his study, the literature on efficiency measurement and the construction of frontiers has grown substantially. One part of that literature, popularly known as "Data Envelope Analysis", deals with non-parametric frontiers and their construction by non-statistical techniques [see, for instance, Charnes, Cooper and Rhodes (1978, 1985)] and Seiford and Thrall (1990)]. The other part, on which this thesis is based, focuses on the measurement of efficiency from parametric frontiers and their estimation by primarily econometric methods [see the survey papers by Forsund, Lovell and Schmidt (1980), Schmidt (1986) and Bauer (1990)]. Under the latter approach, efficiency can be modeled and measured in different ways. Thus, if the production frontier is known, one can construct an output-based technical efficiency index which expresses actual output as a proportion of frontier output. Alternatively, one can construct an input-based technical efficiency index which measures technical efficiency in terms of the proportionate amount by which a firm's employment of factors exceeds the minimum required by the output level produced. This index is, as shown by Kopp (1981), a generalization of the Farrell technical efficiency index in that it can be computed for any any technology and is not restricted to constant-returns to scale technologies, as is the case with the Farrell index. The generalized Farrell index is radial in nature and differs from the output-based measure. The two coincide only under conditions of constant returns to scale. The radial nature of the generalized Farrell index means that it can be given a useful cost interpretation. In particular, one minus the input-based index indicates the proportionate cost saving that could be achieved by eliminating technical inefficiency. The output-based index does not lend itself to such a cost interpretation. In this study, we estimated both indices but found them to be very similar.

The generalized, input-based approach also enables the measurement of allocative efficiency in a straightforward manner from the production frontier. The allocative efficiency index is a measure of the proportionate amount by which the relative factor proportions employed by a firm differ from the cost-minimizing ones. Again, one minus this index measures the cost saving that could be realized by eliminating allocative inefficiency. The product of the input-based technical and allocative efficiency indices is the generalized Farrell index of economic efficiency. One minus this index shows the proportionate saving in costs that could be realized by eliminating both technical and allocative inefficiency. The economic efficiency index is, therefore, an indicator of the proportionate amount by which a firm departs from its cost frontier. We estimated the aforementioned allocative and economic efficiency indices in this study. Note that the measurement of allocative and/or economic efficiency can also be approached in other ways - see, for example, the studies by Schmidt and Lovell (1979, 1980), Kopp and Diewert (1982) and Kumbhakar (1987, 1989, 1990) to cite a few examples. These alternative approaches were also reviewed in Section 2.3.

We also estimated a set of factor-specific efficiency indices [Kopp (1981)]. The technical and allocative efficiency indices discussed above are multi-factor indices in that they measure the efficiency of total factor usage. However, they do not tell us anything about the relative inefficiency of various inputs. Our factor-specific technical efficiency index measures the inefficiency of any given factor, given the actual employment levels of all other factors. This index is not radial in nature and thus does not have a cost interpretation. However, by bringing in factor prices, we can construct a technical cost efficiency index. That index measures the cost saving that could be achieved by eliminating the technical inefficiency in the use of that factor. Note that the factor-specific technical and technical cost efficiency indices can imply very different things. Thus, factor A may be ranked the least efficient in the physical sense; yet it could be the most in the cost sense. In other words, the technical cost efficiency index of a factor is not independent of relative factor prices, while the multi-factor technical efficiency index is. We also estimated a factor-specific allocative efficiency index. While the technical cost efficiency index of a factor indicates the cost saving that could be realized by eliminating the technical inefficiency associated with that factor, the allocative efficiency index of the factor measures the additional cost saving that could be realized by then adjusting all factors to their allocatively efficient levels. An alternative approach to factor-specific efficiency has been proposed by Kumbhakar (1988).

All the efficiency indices mentioned above presume knowledge of the relevant frontier. It is important to distinguish between a deterministic frontier and a stochastic frontier, particularly at the empirical level. Approaches that attribute all departures from the production/cost function to inefficiency assume an intrinsically deterministic frontier. Those that view those departures as reflecting both inefficiency and statistical noise view the frontier as being intrinsically stochastic. Earlier empirical studies, such as those of Aigner and Chu (1968) and Timmer (1970), dealt with deterministic frontiers. In view of the fact that statistical noise is an important component of econometric relationships, subsequent studies invariably adopted the stochastic frontier. Stochastic frontiers were initially proposed by Schmidt and Lovell (1977) and Meeusen and van den Broeck (1977). We estimated both deterministic and stochastic frontiers in this study and used them to obtain the efficiency indices discussed above.

The estimation of frontiers raises a number of important issues. These were reviewed in Section 2.4. We first discussed the problems of specification. A major problem in the estimation of production frontiers (deterministic or stochastic) is the question of functional form. We adopted the Cobb-Douglas functional form. In spite of its restrictive features it has been a popular choice in frontier studies and possesses some advantages not shared by more flexible forms like the translog function. For one thing, it avoids the potential for collinearity in the translog case. More importantly, as our discussion in Section 2.3 showed, a non-homogeneous function raises some awkward difficulties for the estimation of allocative efficiency since a measure of expected output is required to evaluate allocative efficiency accurately. The homogeneous Cobb-Douglas function does not suffer from that problem. The other important specification problem is the assumption about the distribution of the disturbance term - that is, of technical inefficiency in the deterministic case, and additionally statistical noise in the stochastic case. We reviewed some of the commonly made assumptions about the technical inefficiency and statistical noise terms in the production function. In order to examine the sensitivity of the estimates to distributional assumptions we considered two alternative assumptions about the technical inefficiency term - one, that it follows a half-normal distribution and two that it follows an exponential distribution. These are only two of several possibilities. Their main feature is that they are one-sided distributions so that technical inefficiency places the firm on or below the deterministic/stochastic frontier. In the stochastic case, we assumed that the disturbance term reflecting statistical noise is normally distributed with zero mean and constant variance.

Deterministic frontiers raise somewhat different issues for estimation than do stochastic frontiers. In the deterministic case, observations have to lie below the deterministic production frontier. Clearly, ordinary least squares (OLS) would not ensure that. Besides, on our assumption that farmers maximize expected or median profit and that technical inefficiency is unknown, OLS provides consistent estimators of all parameters of the frontier except the intercept since the disturbance does not have a zero mean. We estimated the frontier by "correcting" the OLS method in two alternative ways. In one case, we adjusted the OLS intercept by adding to it the largest OLS residual. We called this method COLS1. In the other case, we adjusted the OLS intercept by adding to it the estimated mean of the disturbance term reflecting technical inefficiency. We called this method COLS2. Both COLS1 and COLS2 are consistent estimators of the intercept. However, while COLS1 is distribution-free, the implementation of COLS2 requires an assumption about the distribution of the technical inefficiency (disturbance) term. We considered the two distributional assumptions indicated above. Note that while COLS1 estimates a frontier in the true sense of the word - that is, at least one firm lies on the frontier and none above it - the COLS2 adjustments do not guarantee that firms do not lie beyond the frontier. We also estimated the deterministic frontier by the maximum likelihood (ML) method under the assumption that the technical inefficiency term is distributed either half-normally or exponentially. In the half-normal case, the ML method involves solving a quadratic programming problem, while in the exponential case, it is a linear programming problem. We estimated the frontier by linear and quadratic programming methods as well.

In the stochastic case, we faced similar estimation problems. An additional difficulty was the separation of inefficiency from statistical noise. We followed the approach suggested by Jondrow et al. (1982). This enabled us to obtain farm-specific estimates of technical and allocative efficiency. In other words, that procedure enables the estimation of the particular realization of the stochastic frontier, which can then be used to obtain farm-specific estimates of technical, allocative and factor-specific efficiency. The parameters of the production function and the assumed distributions were estimated by applying the COLS2 and ML methods. These issues were discussed in Section 2.4 of Chapter 2.

The purpose of Chapter 3 was two-fold. We first outlined the nature of our sample economy, the village of Khilghati. As far as cultivation is concerned, Khilghati is essentially a rice-based economy with that crop accounting for about 90 percent of cultivated area. It grows three varieties of rice, each corresponding to a particular cropping season . The Aus and Aman rice crops are the traditional crops and these are grown during the spring and summer months. They are wet season, rain-fed crops and depend in an important way on the monsoon. Khilghati farmers also grow a new-technology Boro rice crop during the dry, winter months. We measured the efficiency of farmers in the cultivation of each of these crops. Based on our discussion in Section 3.2, land, fertilizer, bullock-power and adult labour (family plus hired) appear to be the major factor inputs, and though the markets for some of those inputs are relatively limited and/or dominated by kinship factors, we could identify the relevant market prices for the services of each. It was assumed that the prices reflect the relevant opportunity costs reasonably accurately. In Section 3.3, we outlined our estimation strategy in greater detail and discussed how the various efficiency indices were actually constructed. Our findings were discussed in Chapters 4 and 5.

In Chapter 4 we discussed the results obtained by estimating deterministic frontiers. The estimates of the parameters of the frontiers were found to be sensitive to the estimation method. While the COLS estimates were identical, except for the intercept term, and appeared to be quite reasonable, they differed quite substantially from the LP and QP estimates. This was particularly so in the case of the Aus frontier. In that case, the estimates of the labour elasticity appeared to be unrealistically low by the COLS method and too high by the LP and QP methods. While the Aus frontier does not appear to be estimated well by either the COLS or programming methods, the latter are highly sensitive to outliers in the data and their results for Aus are more suspect.

The estimates of technical efficiency estimates vary by estimation method and crop. One reason for the differences between the COLS land COLS2 estimates is that the latter method led to estimates of technical efficiency well in excess of 100 percent for a number of households. Otherwise, the differences by estimation method are not large. At any rate, the ranking of firms in terms of their technical efficiency is only marginally affected by estimation method. We found that farm households seem to be the most efficient in the technical sense in Aman cultivation and the least efficient in Aus cultivation. Thus, according to the COLS1 and LP and QP estimates, the average level of technical efficiency is about 80 percent or more in Aman and 65 percent or less in Aus cultivation. These input-based indices, which are very similar to the output-based indices, point to a cost saving of 20 percent or less in Aman and 35 percent or more in Aus if technical inefficiency is eliminated. The estimates for Boro lie in between with an average technical efficiency index of about 70 percent. Thus, while the traditional (and most popular) Aman crop displays the highest technical efficiency, it is interesting to note that technical efficiency in the new-technology Boro rice compares favourably with that in Aman, pointing to the relatively successful adaptation to the newer technology. Nevertheless, we find that technical efficiency varies much more in the cultivation of Boro. In particular, many farmers in Boro cultivation have yet to achieve the average efficiency levels attained in Aman cultivation. Since there appear to be variations in technical efficiency across crops, we also examined correlations among the crop-specific technical efficiency indices. We found that the relatively more efficient farmers in one crop do not tend to be relatively more efficient in other crops as well. This is somewhat surprising but may reflect the possibility that technical skills are crop-specific, or that the technical efficiency indices are contaminated by statistical noise.

The estimates of allocative efficiency are also found to be sensitive to estimation method, especially in the case of Aus rice. The allocative efficiency estimates are particularly sensitive to the estimates of the input elasticities, and the significant differences in the COLS and LP/QP estimates of those elasticities account for those differences. We find that while the allocative efficiency estimates based on the COLS and LP/QP methods for the Aman and Boro crops show quite significant quantitative differences, the results for Aus show major qualitative differences as well. Thus, the estimates show that while average allocative efficiency in Aman and Boro is in the 70-75 percent range according to the COLS1 estimates, it is in the 45-50 percent range according to the LP and QP estimates. That pattern is reversed in the case of Aus, with average allocative efficiency being in the 80-85 percent range according to the LP and QP estimates and just under 50 percent according to the COLS1 estimate. Because of these major differences, even the relative ranking of farmers according to efficiency levels is substantially different depending upon whether we look at the COLS or LP/QP estimates. In light of the likely direction of bias in the estimates of the input elasticities for Aus, we feel that the true average allocative efficiency level probably lies between the COLS and LP/QP estimates. In any event, all indications are that irrespective of the estimation method, the average level of allocative efficiency is lower than the average level of technical efficiency. The inter-crop differences in allocative efficiency are relatively minor, at least as far as the COLS1 estimates are concerned, and suggest that farmers are most efficient in Boro cultivation with an average allocative efficiency level of 74 percent. The corresponding averages in Aman and Aus are 70 percent and 49 percent respectively. Since the economic efficiency index is the product of the technical and allocative efficiency indices, its magnitude and variations are largely determined by the its component indices. Thus, we find that the average level of economic efficiency is about 52 percent according to the COLS1 estimates and 33 percent by the LP/QP estimates in Boro cultivation. The corresponding figures are 57 percent and about 55 percent for Aman and 27 percent and 55 percent for Aus. It seems that the level of economic inefficiency is quite substantial in all crops, pointing to an average cost saving of at least 40 percent through the elimination of both types of inefficiency. Furthermore, given the greater magnitude of allocative inefficiency, a considerable saving in cost can be realized by eliminating allocative inefficiency. Again, we find that the new-technology Boro crop compares very favourably with the traditional crops in terms of efficiency, although efforts to improve allocative skills in all crops would likely bring substantial benefits.

Finally, in the deterministic case, we find that in spite of substantial inter-crop differences, allocative efficiency is not entirely independent between crops. In particular, we find some evidence to suggest that allocative skills in Boro and Aus are positively correlated. However, that evidence is weak. We also attempted to determine whether technical and allocative skills are correlated. However, we found no evidence to suggest that they were in our sample. While we would expect a strong positive correlation between the two over time, there is no compelling reason for static efficiency indices to support that expectation at any given point in time.

The major drawback of the deterministic frontier is that it does not make allowance for statistical noise. Consequently, the technical efficiency indices are more than likely contaminated by statistical noise. We estimated the stochastic Cobb-Douglas frontier by both the COLS2 and ML methods. Of course, the COLS2 estimates differ from the COLS estimates of the frontier in the deterministic case only in terms of the intercept adjustment. The ML estimates can show more fundamental differences. Our ML estimates, under the exponential and half-normal assumptions, did not result in major differences of the production function parameters as compared to the COLS estimates in the deterministic case. They, therefore, differ quite substantially from the LP/QP estimates. One major implication is that the new estimates of the frontier do not radically change the estimates of allocative efficiency compared to those obtained by the COLS method in the deterministic case. The primary gain by adopting the stochastic approach and using the ML method is the greater precision of the production function estimates as evidenced by the drop in the estimated standard errors. In addition, by allowing for statistical noise, we get an idea of the extent to which the deterministic estimates of technical efficiency were contaminated by it.

Our ML estimates indicate that while the relative importance of statistical noise in explaining variations in output across farm households varies across crops, its importance is sufficiently large in all cases to validate the stochastic approach. For example, the ML and COLS2 estimates suggest that technical inefficiency accounts, at best, for about 50 percent and, at worst, no more than 20 percent of the variations in output in Aman cultivation. The corresponding numbers are 80 percent and 45 percent for Boro and 30 percent and 15 percent for Aus. In light of this evidence, there is little doubt that statistical noise is too significant a factor, especially in the traditional Aman and Aus crops, to be ignored. The estimates of technical efficiency clearly support this. Not only is there a clear and marked improvement in average efficiency levels, but inter-farm variations in technical efficiency are also seen to decline. The average level of efficiency is around 90 percent in Aman and around 85 percent in Boro. The most dramatic difference is in the case of Aus cultivation. For that crop, the average level of efficiency rises to the 82-90 percent range. This supports our earlier contention that the rain-fed, traditional crops of Aman and Aus are more likely to be influenced by random factors. The estimates suggest that technical efficiency is generally very high in all crops. Since growing experience most likely correlates with efficiency, it is noteworthy that the new-technology Boro crop continues to compare very favourably with the established Aman and Aus crops.

There is some variation in the estimates of technical efficiency by estimation method. Thus, typically, the exponential assumption leads to higher technical efficiency estimates but the differences are not substantial. We find very high correlations among the technical efficiency indices based on different estimation methods. However, again, there is only limited evidence to indicate that technical skills are common to crops since farmers' technical efficiency rankings across crops do not appear to be correlated.

We also find that the allocative efficiency indices vary only a little by estimation method and the ranking of farmers by allocative efficiency does not depend upon the estimation method. In fact, excluding the LP and QP estimates, the various allocative efficiency estimates are very similar. On balance, it seems that farmers are, on average, about 75 percent allocatively efficient in Boro, 70 percent efficient in Aman and 50 percent efficient in Aus. In light of the more reliable estimates of technical efficiency, the corresponding estimates of economic efficiency can be expected to be more reliable as well. The average level of economic efficiency is in the 60-65 percent range in Aman, in the 60-70 percent range in Boro, and in the 40-45 percent range in Aus. Even though the Aus numbers are pulled down by the unrealistically low labour elasticity, it is clear that a substantial cost saving can be realized through the elimination of economic inefficiency in all crops.

We also estimated factor-specific efficiency using the COLS2 and ML estimates of the production frontier. A significant feature of the results is that, in the physical sense, labour is clearly the most inefficient factor in that its use is relatively the most excessive relative to the minimum required. The degree of labour's inefficiency is substantial, though it is clearly overstated, in Aus in light of the very low productivity of labour implied by its estimated labour elasticity. For Aman and Boro labor employment could be cut by 40 and 60 percent respectively without reducing output. In general, the inefficiency of other factors is also quite high. Thus, while land is the relatively most efficiently used factor, its technical efficiency level is less than 70 percent. This is quite disturbing given the scarcity of land. Interestingly, even though labour is the most inefficient factor in the physical sense, the elimination of technical inefficiency in that factor does not lead to the greatest proportionate saving in costs. For each of the crops, the elimination of technical inefficiency in the use of either one of the other factors would bring about a greater proportionate saving. Of course, the relative importance of different factors in contributing to inefficiency varies in both the physical and cost senses across crops, and it is also likely to vary with relative prices of factors. Since the relative price of land can be expected to rise given its relative scarcity, our estimates clearly point to the importance of a more efficient use of land.

Our final analysis of the results involved examining, in Section 5.5, the role of education in promoting efficiency. A vast number of studies suggest that education increases farm productivity. We calculated the average levels of technical and allocative efficiency of farmers in each crop grouped according to education level and found some evidence to suggest that education does have a positive impact on efficiency. However, that finding was specific to Aman for allocative efficiency and to Boro for technical efficiency. The results also indicate that the positive impact of education is smaller the higher the level of education. We pursued the matter further by considering that relationship in a regression context. In order to allow education to have a positive but declining impact on efficiency, we introduced the education variable non-linearly in the regressions. In terms of fit, all estimated regressions performed poorly, explaining less than 10 percent of the variations in efficiency. Education was found to have a statistically significant positive impact (which declines with the level of education) on allocative efficiency in Aman and on technical efficiency in Boro. The inability to obtain similar results in the other regressions could reflect the rather limited variation in the technical efficiency in Aman and Aus; or, it may be that other factors, such as growing experience and institutional constraints on individual farmers, are important determinants of a farmer's technical and allocative efficiency.

Several policy implications can be drawn from the findings of this study. Farmers appear to be as technically efficient in the new-technology Boro crop as in the traditional Aman and Aus crops. A policy of encouraging the adoption of such HYV crops is thus well-founded. However, attention clearly needs to be paid to improving farmer skills within the existing crops. For instance, rural development policies could be geared to improving allocative skills. Our estimates show that farmers could benefit significantly by raising allocative efficiency. Those policies would probably have to take account of possibly important differences in efficient cultivation practices across crops. Policies aimed at improving the efficiency of highly scarce inputs such as land could go a long way towards improving the overall efficiency of farmers. In fact, since the relative price of land can be expected to increase over time, the cost reductions by improving the efficiency of land use could be substantial. Finally, it may be that institutional constraints on individual behaviour foster inefficiency. For example, the lack of access to timely credit and government-supplied chemical fertilizer for smaller farmers may lead them to choose inefficient input-mixes. Ensuring greater access to those farmers could be important in promoting greater efficiency.

We conclude by touching upon some of the major limitations of the study. First, the quality of the data is unknown. Farmers may not accurately recall the precise amounts of particular crops grown and the quantities of inputs used. Even if they did, there is no guarantee that they would have reported those magnitudes accurately. We hope that, by adjusting for statistical noise, we have been able to minimize the adverse consequence of measurement error. In adopting the parametric approach, we are committed to choosing a particular functional form. Clearly, our choice of the Cobb-Douglas function is a restrictive one. Other possible specification errors arise from our assumptions about the technical efficiency and statistical noise disturbance terms. Thus, for instance, if technical inefficiency is known to the farm household, it is likely that input quantities and the disturbance terms would be correlated. Distributional assumptions are needed to estimate efficiency at the farm level and/or to estimate the parameters of the production function. We saw that the efficiency estimates can be sensitive to distributional assumptions. While our findings appear to be quite reasonable, it needs to be remembered that technical efficiency is essentially measured as a residual, and can be expected, in general, to be sensitive to the choice of functional form, the inputs included and distributional assumptions.

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