economics Division Working Papers

Development Issues

Frontier Economics:

Efficiency of firm performances with technological change

R.T. Shand and K. Kalirajan

93/1

Research School of Pacific Studies ANU

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K.P. Kalirajan is a Senior Research Fellow in the same department. He has the same major interest with a special emphasis on econometric and statistical analysis.

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Preface

This work is made up of parts of an ongoing project study of the dynamics of firm performance under conditions of disequilibrium caused by technological change. Each part is variously intended to contribute to the theory of the dynamics of the adjustment process, to the development of methodology for measuring firm performance, to applications of the theory and methodology and to policy formulation for performance improvement in the process of adjustment to disequilibria.

Neo-classical microeconomics theory underpins the work and the methodology centres primarily on the development and application of the stochastic frontier production function approach. This approach enables measurement of firm performance in terms of economic efficiency and its components: technical and allocative efficiencies. The methodology in these papers is applied to the agricultural sector. Each paper presents estimates of efficiencies of farm samples from countries under various environmental conditions, and over time, and in one case where data permit, an attempt is made to explain observed variations in efficiencies in terms of management and other socio-economic variables.

The first paper utilizes previously estimated technical and allocative efficiencies for samples of farmers drawn from three different environments in Sri Lanka over a number of seasons. Using cross-sectional analysis, it applies canonical discriminant function analysis to identify those factors which enable distinction between more and less technically and allocatively efficient farmers, and draws policy conclusions.

The initial paper estimates efficiencies without consideration of the influence of risk on decision-making. The second paper extends the methodology of frontier economics by dropping this assumption, offers a method of modelling firm-specific behaviour under risk to measure economic efficiency and compares estimates of economic efficiency with and without risk. A considerable gap is identified between actual economic efficiencies with and without risk. Analysis is based on a random sample of farmers growing a modern cotton variety from Madurai district in Tamil Nadu State of India.

The first two papers are cross-sectional studies which ignore the time factor in analysing efficiency. The third paper examines the process of adjustment in firm performance over time, building on the model of firm-specific behaviour under risk offered in the second paper. It tests a number of hypotheses using data drawn from a sample of rice producers from irrigated and non-irrigated farmers in North Arcot, India. Results reveal the problems of achieving the full potential of a new technology over time, the need for public intervention to assist farmers in reaching their potential and directions for further research to guide policy.

The fourth and fifth papers address basic conceptual questions of technical efficiency, of concern to selecting the methodologies which yield the most information about technical efficiency. The questions are: where does technical efficiency come from, and how is it achieved? The literature indicates that technical efficiency is determined by the method of application of inputs and full technical efficiency is obtained by a firm which follows best practice techniques, given the technology. Different methods of applying inputs will thus influence output differently.

In the stochastic framework of measuring technical efficiency, the frontier production function is typically assumed to be a neutral shift from the actual or realized production function of a farm. On this assumption, a methodology can be used which assumes fixed input coefficients. Applications of this methodology give an overall measure of technical efficiency and input-specific measures. The latter are, however, of little use owing to the restrictive assumption of fixed coefficients.

The fourth paper suggests a method to measure firm-specific technical efficiency for individual farms when the frontier shifts non-neutrally from the observed production function. This enables measurement of overall technical efficiency for each farm without the restrictive assumption of fixed coefficients. Analysis of the behaviour of a further sample of rice farmers from Madurai district in Tamil Nadu State of India, reveals substantial variation in actual responses to individual inputs and therefore in firm level technical efficiencies.

The fifth paper builds on the fourth. In the light of the findings that input response coefficients varied, the question arises as to whether these variations in actual responses are reflected in differing efficiencies in applying individual inputs. Using a variation from the previous paper in estimation of a varying coefficient frontier production function model, this paper provides measures of firm-specific and input-specific technical efficiencies using data for a random sample of farms from Madurai district, Tamil Nadu State of India. Further, it sheds light on how the technical frontier is formed and how each farm relates to it in terms of each of its input response coefficients.

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1

efficiencies and their determinants

Literature on the green revolution has strongly emphasized the fact that the foodgrain production breakthrough in Asia from the mid-1960s was made possible by the widespread adoption of seed/fertilizer technology.

During the 1970s, major developments took place in agricultural policy formation and agricultural research at national and international levels. At the national level, policy makers recognized that the primary objective of foodgrain policy was to achieve a high rate of adoption of the new technology by farmers and concentrated on implementing strategies to facilitate it (Shand 1973). As the new technology required assured supplies of inputs such as irrigation, fertilizers and pesticides, governments initiated large scale investment programmes in the 1970s to maintain the momentum of output growth from the new technology. This was aided by many external factors which included, for example, cheap loans from Euro-dollar savings: the outcome of the 1973 oil price hike.

There were two main directions in research. First, scientists in national and international centres concentrated on evolving new high yielding seed varieties to enhance the yield potential of the new technology. This was made possible by generous funding by many national and international development agencies. Second, social scientists were engaged in identifying factors that constrained acceptance of the new technology in order to develop effective policies for achieving high rates of adoption (PEO/ANU 1976; IRRI 1979).

Another group of social scientists examined the problems engendered by the new technology, such as widening income disparities among farmers and labour absorption (Griffin 1974; Lipton 1989; Pearse 1980). A small group of economists were concerned with the question of the effective use of the new technology by farmers (Herdt and Mandac 1981; Kalirajan and Shand 1985; Shapiro and Muller 1977). This last question received scant attention from policy makers.

In the late 1970s and early 1980s, there were healthy signs that the problem of national food shortages in Asian countries had been averted and that income disparities stemming from the new technology did not pose the threat that had been expected. In the early 1980s, however, it became apparent that the growth momentum of the green revolution was slowing down. Studies have suggested that, in the absence of further yield ceiling breakthroughs, and with the reduction in new irrigation investment and the poor operations and maintenance in existing irrigation systems, productivity could decline (Barker and Chapman 1988; Byerlee 1987; Herdt 1988). These studies concluded that the growth rate of rice output had not only peaked but was starting to decline. Pingali et al. (1990) revealed a stagnant rice yield potential. Such results call for an urgent reassessment of the prospects for the contribution of the green revolution technology. In particular, there is a need for clarification of the relationship between adoption and performance of the technology at farm level.

The question is whether it will be possible to sustain the growth momentum of the new technology during the 1990s. Specifically, in the expected absence of further large scale investments in new irrigation and similar absence of further substantial yield augmenting breakthroughs from research, is there still scope for greater exploitation of the yield potential of the technology at field level by improving farm performance?

The present status of the new technology in the light of various recent studies is reviewed. Evidence of farm level variations in efficiencies and of the determinants of those variations from a study in Sri Lanka are presented to highlight the contribution of the efficient application of the technology to output growth and some conclusions and recommendations for appropriate policies to sustain the growth momentum of the green revolution technology are offered.

Application of the New Technology: the neglected component

The general acceptance of Schultz's view (1964) that economic growth from the agricultural sector of a poor country depends predominantly upon the availability and price of modern (non-traditional) factors had the important effect of reorienting policy priorities for agricultural development towards the production of new technology.

Schultz (1985) recognized that such new technology would create disequilibria that would complicate farmer decisions as to resource allocation. Ruttan (1977) argued that efficiency differentials in the use of the green revolution technology among farmers would disappear over time, once the technology had been adopted by sufficient farmers.

Farmer (1977) and Frankel (1971) argued that there was a gap between actual and potential production in developing countries and various works on technical efficiency in the 1970s, following that by Farrell (1957) and Timmer (1970), focused on differences in productivity among farmers. Herdt and Mandac (1981) drew attention to and analyzed the gap between experiment station and farmer yields with the new rice technology in irrigated areas of the Philippines. Their analysis attributed the gap partly to external factors beyond farmers' control (soils, solar radiation, moisture stress, etc.), partly to profit-seeking behaviour and the rest to technical and allocative inefficiencies. From these results they concluded that management shortage was the principal cause of inefficiency. They were not, however, as concerned with the gap in performance between farmers as they were with that between farmers and the experiment station.

The above studies highlight the importance of the third factor in the high payoff input model of the process of agricultural development, namely, investment in the capacity of farmers to use modern agricultural factors effectively (Hayami and Ruttan 1985). We argue here that the present agricultural situation in many developing countries indicates an urgent need to close the gap between farmers' own potential and realized outputs in order to sustain the growth momentum of green revolution technology.

Recognition of the importance of the new technology's performance at farm level, and of the need for a better understanding of the determinants of performance over a spectrum of production environments, led to a large collaborative study which was launched in 1983. The study was conducted in the Philippines and Sri Lanka over a range of physical and socio-economic environments (particularly the less favourable) and a number of crop seasons (Menz 1989). A broad objective of the project was to measure the gap between potential and actual performances of farmers using the new technology for rice and to identify the key determinants of variations in performances at farm level.

Use was made of advances in the techniques of measuring performance in terms of efficiencies and their determinants during the 1970s and 1980s which can now give greater precision to efficiency measurement. Notable among these methodological developments has been the emergence of the stochastic frontier production function approach (Aigner et al. 1977; Meeusen and van den Broeck 1977). Also the technique for estimation of firm specific efficiencies for single and multiple outputs (Kalirajan 1984; Kalirajan and Shand 1988).

Measures of field specific technical and allocative efficiencies from samples of Sri Lankan farms from the above mentioned project are utilized here to identify factors which can differentiate between farmers with relatively high and low efficiencies. This helps to define appropriate directions for policy to improve farmer efficiency and narrow the performance gap between farmers as a means of sustaining the momentum of the green revolution.

Methodology

Choice of methodology was guided by the objective of exploring the efficiency of the use of new rice technology at farm level. This directly measures farmer performance. Farmer performance is, thus, equated here with economic efficiency, which comprises technical and allocative efficiency. The frontier production function approach has been used to measure these components of efficiency. This approach dispenses with the traditional average productivity measures and their inherent weaknesses.

Technical efficiency

(TE) is defined here as the ability and willingness of producers to obtain the maximum output at a given level of conventional inputs and technology.

Allocative efficiency

(AE) is defined as the ability to obtain the maximum profit from the application of conventional inputs with a given set of firm-specific input and output prices and a given technology.

Economic efficiency

(EE) is the product of technical and allocative efficiencies. A farmer who is both technically and allocatively efficient is also economically efficient.

With the estimation of production frontiers, field-specific technical efficiencies can be estimated for each sample observation. This is possible because of the ability of the frontier production function methodology to decompose the total variance around the frontiers into two distinct and independent components. The first denotes the fact that frontiers can vary among farms and fields within farms, and also over time for the same farm. This characteristic is assumed to be randomly distributed among farms and fields. The second component of total variance represents the extent to which a farm field is below its frontier and is associated with its level of technical efficiency.

The allocative efficiency of a farm field is measured as the ratio of the realized profit to maximum feasible profit and can be estimated in two ways. These profits can be based either on the best practice frontier production function, or on the field's own (possibly technically inefficient) current practice production function. The pure allocative efficiency of a farm is better identified by using the latter concept. It is computed by obtaining the ratio of the potential maximum profit (using the relevant first order conditions for profit maximization, given the field-specific production function) and the profit at the output predicted by the field-specific production function, given its input levels.

Using the estimates of the above efficiencies, the methodology focuses on explanations of these performances (Shand et al. 1990). For this, canonical discriminant function analysis is employed (Tatsuoka 1970). The canonical discriminant function technique can separate groups in terms of relatively high and low efficiencies, i.e. above and below any chosen threshold level, and can identify factors that characterize or profile these groups. This technique has particular appeal as, for example, there is strong interest in profiling factors that describe high efficiency performers for the potential policy insights they could offer.

In applying this technique, the first decision is to choose the threshold level or cut off point of efficiency to distinguish between relatively high and low efficiency groups. This will vary according to the distributions of particular sets of efficiencies in relation to the frontiers. The objective then in applying the discriminant function is to obtain convergence with the inclusion of factors that give a high canonical coefficient and the highest proportion of cases correctly classified above and below the selected threshold level of efficiency. The inclusion of unrelated variables will prevent convergence of the function. Omission of relevant variables may still give convergence, but, with relatively low canonical coefficients and limited proportions of grouped cases above and below the threshold being correctly classified, the information on what distinguishes the high and low efficiency groups from each other will be restricted. A complete profile of a group's cases will be indicated by 100 per cent correct classification of that group.

Data

Data for the study were drawn from random samples of farmers in Kurunegala district in the Intermediate Zone of Sri Lanka. The samples were selected from the farmers' register at the Agrarian Service Centre. The same farmers were interviewed throughout five successive seasons covering Maha and Yala seasons from 1983/84 to 1985/86. The Maha (major) season extends from October to February. The lesser Yala season extends from April to June or longer. Samples were drawn from three major environments: major irrigation, minor tanks and rainfed conditions. The same farmers were included for interview throughout, but because fewer grew paddy in Yala than in Maha seasons and other problems, numbers interviewed varied from 150 to 126 under major irrigation, 42 to 34 under minor tanks and 207 to 114 in the rainfed sample.

In 1985/86, it was decided to restrict the survey to the rainfed sample and, in addition, to carry out a close monitoring survey on a sample of 50 farmers from within the rainfed sample who were visited six times rather than the usual two during that Maha season.

Comprehensive data were collected on the usual direct inputs of land, labour and purchased inputs, on prices and on all sources of income including non-farm income. Additionally, because of the central importance of management, detailed data were collected under three headings: technical practices in paddy production, human capital variables and farm/farmer attributes.

Technical practices included paddy variety and duration, establishment method, timing of establishment and harvest, number, types and quantities of fertilizer dosages, use of P and K fertilizers, use of pesticides and herbicides, and use of manual weeding. Under the second and third headings, variables included details of household head and family members' age, farming experience, schooling, occupations, family size, tenure, other farm activities and non-farm employment and income, any conflicts for labour between occupations or between competing crops, availability and use of institutional credit, etc.

Preliminary analysis of variables in the three areas above proved significant for later analysis (De Silva et al. 1990). Despite the fact that the new seed fertilizer technology had been introduced in the 1960s there was no stability in technical practices over the five seasons, nor under any of the three environments. Some changes may have been trends over time but the survey time span was too short to judge this. What is particularly important for this analysis was the variation in technical practices between farmers within each season, as it is hypothesized that this variation influences technical efficiency.

There was virtually no use of traditional or old improved varieties in any of the three environments and all survey farmers used chemical fertilizers. Judging by these indicators it could be said that there was at least partial adoption of the new technology by all survey farmers. Survey data in each environment, however, showed variation within and between seasons in establishment methods, in timing of establishment and in choice of varieties (from growth periods of 3 to 4 1/2 months' duration). Over time this led to marked differences in timing the harvest of new improved varieties. There were variations in fertilizer practices, in numbers of fertilizer dosages, in types used, in particular dosages, and in dosage levels. There were differences in the use of pesticides and herbicides, in application of manual weeding and in the use of institutional credit.

The critical questions are: which were the best sets of practices for each environment and season for full technical efficiency, and to what extent did the variations in choice of practices affect technical efficiency?

There was much similarity in human capital variables and farm/farmer attributes between environments and little change over time in each environment. The ranges in values, however, were substantial within each environment/season sample for many of these variables, for example in age, years of formal schooling and farming experience, in non-farm incomes of household heads and family members, and family size. There were also differences in other important variables such as tenure and occupations (own farm, other farm and non-farm and combinations). The question here is whether these variations affected technical and allocative efficiencies of rice production.

The analysis

Efficiency estimates

The data for the analysis are the estimates of technical and allocative efficiencies by environment, season and year. Since we hypothesize allocative efficiency is dependent upon technical efficiency (Kalirajan and Shand 1992), we commence with technical efficiency.

Technical efficiencies Under major irrigation, mean technical efficiencies were mostly high over the four seasons surveyed ranging from 63 to 98 per cent (Table 1.1). Maha season 1983/84 was exceptional when, with minimal variance, all efficiencies were in the 91 to 100 per cent range, i.e. clustered near each farmer's frontier. Maha 1984/85 also showed generally high levels. The two Yala seasons showed greater ranges, particularly in 1984.

Table 1.1 Frequency distributions of field specific technical and allocative efficiencies for survey farmers under major irrigation by season in Kurunegala district, 1983/84 to 1985

Level of ficiency (per cent)	Maha 1983/84 TE	Maha 1983/84 AE	Yala 1984 TE	Yala 1984 AE	Maha 1984/85 TE	Maha 1984/85 AE	Yala 1985 TE	Yala 1985 AE
<0	-	-	-	8	-	-	-	-
0–10	-	-	-	1	-	3	-	-
11–20	-	-	-	-	-	-	-	-
21–30	-	1	3	1	-	-	-	-
31–40	-	-	13	1	-	-	-	-
41–50	-	-	18	3	-	-	1	1
51–60	-	-	15	7	1	3	5	6
61–70	-	-	11	10	5	5	12	29
71–80	-	3	15	20	13	24	29	55
81–90	-	14	20	28	32	52	33	6
91–100	100	82	5	21	50	16	21	2
Sample mean	98	94	63	64	88	82	80	62

Notes: TE = technical efficiency
AE = allocative efficiency

Table 1.2 Frequency of distribution of plot specific technical and allocative efficiencies for survey farmers under minor tanks by season in Kurunegala district, 1983/84 to 1984/85

Level of efficiency (per cent)	Maha 1983/84 TE	Maha 1983/84 AE	Yala 1984 TE	Yala 1984 AE	Maha 1984/85 TE	Maha 1984/85 AE
0	-	17	-	12	-	-
0-10	-	2	3	-	-	-
11-20	7	5	6	3	-	-
21-30	17	-	-	6	-	-
31-40	10	7	12	-	-	-
41-50	14	19	12	-	-	-
51-60	21	26	3	9	1	-
61-70	14	22	23	13	-	9
71-80	10	2	6	12	-	20
81-90	2	-	12	9	-	65
91-100	5	-	23	36	100	6
Sample mean	50	33	64	50	99	82

Notes: Sample observations in Yala 1985 were too few to warrant analysis.
TE = technical efficiency
AE = allocative efficiency

Under minor tanks, with the exception of Maha 1984/85 when technical efficiencies were uniformly near farmers' frontiers, the ranges were much more pronounced than under major irrigation and means were lower at 50 and 64 per cent (Table 1.2). The record suggests that, in a favourable season, most farmers can attain high technical efficiency, but with water availability for irrigation under minor tanks typically less reliable than under major irrigation, more variation in efficiency can be expected.

Technical efficiency under rainfed conditions varied markedly and in each season, again according to expectations (Table 1.3). Seasonal means ranged from 54 to 70 per cent, and the majority of observations lay between 40 to 80 per cent.

Table 1.3 Frequency distribution of plot specific technical and allocative efficiencies for survey farmers under rainfed conditions by season in Kurunegala district, 1983/84 to 1985/86

Level of efficiency (per cent)	Maha 1983/84		Yala 1984		Maha 1984/85		Yala 1985		Maha 1985/86	
	TE	AE	TE	AE	TE	AE	TE	AE	TE	AE
<0	-	9	-	6	-	1		4	-	1
0-10	-	1	-	-	-	-	-	-	-	1
11-20	6	-	-	2	-	-	4	-	-	-
21-30	11	2	4	6	-	-	-	4	3	1
31-40	17	1	11	6	-	1	8	4	6	1
41-50	13	2	17	7	9	1	8	12	14	5
51-60	17	4	21	7	15	-	24	20	18	11
61-70	12	5	14	16	25	1	16	28	21	39
71-80	13	9	13	20	21	3	24	16	23	33
81-90	7	23	8	15	18	14	12	12	9	8
91-100	4	44	13	15	9	78	4	-	6	-
Sample mean	54	67	63	54	70	93	62	59	65	65

Note: TE = technical efficiency
AE = allocative efficiency

Allocative efficiencies Allocative efficiencies under major irrigation showed remarkably similar patterns to those of technical efficiencies though sample means were slightly lower in each season (Table 1.1). They were generally high in the two Maha seasons and lower in the two Yala seasons. Yala 1984 recorded the poorest performance allocatively, with a number of plots recording losses, but even in this season there was a substantial proportion with high efficiencies (69 per cent were above 70 per cent). The same was true for allocative efficiencies under minor tanks (Table 1.2). These followed the seasonal pattern of technical efficiencies but with lower sample means. These varied greatly, from 33 to 82 per cent. The rainfed sample showed the same wide seasonal range in allocative performance as for technical efficiencies (Table 1.3). Sample means varied seasonally and distributions followed the patterns of technical efficiency fairly closely. Interestingly, they were very high in Maha 1984/85 with a mean of 93 per cent, higher than the mean for technical efficiency.

There was some consistency seasonally in both technical and allocative efficiency distributions across the three environments. For example, there were high technical and allocative efficiencies recorded for Maha 1984/85 and poor performances in both for Yala 1984. It appears likely that in these two seasons, adverse production conditions affected farmers in all three types of environment in a similar fashion. In Maha 1983/84 this consistency was not apparent.

The influence of seasonal production conditions appears to be reflected in the record of mean rice yields over the period of the survey (Table 1.4). This shows highest average yields for all three environments in Maha 1984/85 and lowest in all three for Yala 1984. The evidence also suggests that this influence can be manifest across the full spectrum of environments irrespective of degrees of water control.

Table 1.4 Mean rice yields for survey farmers by season and water regime in Kurunegala district from 1983/84 to 1985/86 (tonnes/hectare)

Season	Year	Major irrigation	Minor tanks	Rainfed
Maha	1983/84	3.42	2.58	2.29
Yala	1984	2.92	2 49	2.06
Maha	1984/85	3.63	3.30	3.27
Yala	1985	2.97	..[a]	1.90
Maha	1985/86	..[b]	..[b]	3.17

[a]Too few sample observations
[b]Survey not undertaken.

Determinants of efficiencies

Technical efficiencies The canonical discriminant function technique was applied to data from the three environments to identify the factors that distinguish relatively high from relatively low efficiency groups.

Under major irrigation, the analysis was not undertaken in Maha season 1983/84 because of the uniformly high levels of technical efficiency. This simply means that the variation in technical practices (field to field and farm to farm as described earlier) had a negligible impact on efficiency. Maha 1983/84 was unusually favourable, with late rains and a long wet season. The high average yield in that season strongly suggests that favourable climatic conditions minimized the impact of the variations in practices, with adequate and timely irrigation water and adequate soil moisture under rainfed conditions.

In the three other seasons covered in the analysis, the explanatory power of the discriminant functions was quite variable (Table 1.5). The percentages of grouped cases with high technical efficiency correctly classified varied from 60 to 76 per cent. The percentages with efficiencies below the thresholds were little different at 64 to 73 per cent. There were a large number of included variables in each season divided by signs between those profiling high and low efficiencies. They varied in importance, reflected by the size of their coefficients, and were seldom consistent between seasons.

First, there were the direct management variables of technical practices. The most important were practices concerned with timeliness of the crop in relation to the production environment. They included month of planting, critical harvest date, choice of variety (mainly on the basis of duration) and timeliness of establishment. A second group comprised fertilizer practices, for example, use of P and K fertilizers, types of fertilizers used in second and third dosages and use of pesticides and herbicides. A third group comprised methods of crop establishment.

Human capital variables and farm/farmer attributes were also included, but were mostly inconsistent between seasons. Characteristics of the household heads and their activities were most prominent.

Table 1.5 Standardized canonical discriminant function analysis of technical efficiencies of survey farmers under major irrigation by seasons, Kurunegala district, 1984-5

Variable	Season/Year	Yala 1984	Maha 1984/85	Yala 1985
	Technical efficiency threshold (per cent)	80	80	70
Coefficients				
Planting month		0.79	-	-
Critical harvest date		-0.57	-	-
Use of Bg 34-8		0.38	-	-
Use of Bg 34-8,276-5 or 11-11		-	0.47	-
Use of varieties more than 3 1/2 months duration		-	-	0.15
Varieties of 4 months or more duration		-	0.21	-
Timeliness of establishment		0.36	-	-
Harvesting date		-	0.19	-
Use of K fertilizer		-0.18	-	-
Use of P fertilizer		-	0.39	-
Urea in 3rd dose		-	-	0.82
NPK in 2nd dose		-	-	-0.13
Fertilizer score		-0.05	-0.22	-
Transplanting		-	0.30	-0.13
Use of pesticides		-0.11	-0.66	-
Use of herbicides		-	0.17	-
Schooling of household head		0.34	0.02	-0.31
Farming experience of household head		-	-0.37	-0.38
Family size		0.19	-0.13	-
Age of household head		-0.08	-0.29	-0.01
Full/part owner		0.21	0.10	0.18
Farming sole occupation of household head		0.18	-0.05	-
Household head full time farmer		0.12	0.44	-0.07
Non farm income of household head		-0.27	-	0.26
Labour conflict of paddy and other crops		-	-0.17	-
Non farm income of family members		-	-	-0.08
Canonical coefficients		0.40	0.32	0.47
Significance of after function		0.04	0.10	0.002
Percentage of grouped cases with technical efficiency above threshold level correctly classified		75.7	0.2	70.1
Percentage of grouped cases with TE below threshold level correctly classified		72.6	64.3	72.9

Note: Positive coefficients are associated with the technical efficiency group above the threshold level. Negative coefficients are associated with the technical efficiency group below the threshold.

Table 1.6 Standardized canonical discriminant functions for analysis of technical efficiency of survey farmers under minor tanks by seasons, Kurunegala District, 1983/84 to 1985

Season/Year	Maha 1983/84	Yala 1984	Maha 1984/85	Yala 1985
Variable: Technical efficiency threshold (per cent)	60	80	a	b
Coefficients[c]				
Harvesting date	-	0.60		
Broadcasting dry seeded	0.26	0.20		
Transplanting	0.08	-		
Seed quantity	0.23			
Varieties 3 1/2 months or more	0.05	-		
Varieties 4 months or more	-	0.15		
Manual weeding	-0.65	-		
Use of herbicides	-0.78	-		
Use of pesticides	-0.78			
Use of P fertilizer	-	-0.32		
Fertilizer score	0.07	0.27		
Age of household head	-0.56	1.09		
Farming experience of household head	0.48	-0.29		
Years of schooling of household head	0.37	-		
Full time farming of household head	0.53	0.46		
Farming as sole occupation of household head	-0.93	-		
Family size	0.61	-		
Labour conflict in crop work	1.07	-		
Labour conflict in farm and non farm work	0.63	-		
Canonical coefficient	0.67	0.67		
Significance of after function	0.26	0.06		
Percentage of grouped cases with technical efficiency above threshold correctly classified	84.6	91.7		
Percentage of grouped cases with technical efficiency below threshold correctly classified	82.8	72.7		

[a] All technical efficiencies were over 90 per cent.
[b] Sample was too small for analysis.
[c] Coefficients with positive signs are associated with high efficiency above threshold levels. Those with negative signs are associated with relatively low efficiency below threshold level.

From this functional analysis it is possible to assemble a seasonal profile of technically efficient farmers by season. For example in Yala 1984, when such a profile had a 76 per cent chance of being correct, they would have planted by broadcasting relatively late using a 3 month duration variety, but not so late as to harvest beyond a certain date after which yields fell. They would not have used pesticides. They would be relatively young, would have received the benefit of a considerable number of years of formal schooling and would have relatively large families. They would be part or full owners, full time farmers with farming as the sole occupation and would not earn off-farm income.

The other two seasons show variations both in best practices and farm/farmer attributes. In these seasons there were relatively few technical practices which recorded large coefficients. The absence of more technical factors and/or their low coefficients may be explained partly by the fact that there was uniformity in many of these practices. Where there were variations, they did not influence efficiency in any substantial way, perhaps because of generally favourable production conditions.

Coefficients of human capital variables and farm/farmer attributes were not high and many had variable and occasionally puzzling signs, for example, negative signs for greater farming experience and variable signs for years of schooling for household heads. Full or part ownership was consistently associated with high efficiency.

The discriminant function analysis for technical efficiency under minor tanks showed high proportions with correct classification especially for the high efficiency groups, 85 and 92 per cent in the two seasons examined (Table 1.6).

During Maha 1983/84, a number of technical variables had sizeable positive values but human capital variables and farm/farmer attributes were more important in that season. While greater age of household heads was associated with lower efficiency in that year, greater farming experience had a positive sign, as did years of schooling, full time farming and family size. Interestingly, conflicts in labour use between paddy and other crops and between paddy and non-farm work had relatively high positive coefficients. As mentioned earlier, this was a climatically unusual season which may have called for more and different talents and attributes and work distribution than in Yala 1984.

Table 1.7 Standardized canonical discriminant function analysis of technical efficiency of survey farmers under rainfed conditions in Kurunegala district, 983/84 to 1985/86

Season/Year	Maha 1983/84	Yala 1984	Maha 1984/85	Yala 1985	Maha 1985/86	Maha[a] 1985/86
Variable: Technical efficiency threshold (per cent)	70	90	70	70	70	70
Coefficients[b]						
Critical harvest time	-0.21	-	0.29	-	-	0.04
Date of harvesting	-	1.21	-	-	0.28	-
Month of planting	-0.31	-0.75	-	-	-	-
Transplanting	-	-	-0.47	-0.43	-	-
Broadcasting dry seeded	-0.10	-	-	-	-0.38	-
Duration of varieties	0.21	-	-	-	0.39	-
Timeliness of establishment	-	0.14	-	-	-	-
Row transplanting	0.55	-	-	-	-	-
Use of Bg 276-5	-0.33	0.14	0.08	-	0.20	-
Varieties of 4 months or more duration	-	-	0.16	-	-	-
Use of Bg 11-11	-	-	-0.33	-	0.30	-
Use of Bg 34-8	-	-	0.55	-	0.29	-
Use of varieties more than 3.5 months	-	-	-	0.58	-	-
Source of seed	-	-	-	-	-	0.59
Previous season's weed growth	-	-	-	-	-	0.52
Use of pesticides	-0.07	0.42	0.04	-	-	-0.07
Use of herbicides	0.38	-	0.17	-	-	-
Use of P fertilizer	-	-	-0.43	-	-0.31	-
Fertilizer score	0.21	-0.02	0.11	-	-0.43	-
Use of urea in 3rd application	-	-	-	-0.27	-	-
Use of NPK in 2nd application	-	-	-	0.09	-	-
Pest damage in periods 2 and 4	-	-	-	-	-	0.89
Age of household head	-	0.87	-0.79	-0.69	-	-0.04
Farming experience of household head	-0.31	-0.67	0.85	0.56	-	0.88
Full time farming of household head	-0.41	0.07	0.35	-0.48	-	-0.11
Farming as sole occupation of household head			-0.23		0.35	
Full/part owner	-	-0.04	0.08	0.28	-	0.21
Years of schooling of household head	0.13	-0.08	-	-	-	0.49
Non farm income of household head	-	-	-	0.05	0.54	0.26
5 or more years of schooling of household head	-	-	-	-	-0.71	-

Table 1.7 (continued)

Season/Year	Maha 1983/84	Yala 1984	Maha 1984/85	Yala 1985	Maha 1985/86	Maha[a] 1985/86
Variable Technical efficiency threshold (per cent)	70	90	70	70	70	70
Family size	-0.40	-	-	0.57	-	0.55
Non farm income of family members	-	-	-	-	0.36	0.08
Labour conflict with own farm and non farm work	0.07	-	-	-	-	-
Canonical coefficient	0.48	0.46	0.32	0.53	0.38	0.54
Significance of after function	0.002	0.007	0.32	0.66	0.002	0.42
Percentage of grouped cases with technical efficiency above threshold level correctly classified	61.1	66.7	71.0	60.0	65.1	76.7
Percentage of grouped cases with technical efficiency below threshold level correctly classified	77.5	77.8	61.0	75.0	69.4	72.2

[a]Close monitoring survey.
[b]Coefficients with positive signs are associated with high efficiency above threshold levels. Those with negative signs are associated with relatively low efficiency below threshold level.

For Yala 1984, the important technical practices for high efficiency were late harvesting, dry seeded broadcasting, use of long duration varieties and pesticides, and adherence to recommendations for fertilizer use (types and number of dosages) although use of P fertilizer was associated with lower efficiency. Among attributes, greater age of household heads was strongly and positively associated with high efficiency and so too was full time farming by household heads.

Discriminant function analysis was rather less successful in achieving high proportions of correctly classified cases of high technical efficiency under rainfed conditions (Table 1.7). Since the range of technical efficiencies was wide in each of the five seasons and, except for Yala 1984 and Maha 1984/85, the proportions of cases at highest levels were low, it was often necessary to pitch the threshold levels for the canonical discriminant function analysis lower than those under major irrigation and minor tanks.

The proportions of grouped cases classified correctly above the threshold levels varied from 60 to 71 per cent in the main surveys. In the close monitoring survey of 50 farmers in Maha 1985/86, a higher proportion of 77 per cent was attained, some 12 per cent above that achieved for the larger survey in that season. This may itself indicate that the success rate with this type of analysis could be related to the intensity and accuracy of data collected on management-related variables. Two variables with large coefficients associated with high technical efficiency were specific to that survey (extent of weed growth in the previous season and of pest damage in various growth periods). There were also differences in human capital variables and farm/farmer attributes between the close monitoring survey and the larger survey. Variables associated with high efficiency in the close monitoring survey, but not in the larger survey, were farming experience and schooling of household heads, family size and ownership of land.

Again, there was no consistent pattern across the seasons for the rainfed environment either in the technical variables included, nor if included, in which group. The number included in one or more seasons was large: 22 as against 16 for major irrigation and 11 for minor tanks. The large number of variables may be indicative of the greater sensitivity of rainfed farming to technical management decisions, but it may also be a reflection of the current lack of a package of best technical practices for rainfed conditions, and the difficulty in predicting a best set of practices from season to season under these conditions.

The foregoing analysis shows that under all three environments, there is a critical interplay as a season progresses between the physical (water/soil) environment and the technical decisions taken by farmers in the face of a range of possible outcomes. The range of decisions was widest under rainfed conditions. Yet even with so-called assured water under major irrigation, there was still uncertainty which required managerial judgement, for there appeared to be no fixed best set of technical practices despite the evolution and dissemination of knowledge of official recommendations. Managerial skill determines a farmer's proximity to the full technical frontier. These surveys show that in most of the sensitive areas of technical judgement farmers' decisions do vary considerably.

There was no single set of human capital variables and farm/farmer attributes that were consistently identified with relatively high or low technical efficiency. The results suggest that technical efficiency may be changing over time and farmers appear to apply the technology through a learning-by-doing method. The results also indicate that previous farming experience and/or greater formal education and sole preoccupation with farming can often help indirectly to inform judgement in the decision making process, but such may be the difficulties of forecasting outcomes that, on occasions, these characteristics may appear as being inversely related to high technical efficiency.

Allocative efficiencies Discriminant function analysis applied to plot-specific allocative efficiencies for the three environments and the various seasons again showed variable success levels (Tables 1.8; 1.9; 1.10). They were frequently very high, ranging up to 100 per cent. One half of survey samples exceeded 80 per cent success in correct classification of highly efficient farmers.

Table 1.8 Standardized canonical discriminant function analysis of allocative efficiency of survey farmers under major irrigation by season, Kurunegala district, 1983/84 to 1985

	Season/Year	Yala 1984	Maha 1984/85	Yala 1985
Variable	Allocative efficiency threshold (per cent)	90	90	67
Coefficients[a]				
Technical efficiency		6.31	0.38	4.06
(Technical efficiency)^2		-6.39	-	-3.97
Schooling of household head		0.44	0.28	-
Age of household head			0.33	-
Farming as sole work of household head		-0.26	-0.47	0.62
Full time farming of household head		0.17	0.35	0.51
Non farm income of household head		0.20	-	0.01
Farming experience of household head		-0.03	-0.10	-0.21
Non farm income of family members		-	0.58	-0.36
Use of credit		-	0.36	
Size of family		-	-0.28	
Head location of plot		-0.08	-0.21	
Conflict between farm and non farm work		-	-	-0.21
Canonical coefficient		0.30	0.31	0.27
Significance of after function		0.16	0.12	0.44
Percentage of grouped cases with allocative efficiency above threshold correctly classified		77.4	59.1	64.0
Percentage of grouped cases with allocative efficiency below that threshold correctly classified		60.5	73.8	61.9

Notes: Sample observations in Yala 1985 were too few to warrant analysis.
[a] Positive coefficients are associated with the allocative efficiency group above the threshold level. Negative coefficients are associated with the allocative efficiency group below the threshold.

Table 1.9 **Standardized canonical discriminant function analysis of allocative efficiency of survey farmers under minor tanks by season, Kurunegaladistrict, 1983/84 to 1984/85**

Season/Year		Maha 1983/84	Yala 1984	Maha 1984/85
Variable	Allocative efficiency threshold (per cent)	60	90	80
Coefficients[a]				
Technical efficiency		-3.29	0.73	0.32
(Technical efficiency)^2		3.11	-	-
Schooling of household head		0.41	-	0.97
Age of household head		0.48	-0.34	
Farming as sole occupation of household head		-0.12	-0.30	0.01
Full time farming of household head		-0.63	-0.35	0.47
Non farm income of household head		-	-0.34	-
Farming experience of household head		-0.03	0.17	0.49
Non farm income of family members			0.13	0.01
Size of family		0.26	-	-0.03
Head location of plot		-		-0.44
Conflict between farm and non farm work		0.05	-	-
Conflict between paddy and highland work		-0.71		
Canonical coefficient		0.57	0.68	0.56
Significance of after function		0.18	0.02	0.22
Percentage of grouped cases with allocative efficiency above threshold correctly classified		80.0	91.7	75.0
Percentage of grouped cases with allocative efficiency above threshold correctly classified		78.6	86.4	80.0

Notes: Sample observations on Yala 1985 were too few to warrant analysis
[a] Positive coefficients are associated with the allocative efficiency group above the threshold level. Negative coefficients are associated with the allocative efficiency group below the threshold.

The major reason for success in profiling the high efficiency groups was the importance of technical efficiency. It was included in every function, and with only two exceptions, had by far the largest coefficients (linear and quadratic). This lends strong support to our hypothesis tested elsewhere with longitudinal data that the achievement of high levels of technical efficiency enables farmers to make accurate allocative decisions.

Other factors associated with high allocative efficiency revealed most of the range of human capital and farm, farming variables included in the analyses of

Table 1.10 Standardized canonical discriminant function analysis of allocative efficiency of survey farmers under rainfed conditions by season, Kurunegala district, 1983/84 to 1985/86

Season/Year	Maha 1983/84	Yala 1984	Maha 1984/85	Yala 1985	Maha 1985/86	Maha[a] 1985/86
Variable Technical efficiency threshold (per cent)	90	90	80	80	70	10
Coefficients[b]						
Technical efficiency	2.47	2.29	2.89	2.67	1.81	4.70
(Technical efficiency)^2	-1.57	-1.47	2.27	-2.74	-1.74	-3.85
Schooling of household head	0.42	0.003	-0.02	0.55	-0.72	0.22
Age of household head	0.42	-0.05	0.21	-	-	-0.21
Farming as sole occupation of household head	0.26	0.04	0.19	-	-0.21	-
Full time farming of household head	-0.03	-0.14	-0.15	-	-	-0.09
Non farm income of household head					0.48	-0.33
Farming experience of household head	0.08	-0.17	-	0.73	-0.25	-0.40
Non farm income of family members	-	0.37	0.11	-0.74	0.42	-0.09
Size of family	0.05		0.09	-0.44	0.07	-0.22
Conflict between farm and non-farm work	-0.07	-	-	056	0.26	-
Conflict between paddy and highland work	0.14	-	-	-	-	-
Ownership of land	-	-	-0.04	-		0.33
Canonical coefficient	0.62	0.29	0.64	0.57	0.36	0.73
Significance of after function	0.00	0.40	0.00	0.21	0.001	0.001
Percentage of grouped cases with AE above threshold correctly classified	85.2	52.6	95.3	100	65.7	96.8
Percentage of grouped cases with AE above threshold correctly classified	76.6	58.8	43.7	92.6	72.2	70.6

[a] Close monitoring survey.

[b] Coefficients with positive signs are associated with high allocative efficiency above threshold levels. Those with negative signs are associated with the allocative efficiency group below threshold level.

The major reason for success in profiling the high efficiency groups was the importance of technical efficiency. It was included in every function, and with only two exceptions, had by far the largest coefficients (linear and quadratic). This lends strong support to our hypothesis tested elsewhere with longitudinal data that the achievement of high levels of technical efficiency enables farmers to make accurate allocative decisions.

Other factors associated with high allocative efficiency revealed most of the range of human capital and farm/farming variables included in the analyses of technical efficiency. These factors are assumed to influence both technical and allocative efficiencies in the literature. Coefficients were not large and were frequently inconsistent seasonally and across environments. Multicollinearity between technical efficiency and these factors could be one reason. Few were included in all three environmental analyses. Exceptions were full time farming of household heads and farming experience of household heads, but their signs were inconsistent over seasons and across water regimes, making interpretation difficult.

Finally, it is interesting to note that in Maha 1985/86, the small close monitoring survey again yielded a far more accurate description of the high efficiency group than the larger survey in the same season. Aside from differences between variables included (other than technical efficiency), it appears that the main reason was the much greater size of coefficients of technical efficiency. This could mean that technical efficiency was more accurately measured in the intensive survey and in turn enabled the strength of its relationship with allocative efficiency to be revealed more accurately.

Conclusions

How efficient are farmers?

Given the positive dependency of allocative efficiency upon technical efficiency, overall farmer performance is largely determined by technical efficiency. Variations in technical efficiency were found to be partly explained by differences between farmers in a range of technical practices applied within each environment and season. Even after 20 years or more experience with the new rice technology our surveys revealed wide differences in technical practices between environments and for each environment, within each season and between seasons. These differences represented the managerial judgements of individual farmers as to the best set of practices for their particular production conditions in any one season and over time. Production conditions vary within each environment owing to microphysical and microclimatic factors.

A farmer's technical efficiency *ex post facto* is only as good as his forecast of production conditions translated into the set of technical practices he thinks is best suited to actual and expected conditions. While a few farmers were very near their individual frontiers, most were currently below them. There were only rare exceptions where most farmers were clustered near their frontiers. Sub-optimal performances in terms of efficiency were the norm for most farmers.

What determines technical and allocative efficiencies?

In attempting to profile, or characterize those farmers who were found to be technically and/or allocatively most efficient, it was hypothesized that three basic groups of variables might determine the levels of efficiency: choice of technical practices, human capital variables and farm/farmer attributes. In all environments and seasons all three contributed to the profiles. Generally, the influence of technical practices predominated, but the pattern of influence in terms of individual practices was not consistent. This meant that the profile of a technically efficient (or relatively inefficient) farmer varied across environments and by seasons in each environment.

There are two major reasons for this variation. First, farmers' applications of the technology are highly dependent on their learning-by-doing approach to farming. In turn, this could lead to variations in technical efficiency over seasons and environments. As technical efficiency changes over time, the factors influencing it also vary over time in any environment. For example, under major irrigation during Yala 1984, the contribution of fertilizer score to improving technical efficiency was almost negligible (Table 1.5). Low technical efficiency farmers may thus be expected to pay little attention to the technique of fertilizer application in the following season (Maha 1984/85). The contribution of the fertilizer score would then be expected to be large in this season due to its neglect. The results show that it was indeed large (Table 1.5).

Second, the fact that each profile constructed on the basis of these three categories of variables did not fully describe the technically efficient group of farmers is important. It signals that the various practices and farmer/farm related variables could be expanded and/or improved upon. For example, the close monitoring survey achieved a better profile than the larger, less precise survey in the same season.

Attempts to profile allocatively efficient farmers by environment and season revealed that, although the profiles varied, a number for the highly efficient groups were complete, or almost so. The dominance of technical efficiency across all environments and seasons gives clear support to our dependency hypothesis, though with the cautionary note that there may be occasional circumstances where the relationship differs. Human capital variables and farm/farmer attributes also contributed to profiles, but inconsistently. The profile of the allocatively efficient groups was almost unequivocally that of the technically efficient farmers.

What are the policy implications?

Available evidence suggests that the green revolution is either in the process of losing its momentum in promoting agricultural development, or is in imminent danger of doing so. The lack of prospects for further yield breakthroughs currently rules out any substantial outward shift in the production frontier. Also, since evidence is mounting that leading farmers are at least as productive as researchers in field trials, the performance gap between the two has virtually closed, except in certain less favoured environments in which only limited research has been undertaken. Broadly, this suggests that the information flow from the experiment stations cannot significantly enhance the current performance of leading farmers.

There remains, however, a substantial gap in efficiency between farmers. The fact that this gap is so substantial more than two decades after the introduction of the new technology is partly because it has been ignored until now and partly because the learning-by-doing and the technological trickle-down effects have only worked for a minority of the most progressive farmers.

A necessary and logical direction for policy is to identify and implement measures which will reduce this gap and improve the overall performance of farmers. This direction calls for fine tuning of the new technology in its various environmental settings to identify best practice technology at local levels. One way is to improve knowledge of outcomes of technical decisions in existing environments. This can only be done through research to develop location specific recommendations as to combinations of best practices and extension agencies to disseminate such recommendations to farmers.

Currently, recommendations are typically broad spectrum rather than location specific. For example, there are none that are specific for rainfed conditions. Quite clearly, this would require a significant input from extension agencies, which should be tasked with identifying best practices. To this end, leading or most efficient farmers should be identified and encouraged to participate in such programs. They might well contribute through local farmer associations which could act not only as a link between government and farmers but could disseminate information and ideas about best practice technology within the farming communities. Given the frequent weakness of existing extension agencies, linkages to farming communities for such targeted objectives could help generate a greater impact upon farmer performance.

2

economic efficiency under risk

Economic efficiency plays a central role in the decision-making process of producing units. Recent literature provides a number of methods for measuring economic efficiency based on various assumptions. These methods can be classified into two groups according to their estimation techniques. One group uses the programming approach while the other uses the statistical approach. Naturally, one expects the emergence of another group which uses both the programming and statistical methods.[1]

There are two major concepts which are common to these approaches. The first is efficiency, measured relative to some set of norms representing the production and decision-making process. The second is risk. Risk has not been appropriately incorporated into the analysis, and is usually assumed to be distributed randomly across observations. It is rational to argue that the behaviour of firms operating under risk need not conform to their behaviour under certainty (Newbery and Stiglitz 1981). The implication is that economic efficiency under certainty need not be the same under risk.

The objective of this paper is to provide a measure of economic efficiency when firms are faced with risk using the frontier approach, and to calculate the efficiency foregone due to firms' perceived risk and actual behaviour in response to that risk. The conceptual model of production involving risk is discussed and estimation procedures are outlined. Data are briefly reviewed and empirical results are analysed in order to draw conclusions.

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[1] For a comprehensive review of all these approaches, see *Journal of Econometrics* 46, 1990.

Risk: conceptual approaches

In the existing literature on risk, there is a basic approach which can be summarized as follows: for each firm, there exists a critical minimum threshold income and a maximum income which are possible under the existing technology and the prevailing prices. Firms are not certain about the level of this maximum possible income. They tend to generate a series of income distributions by selecting varying amounts of factors of production (variable factors of production in the short run) with different means and variances. Firms are seen as setting up a very low probability for income occurrence below the threshold levels, and then choosing input levels which would maximize their expected incomes subject to the above probabilities. This approach is known as the safety-first rule in the literature. In the context of developing countries' agriculture, it has been demonstrated by researchers that the safety-first rule appears to be a satisfactory approach to modelling risk (Dillon and Anderson 1971).

Risk aversion can be measured either directly or indirectly. The direct approach, developed by von Neumann and Morgenstern (1944) is concerned with mathematically elucidating answers to some randomly arranged hypothetical questions by different participants. In the indirect approach, the degree of risk aversion is measured using *ex post* production behaviour of firms. Generally, using a stochastic production function with a heteroscedastic error term, yield variability is estimated as a function of inputs (Just and Pope 1979; Anderson and Griffith 1981). Random coefficient regression models, in which input response is purely random, have also been used by some researchers to estimate the mean yield level (Huysman 1983).

Although the safety-first rule discussed by Telser (1956) is more appealing from a theoretical viewpoint, for empirical estimation, the safety-first rule suggested by Kataoka (1963) provides computational convenience. In Kataoka's approach, the critical threshold of income itself is maximized subject to the probability constraints discussed.

Let h be the critical threshold of income then

$$p_r(g \leq h) \geq \alpha \qquad (2.1)$$

where g is the random net income with known mean μ and variance σ^2, and α is the accepted low probability constraint. For endangered firms with perfect risk aversion, α takes the value zero. Further, α is assumed to be determined by the socioeconomic conditions (M) faced by firms:

$$\alpha = \phi(M) \tag{2.2}$$

Let

$$g = p_y^E\left[y(x,z)e^v\right] - \Sigma p_i x_i \tag{2.3}$$

where p_i and p_y are prices of inputs and output respectively; x and z are levels of variable and fixed inputs respectively used in the production of y.

Following Kataoka's approach, maximize h subject to

$$p_r(g \leq h) \geq \alpha \tag{2.4}$$

Based on Chebychev's inequality, Equations 3 and 4 can be rewritten as follows (Just and Pope 1979):

$$h \leq y(x,z)e^{\lambda\sigma} - \sum_i^m p_i x_i \tag{2.5}$$

where $\lambda = F^{-1}(\alpha\ )^{-1}$. This means that maximizing h with respect to the probability constraint Equation 1 is equivalent to maximizing the upper bound of the critical threshold net income, h. The risk aversion parameter is then calculated as a residual by solving the first order marginal productivity conditions.

The basic assumption inherent in these risk studies is that firms achieve their maximum possible production potential all the time. With the recent growing literature on production efficiency, the above assumption turns out to be invalid. This has serious implications for the measurement of risk. Since the risk aversion parameter is calculated as the residual in the first order conditions, risk might be overestimated because the residual might also include productive inefficiency in addition to risk. It is in this context that application of frontier production function models assumes added importance.

The frontier production function literature, however, has paid little attention to incorporating risk into the analysis as empirical studies to date have used data mostly from minimum risk or risk-free production environments. To introduce more generality into frontier production function models, it is necessary to include risk. The following assumptions are made to facilitate the modelling of risk in frontier production functions.

- Risk perceived by firms may be divided into two components: production risk, concerning the given production technology; and market risk, associated with prices, input availability, etc.

- Risk is used in the Knightian sense that it has a known probability distribution, whereas the probability distribution of uncertainty is not known. The latter is not considered in this study.
- The selected levels of inputs reveal the amount of production and market risk perceived by firms.
- Realized output is the result of a firm's productive efficiency and its perception of both risks.
- The objective of the firm is to maximize its expected utility of gains, given its level of perception of risk and realized level of economic efficiency, comprises both its technical and allocative efficiencies.

The i[th] firm thus selects its variable input levels at $x_1, x_2, ...x_m$ to maximize

$$E\left(w_i\right) = E\left[w\left(\pi_i\right)\right] \tag{2.6}$$

where $w(\pi_i)$ is the function of utility of gains for the i[th] firm. Now, in order to specify the gains function, π_i, it becomes necessary to make the following assumptions (Aigner, Lovell and Schmidt 1977; Meeusen and van den Broeck 1977):

$$y^* = f(x,z)e^v \tag{2.7}$$

represents the true technical relationship between output y^* and variable x and fixed z inputs, and v is the random disturbance term with normal properties. In other words, y^* denotes the statistical frontier production function whose parameters may or may not be known to all firms. Assuming that firms may not know the parameters of the frontier production function exactly for various reasons, such as lack of effort, firms may formulate a subjective density on the values of the parameters of Equation 2.7 according to their perception of production risk, etc. Let the subjective realized production function of the i[th] firm be

$$y = f_i(x,z)e^{u+v} \tag{2.8}$$

where $u < 0$ which denotes firm-specific characteristics that constrain the i[th] firm from realizing the true technical parameters given in Equation 2.7. The subjective parameters of Equation 2.8 are determined by the i[th] firm's ability, experience and access to technical information and extension services.

The gains function π_i in Equation 2.9, may be defined as the net returns which the i[th] firm may expect from its selection of an input set. Then,

$$E[\pi_i] = p_y E\left[f(x,z)e^{u+v}\right] - \Sigma p_i x_i \tag{2.9}$$

The objective of the i^th^ firm is to maximize Equation 2.9. Further, Equation 2.9 indicates that the i^{th} firm's objective function depends on its perception of the true technical relationship between output and inputs (rather than on the existing true relationship), and its perception of risk.

A measure of the net gains foregone due to the i^{th} firm's perception both of its production function and of risk can be defined as follows:

$$E[\pi^*] - E[\pi_i] \geq 0 \tag{2.10}$$

where π^* is the optimum net gains which the i^{th} firm would receive and is determined by the level of inputs the i^{th} firm would have chosen if Equation 2.9 and prices were known with certainty and without any risk.

The interesting questions are: what net gains are foregone due to risk alone, and what are the levels of technical and economic efficiencies without the influence of perceived risks?

The true technical frontier relationship between output and inputs, i.e. the frontier production function is represented by FF* (Figure 2.1). This is not known to the i^{th} firm. AA' is the i^{th} firm's perception of the technical relationship between output and inputs, i.e. its perceived production function with its chosen set of technical practices. When the i^{th} firm operations at A_1 on AA', it produces y_1 by choosing x_i. The chosen level x_1 is the result of the i^{th} firm's perception of both production and market risks. The associated net returns π_1 which are realized, incorporate the firm's economic inefficiency in the face of both production and market risks. Its objective of maximizing net returns (π_2) would be achieved at x_2 when technical relationships and prices are known. Here the firm knows its perceived production function parameters. So any errors in choosing the levels of inputs to achieve its objective will be mainly due to perceived risks.

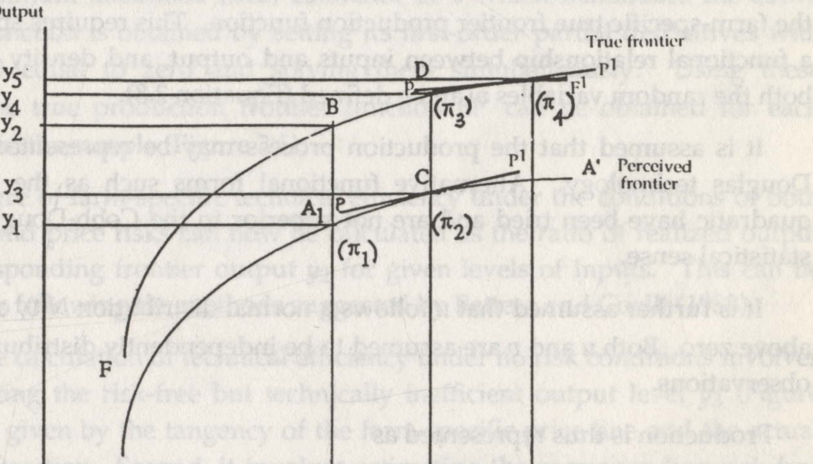
This means that the i^{th} firm has chosen x_1 rather than x_2 because of both production and market risks. It follows that gains in net returns foregone due to both types of risks can be measured as $E(\pi_2) - E(\pi_1) \geq 0$. Had the i^{th} firm used the risk free input level x_2, the output it could achieve, y_3, reveals the situation of no risk. But still, it is not the fully efficient output level as it is obtained from the perceived production function and not from the frontier function FF'. The fully efficient output level is y_4 is achieved when the i^{th} firm knows the true frontier and has no risk. Technical efficiency (TE) is measured by the ratio of y_3 to y_4, i.e.

$$TE = \frac{Y_3}{Y_4} \tag{2.11}$$

It may be noted here that in the conventional frontier production function approach, technical efficiency is measured as Y_1/Y_2. This includes risk perceived by the i[th] firm.

The output level, y_4 reveals the situation when the i[th] firm operates with full knowledge of the true frontier and without any perceived risk (Figure 2.1). Its level of net returns is now π_3 and net gains from achieving full technical efficiency are π_3 - π_2. The firm still will not have achieved its objective of maximizing its net gains if the i[th] firm makes allocative errors, i.e. is allocatively inefficient. A recent study strongly suggests, however, that this would be a rare situation (Kalirajan and Shand 1992). This study shows a unidirectional causal relationship between allocative and technical efficiencies meaning that once a firm becomes technically efficient it will also become allocatively efficient.

Figure 2.1 Technical efficiency and economic efficiency with and without the perception of risk



In practice, it may take some time for the i[th] firm to adjust its operation by moving from its perceived production function to its frontier function due to the learning process involved. Now, with the knowledge of the frontier production function parameters, the firm has to shift to the higher input level, x_3 to achieve its objective of maximizing its net gains, given the prices. The net returns associated with input level, x_3 and the frontier output y_5 are at a maximum and may be called π_4.

A measure of economic efficiency (EE) which is free from risk can now be defined as follows:

$$EE = \frac{\pi_2}{\pi_4} \tag{2.12}$$

It should be noted that in the conventional frontier production function approach, economic efficiency is calculated as, π_3/π_4. This, however, includes both the risks involved in the perceived production function as well as those involved in achieving economic efficiency on the frontier production function.

Estimation procedures

Given the data on actual levels of inputs used, output produced, and prices paid and received all of which are farm-specific, the above measures of technical and economic efficiency with and without the consideration of risk can be estimated. Maximum likelihood methods are used. First, it becomes necessary to estimate the farm-specific true frontier production function. This requires specification of a functional relationship between inputs and output, and density functions for both the random variables w and v defined (Equation 2.8).

It is assumed that the production process may be represented by a Cobb-Douglas technology. Alternative functional forms such as the translog and quadratic have been tried and are not superior to the Cobb-Douglas form in a statistical sense.

It is further assumed that u follows a normal distribution $N(0, \sigma_u^2)$, truncated above zero. Both u and v are assumed to be independently distributed for all the observations.

Production is thus represented as

$$\ln y = \beta_0 + \sum_{1}^{k} \beta_j \ln x_j + v - u \tag{2.13}$$

where $x_1, \ldots x_m$ are variable inputs and $x_{m+1}, \ldots x_k$ are fixed inputs.

$$f(u) = \frac{\exp\left[\frac{1}{2}\frac{(u-\lambda)^2}{\sigma_u^2}\right]}{\sqrt{2\pi}\sigma_u\left[1-\phi\left(\frac{-\lambda}{\sigma_u}\right)\right]} \qquad u \geq 0$$

The log-likelihood function for the sample observations y_i denoted by $L^*(\theta;y)$ when ($\theta = \beta', \sigma^2, \lambda, \gamma$) is written as follows:

$$L^*(\theta;y) = \frac{n}{2}\ln\sigma^2 - \frac{n}{2}\ln 2\pi - \frac{l}{2\sigma^2}\Sigma(e-\lambda)^2$$

$$+\Sigma\ln\left[1-\phi\left\{\frac{1}{\sigma}\left(-\lambda\sqrt{\frac{1-r}{r}}-e\sqrt{\frac{r}{1-r}}\right)\right\}\right]-n\ln\left[1-\phi\left(-\frac{\lambda}{\sigma\sqrt{r}}\right)\right] \quad (2.14)$$

where $e = \ln y - \beta_0 - \Sigma\beta_j \ln x_j$

$$\sigma^2 = \sigma_u^2 + \sigma_v^2$$

$$\gamma = \frac{\sigma_u^2}{\sigma^2}$$

The maximum likelihood (ML) estimator of θ which maximizes the above likelihood function is obtained by setting its first-order partial derivatives with respect to θ equal to zero and solving them simultaneously. Using these estimates, the true production frontier function FF' can be obtained for each observation in the sample (Figure 2.1).

A measure of farm-specific technical efficiency under the conditions of both production and price risks can now be calculated as the ratio of realized output to the corresponding frontier output y_2 for given levels of inputs. This can be calculated by following the methods suggested by Battese and Coelli (1988).

Next, the calculation of technical efficiency under no risk conditions involves first, estimating the risk-free but technically inefficient output level y_3 (Figure 2.1). This is given by the tangency of the farm-specific price line and the actual production function. Second, it involves estimating the corresponding risk-free but technically efficient frontier output y_4 (Figure 2.1).

The ratio of the former to the latter outputs gives a measure of risk-free technical efficiency. The risk-free but technically inefficient output y_3 is estimated by solving the following simultaneous equations of the actual production function and the marginal productivity conditions:

$$\beta_1 \ln x_1 + \beta_2 \ln x_2 + \ldots + \beta_m \ln x_m - \ln y = -\beta_{m+1} + \ldots + \beta_k \ln x_k - \beta_0 - u$$

$$\ln x_1 - \ln y = \ln\beta_1 - \ln p_1 - \ln p_y$$

$$\ln x_m - \ln y = \ln\beta_m - \ln p_m - \ln p_y \quad (2.15)$$

There are $(m+1)$ equations in $(m+1)$ unknowns, $x_1, \ldots x_m$ and y; the production parameters $\beta_0, \beta_1, \ldots \beta_m, \beta_{m+1}, \ldots \beta_k$ are maximum likelihood estimates of Equation 2.13, as the frontier production has been defined as a neutral shift from the actual production function by the amount of its technical inefficiency, and u is the logarithm of the estimated technical inefficiency. The calculated inputs x_i^*, $x_2^*, \ldots x_m^*, x_{m+1}, \ldots x_k$, represent the levels of inputs which the farm would have chosen had there been any perceived risk. But, the farm still does not know the parameters of its frontier and, therefore, the associated calculated output y_3 represents risk-free but inefficient output. The corresponding frontier output y_4 for the risk-free inputs $x_1^*, x_2^*, \ldots x_m^*, x_{m+1}, \ldots x_k$ indicates the output level which is risk-free but is also technically efficient (Figure 2.1).

Although y_4 is the risk-free technically efficient output, it may not conform with the objective of maximizing net returns. This could happen owing to the firm's allocative inefficiency. Therefore, the output y_5 is production and market risk-free, is both technically and allocatively efficient (maximizing net returns) and is calculated as follows:

$$\beta_1 \ln x_1 + \beta_2 \ln x_2 + \ldots\ldots + \beta_m \ln x_m - \ln y = -\beta_{m+1} \ln x_{m+1} + \ldots + \beta_k \ln x_k - \beta_0$$

$$\ln x_1 \qquad - \ln y = \ln \beta_1 - \ln p_1 - \ln p_y$$

$$\ln x_m - \ln y = \ln \beta_m - \ln p_m - \ln p_y \qquad (2.16)$$

The maximizing net returns are calculated as:

$$\pi_3 = p_y y_5 - \sum_i^m p_i \tilde{x}_i$$

where y_5 and x_i are obtained by solving Equation 2.16.

Data and empirical results

The data for the present study comes from an earlier project on the cost of cultivation conducted by the Tamil Nadu Agricultural University in 1986. A random sample of 64 farmers growing the modern cotton variety MCU-5 on their blocks in Madurai district, Tamil Nadu state in India, has been chosen for analysis. Cotton is an important commercial crop in India and Tamil Nadu state is one of the nine major cotton producers.

The following Cobb-Douglas type of production function has been estimated:

$$\ln y = \beta_0 + \sum_{i=1}^{m} \beta_i \ln x_i + v - u \qquad (2.17)$$

where y = cotton measured in tonnes
x_1 = labour in worker days
x_2 = fertilizer in kilograms
x_3 = animal power measured in bullock-pair days
x_4 = area cultivated in acres and multiplied by a soil fertility index.

This is assumed to be a fixed input
u = a technical efficiency related random variable
v = statistical white noise

It is assumed that u follows a normal distribution $N(0, \sigma_u^2)$ truncated above zero and v is $N(0, \sigma_v^2)$. The maximum likelihood estimates of Equation 2.17 are given (Table 2.1). All the coefficients are statistically significant at the 5 per cent level and have theoretically acceptable signs and magnitudes.

Table 2.1 Maximum likelihood estimates of the stochastic frontier production function

Inputs	Units of measurement	Parameter	Maximum likelihood estimates
Constant		β_0	4.22
Labour	worker days	β_1	0.21 (0.07)
Fertilizer	kilograms	β_2	0.14 (0.07)
Animal power	bullock pair days	β_3	0.09 (0.04)
Land	acres	β_4	0.56 (0.14)
		σ^2	1.86 (0.58)
		λ^a	0.78 (0.14)
			0.64 (0.15)
Log likelihood		-178.25	
Number of observations		64	

Notes: Figures in parentheses are standard errors of estimates.

a $\gamma = \dfrac{\sigma_u^2}{\sigma^2}$

First, the statistical significance of the inclusion of u in the production function has been examined by using the lagrange multiplier test statistic suggested by Lee (1983). This is asymptotically distributed as an x^2 with two degrees of freedom (Equation 2.17). The computed value of the test statistic is 14.69, which is greater than the critical value (5.99) of x^2 with two degrees of freedom at the 5 per cent level. The result implies that u significantly contributes to the variation in y and that the assumption of the truncated normal distribution for u cannot be statistically rejected for this data set.

Second, the significance of the variance ratio, γ, indicates that sample farmers have not achieved their potential outputs and that their realized outputs are lower than their potential outputs. This results is further strengthened by the results of the joint testing of $\lambda = 0 = \lambda$, which is significant at the 5 per cent level.

Third, the farmer-specific technical efficiencies for individual observations are given in the form of a frequency distribution (Table 2.2). These efficiency measures are calculated under the assumption of both production and market risk. The mean technical efficiency is 78.56 per cent.

Table 2.2 Farm-specific technical efficiencies under production and market risk

Technical efficiency (per cent)	Number of farms	Number of farmers
65-70	10 (15.62)	4,7,10,13,18,21,27,31,32,38
71-75	11 (17.19)	6,11,17,22,25,33,36,39,45,49,64
76-80	14 (21.88)	2,9,14,20,29,35,37,40,44,48,52, 56,59,62
81-85	15 (23.44)	1,12,19,24,26,41,43,46,50,53,57, 58,60,61,63
86-90	10 (15.62)	3,8,16,23,30,34,42,47,51,55
91-95	4 (6.25)	5,15,28,54
Total	64 (100)	

Note: Figures in parentheses are percentages.

Fourth, the farm-specific technical efficiencies for individual observations under no risk conditions are calculated as explained above (Table 2.3). The mean technical efficiency is 78.56 per cent. Comparing the results it is easily seen that the distribution of farm-specific technical efficiencies both under risk and no-risk conditions are the same (Tables 2.2 and 2.3). The third column in both tables indicates that the technical efficiency measure does not change for any farm whether it is calculated with or without the assumption of risk. Therefore, the assumption of risk does not appear to exert any influence in the calculation of technical efficiency measures.

Table 2.3 Farm-specific technical efficiency under no risk

Technical efficiency (per cent)	Number of farms	Number of farmers
65-70	10 (15.62)	4,7,10,13,18,21,27,31,32,38
71-75	11 (17.19)	6,11,17,22,25,33,36,39,45,49,64
76-80	14 (21.88)	2,9,14,29,29,35,37,40,44,48,52, 56,59,62
81-85	15 (23.44)	1,12,19,24,26,41,43,46,50,53,57, 58,60,61,63
86-90	10 (15.62)	3,8,16,23,30,34,42,47,51,55
91-95	4 (6.25)	5,15,28,54
Total	64 (100)	

Notes: Figures in parentheses are percentages.

Fifth, the farm-specific measures of economic efficiencies are calculated as explained above (Table 2.4). The mean economic efficiency, calculated with the assumption of perceived risk is 68.25 per cent. A comparison of the third column indicates that a majority of the farmers who have low technical efficiency also have low economic efficiency (Tables 2.2 and 2.4). This indirectly supports the hypothesis that technical efficiency exerts a major influence on allocative efficiency. Low (high) technical efficiency leads to low (high) allocative efficiency and thereby leads to low (high) economic efficiency.

Table 2.4 Farm-specific economic efficiency under risk

Technical efficiency (per cent)	Number of farms	Number of farmers
56-60	13 (20.31)	2,7,13,18,21,27,31,33,38,39,49, 62,64
61-65	10 (15.62)	4,8,9,17,22,25,32,36,40,45
66-70	16 (25.00)	1,10,14,20,29,35,37,44,48,51,52, 54,55,59,61,63
71-75	12 (18.75)	6,11,19,24,26,30,41,42,43,46,50,53
76-80	10 (15.62)	3,12,16,23,34,47,56,57,58,60
80-85	3 (4.70)	5,15,28
Total	64 (100)	

Notes: Figures in parentheses are percentages.

Table 2.5 Farm-specific economic efficiency under no risk

Technical efficiency (per cent)	Number of farms	Number of farmers
66-70	7 (10.94)	2,13,18,27,31,39,62
71-75	8 (12.50)	4,7,9,17,21,25,33,36
76-80	12 (18.75)	1,8,10,14,20,29,35,37,38,44,48,64
81-85	13 (20.31)	6,11,12,16,19,24,26,30,40,41,42, 43,49
86-90	12 (18.75)	3,16,23,34,45,46,47,50,51,52,57,60
91-95	8 (12.50)	53,54,55,56,58,59,61,63
96-100	4 (6.25)	5,12,15,28
Total	64 (100)	

Notes: Figures in parentheses are percentages.

Finally, the farm-specific economic efficiencies calculated with no risk conditions are presented (Table 2.5). The mean economic efficiency with no risk assumption is 73.42 per cent. In general, the level of economic efficiency under no risk appears to be higher than the level of economic efficiency under risk. Therefore, the conventional method of calculating economic efficiency by taking the ratio of realized net gains to potential maximum net gains, $\frac{\pi_1}{\pi_4}$ underestimates the true measure of economic efficiency, as the former includes the influence of risk. A comparison indicates the level of economic efficiency for all the sample farmers has changed and is higher under no risk than under risk (Tables 2.4 and 2.5). These results do not, however, disprove the conclusion reached about the relationship between technical and allocative efficiencies (Table 2.4). The assumption of risk is therefore an important phenomenon influencing the calculation of economic efficiency. The net gains foregone due to risk are significantly large and vary among the sample farmers.

Conclusion

When technical efficiency is measured as the ratio of actual to potential output, the influence of risk on technical efficiency cannot be examined. There are several reasons, one of which could be the restrictive assumption that the frontier is a neutral shift from the actual production function. Although economic efficiency is also measured in relative terms, the influence of risk on economic efficiency can be worked out. Empirical results indicate that technical efficiency is a major determinant of allocative efficiency and that the true level of economic efficiency is underestimated by conventional methods of measurement.

3

Paths of efficiency over time

Whilst there has been growing interest in the measurement of firm-specific performance with new technologies in terms of efficiency in recent years, little attention has been paid to the important question of how performance varies over time (Jondrow et al. 1982; Kalirajan and Flinn 1983; and Huang and Bagi 1984). Ruttan (1977) hypothesized that efficiency differentials in the use of the green revolution technology will disappear over time, once the new technology has been adopted by a sufficient number of farmers. Barker and Herdt (1985), through the International Rice Research Institute Constraints Project, proved that there were efficiency differentials among farmers due to technical and/or socioeconomic constraints. The total yield gap was attributed to three factors: profit-seeking behaviour, allocative efficiency and technical efficiency. Most of the yield gap (67 per cent) was attributed to technical inefficiency.

A number of cross-sectional studies have demonstrated wide inter-firm variations in technical and allocative efficiencies and have analysed their determinants many years after adoption of the new technology (Shand, De Silva and Ranaweera, 1989; Shand, Mangabat and Jayasuriya 1990; Kalirajan and Shand 1990). There has, however, been no systematic study of how these efficiencies change over time. This is surprising in view of the widespread interest in the impact of disequilibria caused by the introduction of new technology and in firm reactions to disequilibrium (Schultz 1975).

In one sense, albeit it an indirect one, there has been some consideration of a time dimension in the distribution of benefits from the new technology. Earlier literature has dealt at length with the question of who the beneficiaries are, and when benefits were received from the green revolution. There is controversy over the question of neutrality in the distribution of benefits and availability of inputs, etc.

Differences have been noted with respect to the rate of adoption which have shown that time is a factor in the distribution of benefits, but up till now, evidence has shown that the time differentials in this respect have not lasted long and the argument of those who claim neutrality in benefits from the new technology has prevailed (Hayami, 1981). Adoption of the new high yielding seeds and the package of associated inputs has been remarkably widespread. Research is extending the geographical boundaries of adoption, with new varieties tolerant of less favourable environmental conditions. On the other hand, the literature indicates that the time dimension cannot easily be discarded due to farmers' need to make adjustments to reach the optimum combination of the various components of the new technology, such as use of fertilizer, after adoption (Barker and Herdt 1985).

It is important at this stage of maturity of the new technology to distinguish between the adoption of the constituent inputs in the new technology and the ways in which farmers perform in combining these inputs after adoption. While adoption has led to substantial productivity gains (impressive in the aggregate), adoption measures give no satisfactory indication of the level of, and variation in, benefits which are available if firms realize their technical and allocative potential with the new technology. For this an additional measure is required and measures of firm-specific efficiency are employed.

The main hypotheses tested here are:

- initial overall firm performances are characterized by low average and widely varying economic efficiencies, owing to similar characteristics of their component technical and allocative efficiencies;
- mean levels of economic efficiencies increase over time;
- that technical and allocative, and thus economic, efficiencies will vary inversely with the degree of risk that farmers face;
- without external intervention, long terms economic efficiency growth will be slow, principally because of the difficulties faced by farmers in identifying optimal technical practices.

Technical, allocative and economic efficiencies are defined here with a discussion of how each can be measured. It is assumed that a firm can be both technically and allocatively inefficient at any one time. A conceptual model for the study is presented and data and methods of estimation are discussed. Results are presented and, finally, conclusions are drawn from the study.

Definitions of efficiencies

A firm is defined as being technically efficient for a given technology if it fully realizes its own technical efficiency potential and produces on its outer bound production frontier consistent with its socioeconomic and physical environment.

Technical efficiency (TE) is defined and measured as the ratio of the firm's actual observed output to its own maximum possible frontier output for given levels of inputs. Using the established model:

$$y^* = f(x,z)e^v \tag{2.7}$$

$$y = f_i\,(x, z)e^{u+v} \tag{2.8}$$

Equation 2.8 may be rewritten

$$y = y^*e^u \tag{3.1}$$

Technical efficiency is thus seen as a random residual term which accounts for variations in output unexplained by x and is realistic in a world where individual firms using a given technology are observed to be achieving varying output levels for a given level of measurable inputs. The frontier function is shifted neutrally from the observed production function by the level of the firm's technical inefficiency.

When u takes the value zero on the frontier it means that the firm obtains its maximum possible output. When u takes a value less than zero, it implies that the firm is producing less than its maximum possible output. In this way e^u refers to firm-specific technical efficiency given the socioeconomic and physical environments faced by the firm. Schmidt (1986) provides a critical analysis of efficiency measures derived from frontier production methodology.

Following from Equation 3.1, technical efficiency is measured as follows:

$$e^u = \frac{y}{y^*} \tag{3.2}$$

Mean technical efficiency is then calculated for further analysis. Firm specific technical efficiency can also be measured for individual observations (Jondrow et al. 1982; Kalirajan and Flinn 1983).

Allocative efficiency (AE) is defined as the ability to obtain maximum profits from the application of conventional inputs with a given set of firm-specific input and output prices and a given technology. The index of allocative efficiency for the output of firms in each crop season is derived by, first, simultaneously solving the firm-specific production function and the marginal productivity conditions yielding the optimum variable inputs, and second, by calculating the ratio of profits observed, (at the given level of inputs, to the above solved maximum profit at the optimum set of inputs. Profit is defined as the differences between total revenue and total variable costs.

Let the optimal output-input combination, for variable inputs only, obtained by simultaneously solving the frontier production function and the marginal productivity conditions (MVP = MC calculated from actual output), be represented as $y,\ x_1^*, ..x_m^*$.

Allocative efficiency is then calculated as follows:

$$AE = \frac{p_y(y) - \sum_{1}^{m} p_i x_i}{p_y(\tilde{y}) - \sum_{1}^{m} p_i x_i^*} \tag{3.3}$$

where p_i's and p_y are respectively unit prices of inputs and output. The mean allocative efficiency is also obtained by averaging the above measure over observations.

Economic efficiency (EE) is the product of technical and allocative efficiencies. A farmer who is both technically and allocatively efficient is also economically efficient.

Conceptual model

There are three possible directions which technical and allocative efficiencies might take over time. First, they may both increase. This might logically be expected with the introduction of a new technology which raises physical productivity as firms adopt it. As firms become more familiar with the technology over time they are progressively more able to improve their decision-making efficiency and should also be capable of making increasingly accurate allocative decisions as both production and market risks are reduced in the learning process.

Second, they could both decline over time. This could occur if management is poor and/or if constraints are placed on firms which remove their incentive for achieving efficient performance.

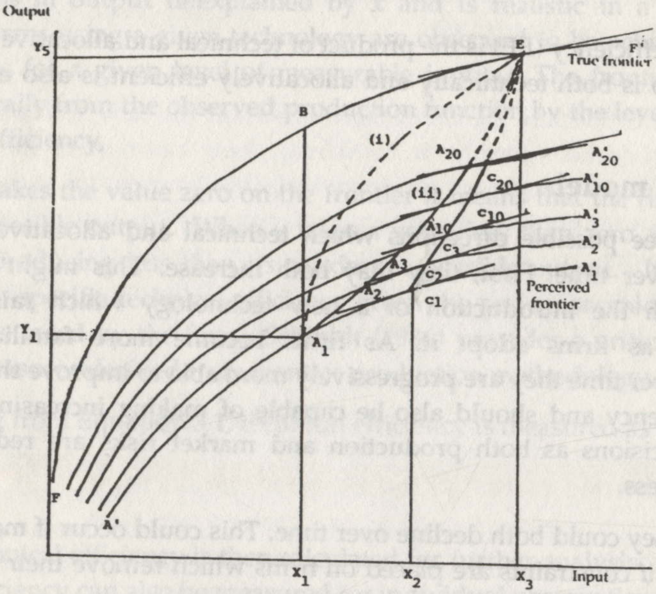
The third possibility is that the two efficiencies could fluctuate over time without discernible trend. This could occur in situations where technology is static or stagnant, where input/output relations are not stable and firms have to make educated guesses as to the best set of technical practices to apply and the most appropriate decisions as to input levels. This may happen in agriculture when climatic variation is pronounced and risk parameters cannot be calculated, for example under marginal rainfed conditions. Our hypothesis is that both increase over time. This raises the further question as to the time pattern of increases in the two efficiencies.

In the context of achieving higher efficiency, the question of the influence of risk on decision-making arises. Our third hypothesis is that technical and allocative, and thus economic, efficiencies will vary inversely with the degree of risk that farmers face. In this case study, two different production environments are considered. Random samples of farmers were chosen from irrigated and non-irrigated conditions respectively to represent different degrees of risk and to test the validity of the above three hypotheses.

These issues can be visualized with the help of the established model (Equations 2.1 to 2.12).

In this analysis, we are concerned with both types of risk and make A our starting point and E the new equilibrium point (Figure 3.1).

Figure 3.1 Time paths of economic efficiency



If our second hypothesis holds, there are two possible time patterns for increases in efficiencies. First technical efficiency could increase faster than allocative efficiency. This would mean that a firm's economic efficiency would approach E from A_1 along an arc convex to the origin as in time path (i) (Figure 3.1). This could occur, for example, if research and extension agencies undertook active programmes at field level, in conjunction with farmers, to identify best technical practices under specific environmental conditions. Second, allocative efficiency could increase more rapidly than technical efficiency, which would mean a firm's increasing economic efficiency would follow an arc concave to the origin from A_1 to E as in time path (ii) (Figure 3.1). This could occur in the absence of effective research and extension programmes to identify best technical practices and farmers were left to discover these in a learning-by-doing process, and/or through the interaction between farmers in this process. In practice, the latter situation has been the norm, and for this case study, it has led to a further hypothesis: the time path will be the second one, i.e. (ii) (Figure 3.1).

Data and estimation

The data are drawn from a regular ongoing project on the cost of cultivation conducted by the Tamil Nadu Agricultural University. For empirical analysis, data from irrigated and non-irrigated paddy farms from North Arcot, India, were used. Within the region, farms with reasonably homogeneous land and equipment were sampled. The data covers the 10 year period 1973 to 1982, and each year has two seasons of similar crops which give a total number of twenty periods. In each crop period, longitudinal data from 25 irrigated and 25 non-irrigated farmers were selected for the survey. In the expectation that greater risks are present for non-irrigated than for irrigated farmers, the paper tests the third hypothesis by comparing performance in terms of efficiencies between farmers under irrigated conditions with those of farmers under non-irrigated conditions.

Alternative functional forms such as translog and quadratic were tried, but because of high R^2 values and the number of significant variables, the Cobb-Douglas form was preferred for further analysis. In addition, in the translog form, all null hypotheses of linear and non-linear separabilities could not be rejected at the 5 per cent level. Apparently, complete global separability could not be rejected. Thus, the Cobb-Douglas function can be considered as an appropriate model describing the technology for the given data set.

The following farm-specific stochastic Cobb Douglas production frontier was separately estimated for each crop season:

$$\ln y_{it} = \alpha_0 + \sum \alpha_{jt} \ln x_{ijt} + \beta_{1t} \ln x_{4t} + u_{it} + v_{it} \tag{3.4}$$

$i = 1,2,..n$ (observations)

$t = 1,2,..t$ (periods)

where y = observed paddy output in kilograms

x_1 = pre-harvest labour in man-days

x_2 = fertilizer in kilograms

x_3 = animal power in bullock-pair days

x_4 = area operated in acres, multiplied by a soil fertility index. This is considered here as a fixed input.

e^u = firm-specific technical efficiency defined above

u = a non-positive random variable.

v = a statistical random variable.

It is assumed that u follows a truncated normal distribution with mean μ and variance σ_u^2 and v follows a normal distribution $N(0,\sigma_v^2)$.

Maximum likelihood estimation provides estimates of the parameters of the maximum possible output frontier and mean technical efficiencies (Kalirajan and Shand 1985). The mean parameter estimates of the frontier production function for the sample participants in the irrigated and non-irrigated environments respectively are:

$$\ln(\text{paddy}) = 3.1628 + 0.2432 \ln(\text{labour}) + 0.1712 \ln(\text{fertiliser}) + 0.0804 \ln(\text{animal power}) + 0.5301 \ln(\text{land})$$

$$\ln(\text{paddy}) = 2.4627 + 0.2263 \ln(\text{labour}) + 0.1328 \ln(\text{fertilizer}) + 0.1269 \ln(\text{animal power}) + 0.5185 \ln(\text{land}).$$

The mean technical efficiency for each crop period is calculated as follows (Table 3.1):

$$E(e^{u_i}) = \Phi(\sigma_u - \lambda/\sigma_u)\Phi(-\lambda/\sigma_u)^{-1}\exp(-\lambda + \sigma_u^2)$$

where $\lambda = \sigma_u / \sigma_v$

Table 3.1 Calculated mean technical efficiencies of sample farmers from North Arcot, Tamil Nadu, India 1973-82

Sl. No	Crop period		Irrigated TE	Non-irrigated TE
1	1973	1	0.68	0.63
2		2	0.68	0.63
3	1974	1	0.68	0.62
4		2	0.68	0.63
5	1975	1	0.68	0.64
6		2	0.67	0.63
7	1976	1	0.68	0.63
8		2	0.68	0.64
9	1977	1	0.69	0.64
10		2	0.69	0.64
11	1978	1	0.70	0.64
12		2	0.70	0.65
13	1979	1	0.71	0.65
14		2	0.73	0.65
15	1980	1	0.74	0.65
16		2	0.75	0.65
17	1981	1	0.75	0.66
18		2	0.75	0.66
19	1982	1	0.75	0.66
20		2	0.75	0.66

TE = Technical Efficiency

Allocative efficiency for the output of each farmer for each crop season is derived first by simultaneously solving the firm-specific observed production function and the marginal productivity conditions yielding the optimum output and variable inputs, and second, by calculating the ratio of observed profit to the optimum maximum profit (Table 3.2):

$$\alpha_1 \ln x_1 + \alpha_2 \ln x_2 + \alpha_3 \ln x_3 - \ln y = -\beta_1 \ln x_4 - \alpha_0 - u \tag{3.5}$$

$$\ln x_1 - \ln_y = \ln\alpha_2 - \ln p_2 - \ln p_y$$

$$\ln x_2 - \ln y = \ln\alpha_2 - \ln p_2 - \ln p_y$$

$$\ln x_3 - \ln_y = \ln\alpha_2 - \ln p_3 - \ln p_y$$

There are four equations in four unknowns x_1, x_2, x_3 and y; the production parameters α_o, α_1, α_2, α_3, u and β_1 are MLE estimates of (Equation 3.4). If the calculated optimal output ($\tilde{y}$), along with the concerned optimal inputs x_1^*, x_2^*, x_3^*, and their relevant prices are used to work out the maximum profit. The ratio of the observed to the above optimum profit for each observation is calculated for each crop season. A simple average of these ratios for each crop season is worked out which then serves as a measure of allocative efficiency for that particular crop season (Table 3.2).

Table 3.2 Calculated mean allocative efficiencies of sample farmers from North Arcot, Tamil Nadu, India 1973-82

Sl. no	Crop period		Irrigated AE	Non-irrigated AE
1	1973	1	0.75	0.76
2		2	0.76	0.77
3	1974	1	0.78	0.78
4		2	0.77	0.79
7	1976	1	0.80	0.81
8		2	0.81	0.82
9	1977	1	0.81	0.82
10		2	0.82	0.82
11	1978	1	0.83	0.83
12		2	0.83	0.83
13	1979	1	0.83	0.83
14		2	0.84	0.84
15	1980	1	0.86	0.85
16		2	0.90	0.89

AE = Allocative Efficiency

The estimated farm-specific Cobb-Douglas production frontiers for the irrigated and non-irrigated environments are presented in Tables 3.3 and 3.4. Importantly, in both samples, the values of the intercepts and the input coefficients increased continuously over time throughout the period under study. This implies that, in each environment, there was a continuous outward shift in the production frontiers, indicating continuous technological change and increasing productivity over the whole period.

Table 3.3 Frontier production function coefficients for irrigated sample farms by season from North Arcot, India, 1973-82

Year	Season	Intercept	Labour	Fertilizer	Animal	Land power
1973-	1	3.0246	0.2151	0.1245	0.0613	0.4786
	2	3.0315	0.2159	0.1289	0.0654	0.4825
1974-	1	3.0398	0.2164	0.1315	0.0682	0.4896
	2	3.0426	0.2175	0.1394	0.0693	0.4909
1975-	1	3.0502	0.2186	0.1426	0.0672	0.4982
	2	3.0672	0.2194	0.1486	0.0734	0.5011
1976-	1	3.0713	0.2218	0.1511	0.0765	0.5083
	2	3.0854	0.2292	0.1568	0.0791	0.5096
1977-	1	3.0916	0.2324	0.1599	0.0798	0.5113
	2	3.0998	0.2396	0.1623	0.0805	0.5286
1978-	1	3.1059	0.2425	0.1685	0.0822	0.5292
	2	3.1250	0.2501	0.1719	0.0845	0.5314
1979-	1	3.1345	0.2534	0.1783	0.0867	0.5332
	2	3.1487	0.2597	0.1796	0.0876	0.5416
1980	1	3.1612	0.2634	0.1821	0.0878	0.5439
	2	3.1674	0.2705	0.1859	0.0882	0.5446
1981-	1	3.1837	0.2843	0.1925	0.0893	0.5461
	2	3.2078	0.2915	0.1942	0.0899	0.5472
1982	1	3.2264	0.2942	0.1964	0.0902	0.5483
	2	3.2516	0.2973	0.1983	0.0907	0.5492

AE = Allocative Efficiency

Table 3.4 Frontier production function coefficients for non-irrigated sample farms by season from North Arcot, India, 1973-82

Year	Season	Intercept	Labour	Fertilizer	Animal power	Land
1973-	1	2.4568	0.2086	0.1276	0.1189	0.5085
	2	2.4589	0.2092	0.1278	0.1192	0.5089
1974-	1	2.4592	0.2012	0.1282	0.1196	0.5092
	2	2.4596	0.2019	0.1285	0.1198	0.5096
1975-	1	2.4612	0.2021	0.1288	0.1205	0.5098
	2	2.4625	0.2029	0.1291	0.1215	0.5105
1976-	1	2.4638	0.2034	0.1293	0.1218	0.5113
	2	2.4649	0.2038	0.1296	0.1221	0.5119
1977-	1	2.4655	0.2042	0.1298	0.1229	0.5120
	2	2.4668	0.2051	0.1302	0.1231	0.5125
1978-	1	2.4673	0.2055	0.1305	0.1235	0.5131
	2	2.4683	0.2059	0.1309	0.1239	0.5138
1979-	1	2.4688	0.2063	0.1311	0.1241	0.5142
	2	2.4692	0.2065	0.1315	0.1246	0.5148
1980	1	2.4699	0.2069	0.1319	0.1251	0.5156
	2	2.4706	0.2071	0.1320	0.1255	0.5164
1981-	1	2.4708	0.2074	0.1322	0.1259	0.5178
	2	2.4711	0.2076	0.1329	0.1261	0.5186
1982	1	2.4716	0.2078	0.1330	0.1265	0.5192
	2	2.4719	0.2079	0.1330	0.1268	0.5198

Results

The estimated farm-specific Cobb Douglas production function frontiers for the irrigated and non-irrigated environments are presented in Tables 3.1 and 3.2. Importantly, in both samples, the values of the intercepts and of the individual input coefficients increased continuously over time throughout the period under study. This implies that in each environment, there was a continuous outward shift in the production frontiers, denoting continuous technological change and increasing productivity over the whole period.

At the outset, the specification of Equation 3.4 is tested for the inclusion of the technical efficiency related variable u by using a generalized likelihood ratio (Battese and Coelli 1988). If the random variable u is absent from the model, then the ordinary least squares estimates of the remaining parameters of Equation 3.4 are maximum likelihood estimates. Therefore, the negative of twice the logarithm of the generalized likelihood ratio has approximately x^2 distribution with parameter equal to 1. If the calculated ratio worked out to be greater than the tabulated value, then the null hypothesis is rejected. This implies that the model without the observation-specific technical efficiency related variable u cannot explain significantly the variations of outputs from the maximum possible levels. The tests on all these equations in (3.4) indicate that the inclusion of u in each equation is relevant (Equation 3.4).

Mean technical efficiencies with risk incorporated show an increasing trend over time for the irrigated sample, technical efficiency increased slowly, season by season, with few fluctuations giving a 7 percentage point rise over the period. In the non-irrigated sample, the increase was even slower, only 3 percentage points for the period. The fact that both samples improved in technical efficiency, albeit at slow rates, is significant and suggests that there was a learning process in both environments over the period. It should be noted that these increases were achieved as the production function frontiers were shifting outward over time.

Mean allocative efficiencies with risk incorporated in both environments showed more impressive gains over the same period (Table 3.2). Under irrigated conditions, sample farmers raised mean allocative efficiency 20 percentage points over the 9 years from 1973. The performance under non-irrigated conditions was no less impressive. The initial mean, at 76 per cent, matched that of the irrigated farmers and the gain of 19 percentage points was also almost identical with the gain under irrigation. As with technical efficiencies, the increases were achieved with outward shifting production frontiers over time.

Mean economic efficiencies for both farm samples show the combined influence of the two component efficiencies (Table 3.5). Both samples showed low initial accomplishments. The improvement was quite rapid for both. The difference of 8 percentage points between the two samples in the final year of study reflected the margin between them in levels of technical efficiency at that time, as it did throughout the period.

The results offer a number of important insights into performance over time with the new technology. First, they provide support for our hypothesis that in the early years after adoption of the new technology, performance, measured in terms of economic efficiency, and as the product of the component efficiencies, is low. Interestingly it was higher for allocative than for technical efficiency. This could indicate that all North Arcot farmers faced a low level of market risk which enabled them to judge their allocative decisions more accurately than their technical decisions at that time. Or it could mean that farmers have used the technology on their perceived production functions long enough to be able to judge allocative decisions relatively accurately.

Table 3.5 Calculated mean economic efficiencies of sample farmers from North Arcot, Tamil Nadu, India 1973-82

Sl. no	Crop period		Irrigated	Non-irrigated
		EE	EE	
1	1973	1	0.51	0.48
2		2	0.52	0.48
3	1974	1	0.53	0.49
4		2	0.52	0.47
5	1975	1	0.54	0.49
6		2	0.54	0.50
7	1976	1	0.54	0.51
8		2	0.55	0.52
9	1977	1	0.56	0.53
10		2	0.57	0.53
11	1978	1	0.58	0.53
12		2	0.58	0.54
13	1979	1	0.59	0.54
14		2	0.62	0.55
15	1980	1	0.63	0.55
16		2	0.90	0.58
17	1981	1	0.66	0.59
18		2	0.69	0.60
19	1982	1	0.70	0.62
20.		2	0.71	0.63

EE = Economic Efficiency

Second, the improvements in technical and allocative efficiencies over the period of our study support our second hypothesis and suggest that a learning-by-doing process was at work. Third, the fact that allocative efficiency rose faster than technical efficiency over time suggests that, at least in this case study, the patterns of increasing economic efficiency follow a concave time path and therefore support our fourth hypothesis.

This time path moves along the concave curve (ii) from A_1, through A_2 to A_{20} (Figure 3.1). However, it falls well short of E because mean technical efficiencies are still only 75 and 66 per cent respectively of full technical efficiencies in the two samples in 1982 (Table 3.1). The relevant points showing maximum profit on each perceived production function are given on the curves C_1 to C_{20}. Comparing the two curves A_1 to A_{20} and C_1 to C_{20} illustrates the rapid narrowing of the gap in allocative efficiency over time and the more substantial and persistent technical efficiency gap shown as the vertical distances from the points A_1, A_2, ...A_{20} to the true frontier. This finding strongly suggests that the task of achieving full technical efficiency is more difficult for farmers than that of achieving allocative efficiency on perceived production functions as they shift upwards over time with gradual improvements in technical efficiency. Notably, the time paths are similar for the irrigated and non-irrigated samples.

Increases in allocative efficiency were responsible for most of the improvements in economic efficiencies. However, with mean allocative efficiencies at 95 per cent in both samples in 1982, little further contribution can be expected from this source. Prospective rates of increase in economic efficiencies will be much slower than were achieved in the period under review since these must come almost exclusively from improvements in technical efficiency. Indeed, the times required to achieve full economic efficiency will match those required to reach full technical efficiency. The average annual rates of increase in technical efficiency in this case study were 0.7 per cent for the irrigated sample and 0.3 per cent for the non-irrigated sample. On the basis of these rates, it would take almost 40 years from 1982 for irrigated farmers to achieve full technical and economic efficiency and more than 100 years for non-irrigated farmers to achieve the same result.

Further insights are provided by comparing improvements in technical and allocative efficiencies under irrigated conditions with those in the more risky non-irrigated environment. This shows first that the greater risk under rainfed conditions did not alter the time path of change in economic efficiency. Second, economic efficiency was initially, and remained at, higher levels for irrigated than for non-irrigated farmers. This is consistent with a priori expectations that decision-making is more difficult under non-irrigated conditions because of the higher level of risk and uncertainty without irrigation. Nevertheless, it should be noted that, even under rainfed conditions, high levels of allocative efficiency were attained by the end of the period under review.

Causality between technical and allocative efficiencies is examined by applying the Sims' test (1972). The basic principle of the test is that causality runs from the independent variable (x) to the dependent variable (y), if the influence of the future values of the independent variables (x_{t+1}) as a group is not significant in the regression involving the dependent variable and the past (x_{t-1}), present (x_t) and future (x_{t-1}) values of the independent variable (Hsiao 1979; Schmidt and Lovell 1980) applying the Sims' test to examine the direction of causality between technical and allocative efficiencies involves estimating the following equations for the two production environments:

$$TE = \alpha_0 + \alpha_1 AE_t + \alpha_2 AE_{t-1} + \alpha_3 AE_{t-2} + \alpha_4 AE_{t+1} + \alpha_5 AE_{t+2} \qquad (3.6)$$

$$AE = \beta_0 + \beta_1 TE_t + \beta_2 TE_{t-1} + \beta_3 TE_{t-2} + \beta_4 TE_{t+1} + \beta_5 TE_{t+2} \qquad (3.7)$$

and testing whether relevant coefficients are statistically significant.

The results of the Sims' tests for determining the direction of causality between technical and allocative efficiencies are given in Table 3.6. For brevity, only the F statistics, which indicate the results of causality tests, are reported. In the presence of serial correlation, the F-tests are invalid. Therefore, the LM statistics for serial correlation are calculated which follow a x^2 distribution with 1 degree of freedom. The calculated LM statistics for irrigated and non-irrigated equations are 2.1316, 3.7813, 4.2163 and 4.8102 (Table 3.6). The tabulated critical value for a 2 per cent level of significance for $x^2_{(1)}$ is 5.412. In addition, the residual autocorrelograms did not provide evidence of significant coefficients at the 5 per cent level of significance, the highest being 1.97 for the irrigated TE = f(AE) equation with a critical value of 2.23 (Table 3.6). Therefore, the causality tests do not appear to suffer from serial correlation.

Table 3.6 Sims tests of causality between technical and allocative efficiencies for sample farmers from North Arcot, Tamil Nadu, India 1973-82

Characteristics	Irrigated F-ratio	Irrigated Results	Non-irrigated F-ratio	Non-irrigated Results
Allocative efficiency on technical efficiency	3.25 (2,8)	Failed to reject H_0	2.89 (2,8)	Failed to reject H_0
Technical efficiency on allocative efficiency	10* (2,8)	Reject H_0	11.2* (2,8)	Reject H_0
Causal inference	TE	AE	TE	AE

Notes: * Significant at the 1 per cent level.
Figures in parentheses are the degrees of freedom.
H_0: Technical efficiency (allocative efficiency) does not cause allocative efficiency (technical efficiency).
TE = Technical Efficiency
AE = Allocative Efficiency

When testing for causality from technical to allocative efficiency, the null hypothesis is that technical efficiency does not cause allocative efficiency. Rejection of the null hypothesis then implies that technical efficiency causes allocative efficiency. While testing for causality from allocative efficiency to technical efficiency, the null hypothesis is that AE does not cause technical efficiency. Failure to reject the null hypothesis means that allocative efficiency does not cause technical efficiency. The results indicate that causality is not bi-directional but runs from technical efficiency to allocative efficiency only. Further a simple regression of allocative efficiency on technical efficiency shows a significant relationship from technical efficiency to allocative efficiency with high explanatory powers ($\overline{R}^2$) for both samples (Table 3.7).

Table 3.7. Impact of changes in technical efficiency on allocative efficiency

Coefficients	Irrigated farms OLS estimates	Non-irrigated farms OLS estimates
TE	1.8529*	4.6764*
	(0.1658)	(0.4591)
Constant	-0.4763*	-2.1723*
	(0.1173)	(0.2952)
$\overline{R}^2$	0.8670	0.8440

Notes: Figures in parentheses refer to standard errors of estimates.
* significant at the 1 per cent level.

Conclusions

One important overall conclusion which emerges from this study is that the process of adjustment or improvement in performance towards a new equilibrium over time is much more complex than is generally recognized. Our analysis shows that, even with more than a decade of experience with the new technology, average farm performance in terms of economic efficiency in 1982 was still not high. Quite clearly, high levels of performance do not simply follow from the universality of adoption of technology as postulated by Ruttan (1977). Barker and Herdt's (1985) assertion that 'after fertilizer has been used for some time, and assuming enough is available to meet market demand, farmers arrive at their own economic equilibrium levels' may have some relevance to our findings that farmers' capacity to make allocative decisions improves over time, but it does not account for the continuing variations between farmers in technical efficiency and the slow progress towards realization of full technical efficiency on the true frontier.

A second broad conclusion is that, in the achievement of high levels of economic efficiency over time, the allocative efficiency component may not be a major long run constraint. The finding of unidirectional causality from technical to allocative efficiency implies that, provided gains in technical efficiency are achieved, gains in allocative efficiency will follow. This underlines the critical importance of achieving progress with technical efficiency.

Third, there are major drawbacks for farmers who are on time path (ii) (Figure 3.1). The principal difficulty in the long run lies in the slow rate of increase in technical efficiency. Although some progress can be expected as in this case study, technical inefficiency is persistent and thus emerges as the most serious constraint on economic performance over time. It implies that, left to learn from their own experience, farmers will be slow to realize the full potential of a new technology. This is reinforced by the finding that, once high levels of allocative efficiency have been achieved, further improvements in economic efficiency depend almost exclusively upon the achievement of higher technical efficiency. This underlines the limitations of a policy strategy that relies solely on the sector itself for improvements in performance over time. There is a growing urgency for sustained improvements in performance which require a more active role for the public sector and international agencies in research and extension activities in collaboration with farmers to raise technical efficiency significantly over time.

This conclusion is unexpected under irrigated conditions where at least broad recommendations as to best practices are already available. The record of technical efficiency over time in this case study suggests that the recommendations are, however, too general to be of much use to farmers under their own specific conditions. The slow rate of increases in technical efficiency in the two samples over time suggests that the constraint on technical efficiency has been lack of information as to optimal technical practices. In the absence of this information, the shift in farmers' perceived frontiers toward the true frontier is slow, consistent with a learning-by-doing process. In this situation, farmers can gain close to full knowledge of their perceived production functions and of market conditions and so are able to achieve higher levels of allocative efficiency at a relatively rapid rate. But in the long run, improvements in technical efficiency are needed to sustain improvements in economic performance.

Fourth, the fact that this occurred in both irrigated and non-irrigated samples suggests that the same time pattern occurs regardless of the production environment, i.e. the level of risk. The consistently lower level of technical efficiency in the non-irrigated sample over time suggests that the task or process of identifying best practices is more difficult without irrigation.

The final conclusion is that private and social returns from investments in new technology will be seriously constrained over time by inefficiencies in the performance of firms whose performances follow time path (ii) of performance (Table 3.1). This has important implications for projections of returns from projects which include new technology and more broadly, for returns from research.

This study identifies measurement of firm performance with new technology over time as an important new focus for research. In this regard, key questions emerge from this study, suggesting areas for further research.

First, to what extent does the pattern of performance in this study represent a common experience? We expect it to be so, for research till now has not focused in the direction of identifying best technical practices at the individual farm level. This has been left to the farmers themselves. An exception to this is in the area of pest control. Public sector intervention in research and extension in collaboration with farmers has recently been successful in raising productivity through pest control in rice production, particularly through the FAO Integrated Pest Control Programme (Food and Agriculture Organisation 1990). This program is an excellent example of collaboration between research and extension agencies on the one hand, and farmers on the other, to achieve a path (i) shift in technical efficiency over time (Figure 3.1). This has been accomplished by finding a solution to a major technical problem caused by one input in the original package of inputs for modern rice technology, i.e. the use of chemicals for pest control. In Indonesia, for example, farmers found the use of these chemicals led to yield reductions. The farmers and government incurred substantial costs, particularly the latter in subsidies). The government's ecological program for Integrated Pest Control introduced in 1986, has largely replaced use of chemicals with biological measures for control of pests thereby raising yields substantially for those involved and with lower inputs for pest control.

Second, if it is not a common experience, then what are the reasons for the lagged response in performance over time, particularly in gains in technical efficiency? We suggest that a key reason is, in the first instance, that there is a general lack of recognition that a problem exists in performance with a new technology. Policy makers currently assume that, once a technology is given to farmers, it will be efficiently applied and give no consideration to the time span involved and its implications.

Finally, to what extent can levels of performance in technical performance over time be accelerated? We believe that public intervention through research and extension in collaboration with farmers, can provide a way to achieve more rapid increases in technical efficiency which would enable farmers to move between A_1 and E along time path (i) rather than along time path (ii) (Figure 3.1).

4

Formation of frontiers and technical efficiency

Technical efficiency, one of the two components of economic efficiency, is defined as the ability and willingness of any producing unit to obtain the maximum possible potential output from a given set of inputs and technology. In the literature, technical efficiency is measured as a ratio of actual output to the potential output (Aigner, Lovell and Schmidt 1977; Meeusen and van den Broeck 1977). Based on the techniques of estimating the potential output, the approaches to measuring technical efficiency generally vary from programming to statistical estimation (Bauer 1990). In the latter approach, a firm-specific stochastic production frontier involving outputs and inputs is defined as follows:

$$y_i^* = f(x_i) \exp(v_i) \tag{4.1}$$

where, x_i is a vector of m inputs, v_i 's are statistical random errors with N (o, σ_v^2), and y_i^* is the maximum possible stochastic potential output for the i[th] firm, which varies over time for the same firm and across firms in the same period.

It is rational to assume that firms may not know the parameters of their own frontier production function exactly for various reasons, and that this lack of knowledge is manifest principally as technical inefficiency. Therefore, the realized production function of the i[th] firm may be modelled as follows:

$$y_i = y_i^* \exp(u_i) \tag{4.2}$$

where exp (u) is defined as a measure of observed technical efficiency of the i[th] firm. It is further assumed that $u_i \leq 0$. When u_i takes the value zero, it means that the i[th] firm is technically fully efficient and realises its maximum possible potential output. On the other hand, when u_i assumes values less than zero, it means that the i^th firm is not fully technically efficient and so produces output which is less than its potential output. Now, a measure of technical efficiency for the i^th firm can be defined as,

$$\exp(u_i) = \frac{y_i \text{, given } u_i}{y_i^* \text{, given } u_i = 0} \tag{4.3}$$

To obtain the above measure the denominator has to be estimated, as the numerator is the observed output level. Assuming a functional form to represent the technology in Equation 4.1, and a density function for u in Equation 4.2, the denominator can be estimated by using the maximum likelihood methods.

There are three apparent limitations to this approach. First, the technology is parametized by some *ad hoc* functional forms involving outputs and inputs, which is restrictive. Second, assuming a density function for u_i is not based on any theoretical reasoning. Finally, and most importantly, the frontier production function defined in (1) is assumed to be a neutral shift from the observed production function (2), which is questionable. Statistical tests are available and have been carried out to validate the selection of functional forms and the distributional assumption for u_i, but, the question as to why the frontier should be a neutral shift from the observed production function has not received much attention in the literature.

The objective of this paper is to suggest a method to estimate the frontier production function using cross-section data and to measure firm-specific technical efficiency for individual observations, when the frontier shifts non-neutrally from the observed production function. The following section explains the methodology which is followed by the estimation procedures.

Frontier with non-neutral shift

When technical efficiency is measured by using (4.3), the underlying assumption is that the frontier is a neutral shift from the realized production function. This constant-slope, variable-intercept approach raises a basic question about the concept of technical efficiency. Where does technical efficiency come from? How does a firm achieve its technical efficiency? The literature indicates that a firm obtains full technical efficiency by following the best practice techniques, given the technology. In other words, technical efficiency is determined by the method of application regardless of the levels of inputs. This implies that the different methods of applying various inputs will influence the output differently. That is, the slope coefficients will vary from firm to firm. Therefore, the constant-slope approach of measuring technical efficiency is not consistent with the definition of technical efficiency. The following specification of the production process which is consistent with the concept of technical efficiency, facilitates estimation of firm-specific technical efficiency for individual observations.

Assuming a Cobb-Douglas technology and modifying the Hildreth and Houck (1968) random coefficient model, the production relationship can be written as follows:

$$y_i = \sum_{j=1}^{k} \beta_{ij} x_{ij} + u_i \tag{4.4}$$

i = 1, 2, . . n

where y and x are represented in logarithms.

In addition to the conventional assumptions in the general linear regression model, the following assumptions are made:

- for any given input, the response coefficients β_{ij}, i =1,2, . . . n, and j = 1, 2, ..k are random variables with

  $E(\beta_{ij}) = \bar{\beta}_j$ and $\operatorname{var}(\beta_{ij}) = \sigma_{jj} > 0$

- Cov (β_{ij}, β_{ik}) = 0 for j ≠ k
- Cov (β_{ij}, β_{ik}) = 0 for j ≠ k

Now, with the above assumptions, equation 4.4 can be rewritten as:

$$y_i = \sum_{j}^{k} \beta_j x_{ij} + w_i \tag{4.5}$$

where,

$w_i = \sum (\beta_{ij} - \beta_j)\, x_{ij} + u_i$

$E(w_i) = 0$

$\operatorname{Var}(w_i) = \sigma^2 + \sum_{j=1}^{k} \sigma_{jj} x_{ij}^2$

$\operatorname{Cov}(w_i\, w_i') = 0$ for i ≠ i'

In matrix notation,

$$Y = x\beta + w \tag{4.6}$$

where $E(w) = 0$ and $E(ww') = v$ and where v is a non-singular positive definite diagonal matrix as follows:

$$v = \text{diag}\left(x_1' A x_1, x_2' A x_2, \ldots\ldots x_n' A x_n\right),$$

$$\text{where} \quad A = E\left(\beta_{ij} - \beta_j\right)\left(\beta_{ij} - \beta_j\right)'$$

As $x_{i1} = 1$ for all i, separate estimates of σ^2 and σ_{11} cannot be obtained. Nevertheless, $(\sigma^2 + \sigma_{11})$ can be jointly estimated as $\hat{\sigma}_{11}$ along with other (k-1) variances.

Equation 4.6 is thus a linear regression with constant coefficients of mean responses and heteroscedastic disturbances.

There are two assumptions underlying Equation 4.6. First, technical efficiency is achieved by adopting the best practice techniques which involve the efficient use of inputs without having to increase their levels.

Technical efficiency stems from two sources. One, the efficient use of each input which contributes individually to technical efficiency can be measured by the magnitudes of the varying random slope coefficients (β_{ij}'s excluding the intercepts). Two, when all the inputs are used efficiently, then it may produce a combined contribution over and above the individual contributions. This latter lump sum contribution can be measured by the varying random intercept term.

Second, the highest magnitude of each response coefficient and the intercept form the production coefficients of the potential frontier production function. Let $\beta_1^*, \beta_2^*, \ldots \beta_k^*$ be the estimates of the parameters of the frontier production function:

$$\beta_j^* = \max \{\beta_{ij}\} \quad i = 1, 2, \ldots n$$

$$j = 1, 2, \ldots k$$

Since, $v \neq \sigma^2$ I, the ordinary least squares (OLS) method yields coefficients that are unbiased, but inefficient. Since, Equation 4.6 can be viewed as a classical heteroscedastic linear regression with σ_{jj} as a linear function of x_{ij}, the conventional estimation techniques used under such circumstances can also be used here to estimate v. In this context, the general least squares (GLS) estimator has been acknowledged as the best linear unbiased predictor (BLUP) in the literature (Rao 1970; Zellner 1970; Hildreth and Houck 1968; Swamy 1970).

There is no guarantee, however, that the v matrix would be a positive definite matrix.

The matrix v can be made a positive definite matrix by following different methods suggested in the literature. These approaches can be broadly classified into two groups; one concerns assigning zero values to variance coefficients which are negatives and the other involves estimating the variance coefficients with constraints which guarantee positive definite matrices.

Harville (1977), Raj et al. (1980) and Swamy (1971) proposed a number of alternative estimators. Some of these, such as maximum likelihood (ML) and the restricted maximum likelihood are only defined for legitimate values of v. Although procedures exist to guarantee the estimated v is always non-negative at each iteration, the maximum may be at the boundary. Further, as the likelihood function is not globally concave, it allows for multiple local maxima (Maddala 1971).

This paper uses the method of minimizing a quadratic function of the parameters subject to linear inequalities suggested by Judge and Takayama (1966). Consider the following structure of the variance coefficients:

$$\omega = zv + R$$

where, ω is the square of the estimated OLS residuals; z is the square of the explanatory variables; v is the variance of the random coefficients and R is the random disturbance term.

To avoid negative estimates of v, the following method of estimation is adopted:

Minimize $R'R$ subject to $v \geq 0$. This is also equivalent to maximizing $(-R'R)$, subject to $(-V) \leq 0$; i.e.

$$(-R'R) = -w'w + 2(v'z'w - \tfrac{1}{2}v'z'zv)$$

is maximized subject to the condition that $(-v) \leq 0$. As $w'w$ is a scalar constant, maximization of $(-R'R)$ is equivalent to maximizing $v'z'w - \frac{1}{2}\, v'z'zv$ subject to $c'v \leq d$ where

$$c = \begin{pmatrix} -1 & \ldots & \ldots & 0 \\ 0 & -1 & \ldots & 0 \\ \ldots & \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots & \ldots \\ 0 & \ldots & \ldots & -1 \end{pmatrix} \quad \text{and } d = \begin{pmatrix} 0 \\ \vdots \\ 0 \end{pmatrix}$$

The vector which maximizes $(-R'R)$ without the constraints is

$$\hat{v}_1 = \left(z'z\right)^{-1} z'w$$

If $\hat{v}_i$ satisfies the constraints $(c'v \leq d)$, then $\hat{v}_1$ is the required solution, as a constrained maximum will never exceed an unconstrained maximum. It is possible to have a situation in which $\hat{v}_1$ violates one or more constraints.

Following the suggestions of Theil and van de Panne (1960), finding the solution vector v is equivalent to the problem of finding the subset M out of K constraints given above $(c'v \leq d)$ such that when $v'z'w - \frac{1}{2}\, v'z'zv$ is maximized with the constraints belonging to M binding, a vector v_M results which is feasible $(c'v_M = d)$ and optimal $(v_M = v)$. Therefore v_M may be defined as the vector maximizing $v'z'w - \frac{1}{2}\, v'z'zv$ with all constraints of M binding, where M is any subset of K constraints. The optimal vector v_M which has r elements (constraints) in the equational form, yields the non-negative variances for $(K - r)$ random coefficients under the restrictions that the variances of the r out of K random coefficients are zero. Hence, the optimum vector v of the order $(K \times 1)$ may now be obtained by incorporating zeros in r appropriate positions in the optimal vector v_M.

The GLS estimates of b in Equation 4.6 can be obtained as follows:

$$\hat{b} = \left(x'v^{-1}x\right)^{-1} x'v^{-1}y \qquad (4.7)$$

whose variance matrix is $(x'v^{-1}x)$.

First, v is estimated based on OLS estimates. Then, the GLS estimates of the mean coefficients and their variance co-variance matrix are obtained by substituting the former estimates in Equation 4.7. Applying the iterative procedure, the new set of GLS coefficients and the variance co-variance matrix are obtained. The iterative procedure is continued until the coefficients are stabilized.

Following Griffiths (1972), the actual firm-specific and input-specific response coefficient predictor for the i[th] observation b_{ij}, which is BLUP, can be obtained as follows:

$$\hat{\beta}_{ij} = \hat{\beta}_j + \frac{Ax_i}{x_i'Ax_i}\hat{w}_i \qquad (4.8)$$

The response coefficients representing the potential frontier production function can be identified as follows from the above estimates:

$$\beta_j^* = \max \{\hat{\beta}_{ij}\} \qquad (4.9)$$
$$i = 1, 2 \ldots n$$
$$j = 1, 2 \ldots k$$

Now, the firm-specific potential frontier output for each observation can be worked out as:

$$y_i^* = \sum \beta_j^* x_{ij} \qquad (4.10)$$

where x_{ij} refers to logarithms of actual levels of inputs used by the i^{th} firm. Calculation of firm-specific technical efficiency for individual observation can then be calculated as

$$TE = \frac{\exp(y_i)}{\exp(y_i^*)}$$

Data and results

Data for the present study came from a random sample of 82 farmers growing high yielding paddy variety IR 36 in Madurai district in Tamil Nadu State of India. The sample farms are well irrigated and they are of medium size, between 5 and 10 acres. The selected village Solavanthan is visited frequently by the extension officials.

The following Cobb-Douglas type of production function has been assumed for the present study.

$$\ln y_i = \sum_{j=1}^{k} \beta_{ij} \ln x_{ij} + u_i \qquad (4.11)$$

$$i = 1, 2 \ldots, 82$$

where y = high yielding (IR 36) paddy output in tonnes

x_1 = a constant term

x_2 = pre-harvest labour days

x_3 = fertilizer in kilograms

x_4 = animal labour days

x_5 = area in acres multiplied by a relevant soil fertility index

u = statistical white noise, which has a normal distribution $N(0, \sigma^2)$.

The iterated GLS estimates of the mean response coefficients of inputs are given (Table 4.1). All the coefficients are significant at the 5 per cent level and they all have theoretically acceptable signs and magnitudes. The range of actual response coefficients of inputs for individual observations are also shown (Table 4.2). The variation in the farm-specific and input-specific elasticity coefficients is substantial. This means that the methods of application of different inputs vary among sample farms and consequently, individual contributions of inputs to output differ from farm to farm. The estimates of the production coefficients of the frontier are derived using Equation 4.9 and the results are given (Table 4.2). These estimates indicate the maximum possible contribution of each input to output when the inputs are applied efficiently following the best practices techniques. Further, these estimates are derived relaxing the conventional assumption that the frontier output is a neutral shift from the realized output.

Table 4.1 Iterated GLS estimates of the mean response coefficients and the variance coefficients

Inputs	Unit of measurement	Iterated GLS estimates: Variance coefficient	Iterated GLS estimates: Mean response coefficient
Constant	-	0.10	0.37
Labour	days	0.11	0.20
Fertilizer	kgs	0.10	0.27
Animal labour	days	0.06	0.06
Area	acres	0.15	0.4
			(0.14)

Notes: Figures in parentheses denote standard errors. Number of observations = 82.
Log likelihood = -138.64. $\overline{R}^2$ = 0.6219.

Table 4.2 Range of estimates of actual response coefficients and estimates of frontier production function

Inputs	Range of actual response coefficients	Estimates of the frontier production function
Constant	0.3424 - 0.4003	0.4003
Labour	0.1896 - 0.2113	0.2113
Fertilizer	0.2619 - 0.2862	0.2862
Animal power	0.0588 - 0.0680	0.0680
Area	0.4636 - 0.4810	0.4810

Following Equation 4.10, the potential frontier outputs for individual observations have been estimated and the calculated farm-specific technical efficiency measures for each sample farmer are shown in a frequency form (Table 4.3). The efficiency measures range from 0.64 to 0.91.

Table 4.3 Frequency distribution of farm-specific technical efficiency measures

Efficiency measures (per cent)	Number of firms	Percentage
64-70	14	17.07
71-75	21	25.61
76-80	24	29.27
81-85	9	10.98
86-90	13	15.85
91-95	1	1.22
Total	82	100

While comparing the mean response coefficients with the estimates of actual response coefficients, some interesting observations can be made about the pattern of following the best practice techniques concerning the use of all inputs. However, only about 30 per cent of sample farmers followed best practice techniques of using labour and fertilizer, while about 80 per cent followed the best method of using animal power.

Conclusions

The analysis revealed substantial variation in the actual farm-specific and input-specific response coefficients. This means that methods of application of different inputs vary among farms and consequently, individual contributions of inputs to output differ from farm to farm. Therefore, depending on which farm uses which best practice technique involving which input, production coefficients vary from farm to farm. With this consideration, this paper suggests a method to measure technical efficiency relaxing the conventional assumption of neutral shifting of the frontier function from the actual production function.

The advantages of the proposed methodology are that the researchers need not impose restrictive *ad hoc* assumptions on the disturbance terms and that it facilitates identifying the contribution of different inputs to overall technical efficiency. Although this methodology has been applied to cross section data, it can readily be extended to be usable with time series or panel data with only slight modifications to estimation procedures.

5

Overall and input-specific technical efficiencies

A firm's performance can be measured in a number of ways. One method is to measure performance at the firm-level to see whether firms can increase output, given the technology, without having to increase their existing levels of inputs. In other words, the question of interest is whether firms can realize the full potential of the technology they adopt. Any answer to this question carries an implication for invoking policies aimed at improving overall economic growth.

The measurement of potential output, whether it is considered at the macro or microlevel, can be approached either by parametizing the production process through some generally acceptable production functions or by identifying the linear segments connecting the best use of the technology through programming techniques. The former method is termed the stochastic frontier method (Aigner et al. 1977 and Meeusen and van den Broeck 1977). The latter method is termed the 'data development analysis' (Charnes et al. 1978; Byrnes et al. 1984; Banker and Maindiratta 1986).

Each approach has its own limitations and attractions, all of which have been adequately documented in the literature (Lewin and Lovell 1990). Recently, there have been attempts to modify the programming approach of measuring technical efficiency by incorporating stochastic characteristics into estimation methods. This modification is intended to enable the programming approach to take care of measurement errors and become less susceptible to outliers. The convex hull, representing the potential output, is derived using only marginal data and not by utilizing all the observations in the sample.

Varian (1985) included stochastic characteristics in data development analysis by introducing two-sided deviations to incorporate random noise and to

Varian (1985) included stochastic characteristics in data development analysis by introducing two-sided deviations to incorporate random noise and to calculate the efficiency measure free of such random noise. Land et al. (1989) discussed another estimation technique, called chance-constrained efficiency analysis, in which the deterministic frontiers are allowed to capture the effects of random noise without themselves being stochastic. Data requirements for the latter approach are more demanding than are those needed for the approach suggested by Varian.

There are four major limitations to the use of the stochastic frontier production function in measuring technical efficiency. First, the production technology is parametized by some *ad hoc* functional forms involving inputs and outputs. Second, the observation-specific, technical efficiency-related random variable is assumed to follow some distribution. Third, technical efficiency is considered as a lump-sum overall increase in output. Fourth, the frontier production function is assumed to be a neutral shift from the observed actual production function.

Considerable progress has been made in the theory of regression and hypothesis testing in generating various statistical testing procedures to validate the selection of functional forms and the distributional assumption for the technical efficiency-related random variable. But the assumptions of technical efficiency being a lump-sum, and the frontier function being a neutral shift from the observed function have not been relaxed adequately in the literature, although there are a few exceptions (Kopp and Diewart 1982; Zieschang 1983; Kumbhakar 1988). The study by Kumbhakar (1988) is more relevant to the present study. Kumbhakar considered a methodology to estimate input-specific efficiency and overall technical efficiency using panel data. He made the implicit assumptions, however, that the frontier shifts neutrally and that input-specific efficiency depends on the levels of inputs. These assumptions are restrictive and there is no theoretical reasoning as to why input-specific efficiency should depend on the level of inputs. Another exception is a recent study by Cornwell, Schmidt and Sickles (1990) which suggests using panel data to measure time-varying technical efficiency from a stochastic production function with coefficients varying over firms. However, they restricted their empirical analysis to the estimation of technical efficiency as a lump-sum, with cross-sectional heterogeneity only in intercepts.

The objective of this study is to suggest a method of measuring firm-specific and input-specific technical efficiency assuming a non-neutral shift of the frontier from the actual production function. This is equivalent to measuring technical efficiency with heterogeneity in both slopes and intercepts. Further, the objective is to measure technical efficiency using cross-section data which is readily available in many developing countries. The third and fourth limitations of the stochastic frontier production function, considering technical efficiency as a lump-sum and potential output as a neutral shift from actual output, are eliminated along with the second limitation of assigning a distribution to the efficiency related variable. The advantage of this method is that it is possible to identify not only the overall technical efficiency but also the input-specific technical efficiency for each observation.

The modelling of the frontier production function with cross-sectional heterogeneity in slopes and intercepts, used to measure firm-specific potential output and to provide firm-specific and input-specific technical efficiency measures, is explained. The estimation procedures, are discussed and are followed by an analysis of the empirical results and conclusions.

The model

Technical efficiency, one of the two components of economic efficiency, is defined as the ability and willingness of any producing unit to obtain maximum possible potential output for a given set of inputs and technology. The interesting question is: how does a firm achieve full technical efficiency? The literature indicates that a firm obtains its full technical efficiency by following the best practice techniques given the technology. In other words, technical efficiency is determined by the method of applying inputs, regardless of the 'levels of inputs. The closer the method of application is to the best practice technique, the higher the firm's technical efficiency. Alternative methods of applying various inputs will influence output differently, i.e. the production coefficients will vary from firm to firm. This situation has been discussed in the literature on random coefficient regressions (Swamy 1970). The literature argues that the conventional constant-slope approach of measuring potential output and technical efficiency is not consistent with the concept of technical efficiency.

Once again the random coefficient regression framework using Cobb Douglas technology and a slight modification of the Hildreth and Houck (1968) model, facilitates estimation of potential output consistent with the concept of technical efficiency (Part 4).

Assuming a Cobb-Douglas technology and modifying the Hildreth and Houk (1968) random coefficient model we derive the production relationship which has been given in and explained by Equations 4.4, 4.5 and 4.6.

Given the nature of the problem of the present study, a recent approach proposed by Bartels and Fiebig (1990) has been used with a minor modification in this paper. Their method uses the variation of the actual response coefficients from the mean-response coefficient. Following Griffiths (1972) with slight adaptations, the BLUP for actual-response coefficients may be written as follows:

$$\hat{\beta}_{ij} = \hat{\beta}_j + \sqrt{\frac{A}{x_i^{'} A x_i}}\, G^{'} x_i \hat{u}_i \tag{5.1}$$

where $\sqrt{A}$ is the Cholesky triangular decomposition matrix such that

$A = \left(\sqrt{A}\right)\left(\sqrt{A}\right)^{'}$ and where $H = \frac{\left(x^{'} x\right)^{-1}}{n}$ such that $H = HH^{'}$

Now, $\hat{\beta}_{ij} - \hat{\bar{\beta}}_{ij} = \sqrt{\frac{A}{x_i^{'} A x_i}}\, G^{'} x_i \hat{u}_i$

therefore

$$\frac{1}{n}\Sigma\left(\hat{\beta}_{ij} - \hat{\bar{\beta}}_j\right)\left(\hat{\beta}_{ij} - \hat{\beta}_j\right)^{'} = \frac{1}{n}\Sigma\sqrt{A}\, G^{'} \frac{x_i x_i^{'} u_i \hat{u}_i^2}{x_i^{'} A x_i} G\left(\sqrt{A}\right)^{'} \tag{5.2}$$

Applying the principles suggested by Swamy (1970) for panel data, an estimator for A may be obtained as:

$$\hat{A} = \frac{1}{n}\Sigma\left(\hat{\beta}_{ij} - \hat{\bar{\beta}}_j\right)\left(\hat{\beta}_{ij} - \hat{\bar{\beta}}_j\right)^{'}$$

The following iterative estimation procedure can be derived, by substituting the above estimator for A on the left hand side of Equation 5.2 and replacing the A on the right hand side with some initial estimates of the elements of A as follows:

$$\hat{A}^{(1)} = \frac{1}{n}\sqrt{\hat{A}^{(0)}}\, G^{(0)'} \Sigma \frac{x_i x_i^{'} \hat{u}_i^2}{\left(x_i^{'} A^{(0)} x_i\right)^2} G^{(0)}\left(\sqrt{A^{(0)}}\right)^{'} \tag{5.3}$$

Iteration is carried out until convergence is achieved. The final estimate $\hat{A}$ is consistent and is guaranteed to be a positive definite matrix if the process does not converge to a zero solution, and the initial estimate $\hat{A}^{(0)}$ is consistent. From the estimate of A, the elements of matrix v can be obtained and following Griffiths (1972), individual input-specific response coefficients can be estimated directly.

The response coefficients representing the potential frontier production function can be identified from the above individual input-specific response coefficients as follows:

$$\hat{\beta}_j^* = \max \ \hat{\beta}_{ij} \qquad i = 1,2,3.........n \qquad j = 1,2,3.........k \tag{5.4}$$

An important observation can be made about the coefficients of the frontier production function. These coefficients need not necessarily coincide with the response coefficients for any single individual observation. They may represent the best combination of response coefficients derived from different individual observations. This implicitly assumes that not all individuals use all the inputs efficiently.

From the above estimates of the frontier production function coefficients, two different kinds of efficiency measures can easily be derived. One, the firm-specific overall technical efficiency measure for individual observations can be calculated. This involves first calculating the firm-specific potential frontier output for each observation and then working out the ratio of realized output to potential output, thus,

$$\hat{y}_i^* = \Sigma \hat{\beta}_j^* x_{ij} \tag{5.5}$$

where x_{ij} refers to the levels of input j used by the i[th] firm and $\hat{y}_i^*$ is the potential frontier output of the i[th] firm.

$$E_i = \frac{\exp(y_i)}{\exp(\hat{y}_i^*)} \tag{5.6}$$

where E_i refers to the estimate of technical efficiency for the i[th] firm and y_i is the actual realized output of the i[th] firm.

Two, estimates of input-specific efficiency measures for individual observations can be calculated as the ratios of the actual-response coefficients to the frontier-response coefficients. Expressed in percentage terms, the efficiency of using the j^{th} input by the i^{th} firm is given by:

$$K_{ij} = \frac{\hat{\beta}_{ij}}{\hat{\beta}_j^*} \times 100 \qquad (5.7)$$

$i = 1,2,3, ..., n$

$j = 1,2,3, ..., k$

Data and results

Data for this estimation were drawn from a random sample of 68 farmers growing the high yielding paddy variety IR 36 in the village of Solavanthan in Madurai district in Tamil Nadu State of India. The sample farms are well irrigated, owner-operated and are of medium size (between 5 and 10 acres). The selected village is visited frequently by extension officials.

The following Cobb-Douglas type of production function has been assumed for the present study

$$\ln y_i = \beta_{i1} x_{i1} + \sum_{j=2}^{k} \beta_{ij} \ln x_{ij} + u_i \qquad (5.8)$$

$i = 1,2, ..., 68$

where, y = high yielding (IR 36) paddy output in tonnes

x_1 = 1, a constant term

x_2 = pre-harvest labour days

x_3 = fertilizer in kilograms

x_4 = animal labour days

x_5 = area in acres multiplied by a relevant soil fertility index

u = statistical white noise, which is normally distributed $N(0, \sigma^2)$.

The mean response coefficients of inputs are estimated (Table 5.1). All the coefficients are significant at the 5 per cent level and all have theoretically acceptable signs and magnitudes. The range of actual response coefficients of inputs for individual observations are shown (Table 5.2).

Table 5.1 Bartels–Fiebig variance coefficients and the estimates of the mean response coefficients

Inputs	Units of measurement	Iterated GLS estimates: Variance coefficients	Iterated GLS estimates: Mean response coefficients
Constant	..	0.12	0.39
Labour	days	0.13	0.20
Fertilizer	kilograms	0.12	0.26
			(0.13)
Animal labour	days	0.08	0.06
			(0.03)
Area	acres	0.14	0.48
			(0.13)

Notes: Figures in parentheses are standard errors of estimates. Number of observations = 68.

Table 5.2 Estimates of actual-response coefficients and coefficients of the frontier production function

Inputs	Range of actual response coefficients	Coefficients of the frontier production function
Constant	0.39 – 0.40	0.40
Labour	0.19 – 0.21	0.21
Fertilizer	0.25 – 0.26	0.26
Animal power	0.06 – 0.07	0.07
Area	0.43 – 0.47	0.47

The variations in the farm-specific and input-specific elasticity coefficients are substantial. This means that the methods of application of different contributions of inputs to output differ from farm to farm. The estimates of the production coefficients of the frontier are derived using Equation 5.4 (Table 5.2). These estimates indicate the maximum possible contribution of each input to output when the inputs are applied efficiently following the best practice techniques. They are derived with a relaxation of the conventional assumption that the frontier output is a neutral shift from the realized output.

Following Equation 5.5, the potential frontier outputs for individual observations have been estimated and the calculated farm-specific overall technical efficiency measures for each sample farmer are shown in a frequency form (Table 5.3). The efficiency measures range from 0.71 to 0.94.

Table 5.3 Frequency distribution of farm-specific technical efficiency measures

Efficiency measures (per cent)	Number of firms	Percentage
71–75	20	29.4
76–80	16	23.5
81–85	14	20.6
86–90	13	19.1
91–95	5	7.4
Total	68	100

Table 5.4 Frequency distribution of input-specific efficiency measures

Efficiency measures (per cent)	Number of farms			
	Labour	Fertilizer	Animal power	Land
85–87	-	-	17 (25.0)	-
88–90	-	-	20 (29.4)	-
91–93	27 (39.7)	-	12 (17.6)	24 (35.3)
94–96	24 (35.3)	33 (48.5)	10 (14.7)	18 (26.4)
97–99	16 (23.5)	33 (48.5)	8 (11.8)	25 (36.8)
100	1 (1.5)	2 (3.0)	1 (1.5)	1 (1.5)
Total	68	68	68	68

Note: Figures in parentheses are percentages to totals.

Input-specific efficiency measures for individual farms have been calculated using Equation 5.6 and are reported in a frequency form (Table 5.4). The results show generally high levels of input use efficiency. Farmers are relatively more efficient in using fertilizers than other inputs and it appears that animal power has been used relatively less efficiently. One reason could be that almost all sample farmers owned a significant number of buffaloes which are used in cultivation and so they may be careless in using them as they do not have to pay for their services.

The input-specific efficiency measures can be interpreted as follows. In the use of animal power, the efficiency measures suggest that farmers with efficiency between 85 and 87 per cent could employ about 13–15 per cent less animal power by moving to their frontiers. The land-specific efficiency measures also indicate that some farmers could reduce their use of this input, without any reduction of output, by following the best practice techniques which would enable them to operate on their frontiers. These input-specific measures bear important policy implications for efficient performance and thus for overall agricultural development.

There is at least one farmer who uses each of the inputs with 100 per cent efficiency (Table 5.4). This does not, however, mean that it is the same farmer who uses all the inputs most efficiently. The detailed results, not shown owing to space constraints, show that farmer number 37 used both labour and fertilizer with 100 per cent efficiency, while he could apply 11 per cent and 7 per cent less animal power and land respectively by producing on the frontier with these inputs. Farmer number 51 appears to use fertilizer and land with 100 per cent efficiency, but was 8 and 6 per cent inefficient in employing labour and animal power respectively. Farmer number 19 seems to employ only animal power with 100 per cent efficiency. Comparison of overall technical efficiency measures for farmer numbers 37, 51 and 19, shows that farmer number 51 has the highest measure of 94 per cent, while farmers number 37 and 19 have 87 and 77 per cent technical efficiency respectively. Further analysis is required to explain these variations in efficiency.

Conclusions

The fixed coefficient frontier production function methodology hitherto used restricts measurement of efficiency to an overall measure. It is rational to argue that, depending on which farm uses which best practice technique with which input, production coefficients would vary from farm to farm. This provides the rationale and the necessity for the use of the variable coefficient frontier efficiencies. The results reveal substantial variation in the actual farm-specific and input-specific response coefficients, indicating that methods of application of different inputs vary among farms and consequently, individual contributions of inputs to output differ from farm to farm.

In the light of this variation, relaxing the conventional assumption of a neutral shift of the frontier function from the actual production function provides valuable additional information on individual farm performance in the form of measurements of individual input efficiencies.

In this sense, efficiency measures derived from the variable coefficient frontier production function provide policymakers with more useful information. Not only can the analysis distinguish which farmers are more or less efficient, but also with respect to which inputs. Importantly, it also sheds light on how the technical frontier is formed and how each farm relates to it in terms of each of its input response coefficients. This should, for example, give greater guidance as to the most appropriate direction for extension advice and highlights the need for research on the reasons for variations in individual input efficiencies.

The advantage of the chosen methodology is that researchers do not need to impose restrictive *ad hoc* assumptions on the disturbance terms. Although this methodology has been applied here to cross section data, it can readily be extended to time series or panel data with only slight modifications to estimation procedures.

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