CHAPTER - VI
TECHNICAL EFFICIENCY IN SERICULTURE FARMING – A FRONTIER FUNCTION APPROACH

6.1. Introduction: Efficiency of the Firm

Economic theory uses to explain economic behaviour of different agents as the result of an optimisation problem (consumers maximise utility while firms maximise profits). From this point of view, efficient firms are precisely those that maximise profits. In real world, however, some inefficiency exists, as not all firms are capable to maximise profits. Profits maximization needs three decisions to be made:

1. The firm must choose the output level that maximises profits (when marginal costs equalise marginal revenues).
2. Among the alternative input combinations that allow the firm to obtain the above output level, the minimum production cost combination should be chosen. The general rule establishes that the firm should use the amount of input that equalise marginal product and input prices.
3. The firm should produce the chosen level of output using the minimum amount of inputs (no resource is wasted). This means that the firm is working along its production function.

Efficiency of the firm can be categorized into three kinds:

**Scale efficiency:** When the firm is producing with an optimum scale, allowing it to maximise profits, then it is termed as scale efficiency.

**Allocative efficiency:** When the firm combines inputs to minimize production costs, it is termed as allocative efficiency.

**Technical efficiency:** When the firm obtains the maximum level of output from the chosen input combination, then it is termed as technical efficiency.

Economists are often concerned with the efficient use of inputs in production. The basic question about the firms in production revolves round the production of more output with the same amount of inputs or to reduce the amount of inputs and achieve the same output level. This type of efficiency is referred to as technical or productive efficiency. Many reports directed to study the utilization of resources in
production in manufacturing industries, agriculture, banks, etc. suggest that not all producers succeed in utilizing the minimum inputs required to produce the output they choose to produce, given the technology at their disposal. These firms are described as being technically inefficient.¹

### 6.1.1. The Measurement of Efficiency

Measurement of efficiency is based on the idea of comparing the actual firm performance with that obtained in a hypothetical situation of profit maximization. However, this is not possible as the researcher has a lack of information about the sector or some technological restrictions that could exist within the firm. Then, what is usually done is to compare the firm’s performance with that of other similar firms belonging to the same sector or industry. This is, precisely, the original idea of the seminal paper by Farrell.² His main contribution was to empirically provide a standard reference with which compares the firms’ efficiency: the frontier. Thus efficiency measures are defined in relative terms, that is, in relation with the best firm in the sector, which defines such a frontier. His method also allowed to distinguish between technical efficiency and allocative efficiency, which is his second main contribution. These two measures can be combined to provide a measure of total economic efficiency.³ According to him technical inefficiency arises when less than maximum output is obtained from a given bundle of factors thus, technical efficiency is defined as the ratio of actual output to the maximum output attainable (often called a frontier) with the given amount of inputs. Allocative inefficiency arises when factors are used in proportions which do not lead to profit maximization.

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6.1.2. Meaning and Definition

Although the importance of efficient use of resources has long been recognized, the mainstream neoclassical paradigm in economics assumes that producers in an economy always operate efficiently. In reality, however, the producers are not always efficient. Two otherwise identical firms never produce the same output, and costs and profit are not the same. This difference in output, cost, and profit can be explained in terms of technical and allocative inefficiencies, and some unforeseen exogenous shocks. Given the resources (inputs), a producer is said to be technically inefficient if it fails to produce the maximum possible output. Similarly, a cost or profit maximizing producer is allocatively inefficient if it fails to allocate the inputs optimally, given input and output prices. Both inefficiencies are costly in the sense that cost (profit) is increased (decreased) due to these inefficiencies. Costs of these inefficiencies are also reflected in lower productivity of inputs. Alternatively, productivity growth will be lower in the presence of any one, or both, of these inefficiencies.4

Koopmans5 defines technical/productive efficiency as a feasible input output vector where it is technically impossible to increase any output (or reduce any input) without simultaneously reducing another output (or increasing another input).

A production frontier describes the technical relationship between the input and output of a production process. It defines the maximum outputs attainable from a given set of inputs. The word “frontier” emphasizes the idea of maximality and represents the “best practice” approach to production. Hence, it reflects the current state of technology in the industry. Firms (or, mines in our case) in that industry operate either on the frontier if they are technically efficient or beneath the frontier if they are technically inefficient.6

6.2. Efficiency and Frontier Production Functions

According to Farrell\(^7\) technical/productive efficiency has two components. The purely technical or physical component refers to the ability to avoid waste through output augmentation with a given set of inputs and/or input conservation for a given amount of output. The other component is allocative efficiency, which refers to the ability to combine inputs and outputs in optimal proportions at their prevalent prices, under a behavioral assumption for the decision-making unit, e.g. cost minimization or revenue maximization.

Farrell\(^8\) distinguishes between technical and allocative efficiency (or price efficiency) in production through the use of a "frontier" production function. Technical efficiency is the ability to produce a given level output with a minimum quantity of inputs under certain technology. Allocative efficiency refers to the ability of choosing optimal input levels for given factor prices. Economic or total efficiency is the product of technical and allocative efficiency.\(^9\)

Farrell\(^10\) used the example of a firm employing two factors of production (\(x_1\) and \(x_2\)) to produce a single product (\(y\)) under conditions of constant returns to scale. Knowledge of the unit isoquant SS’ representing the various combinations of the factors that a perfectly efficient firm might use to produce output permits the measurement of technical efficiency. In the Figure 6.1., the point P represents the inputs of the two factors, per unit of output, that the firm is observed to use. The point Q represents an efficient firm producing the same output as P but using only a fraction OQ/OP as much of each factor. The technical efficiency of the firm P is thus defined to be the ratio OQ/OP, which is the proportional reduction in all inputs that could be theoretically achieved without any reduction in output.

\(^9\) Xiaosong Xu and S.R. Jeffrey (1995) “Efficiency and Technical Progress in Traditional and Modern Agriculture: Evidence from Rice Production in China”, Staff Paper 95-02, Department of Rural Economy Faculty of Agriculture, Forestry, and Home Economics University of Alberta, Edmonton, Canada
When measuring the efficiency, the researcher must choose a direction, that is, the way to arrive to the frontier. As all firms located in the frontier are technically efficient, the problem lies in the selection of the reference firm. In this context, there exist two main ways to measure efficiency. The first one is output oriented and consists of choosing as the reference the efficient firm that uses the same amount of inputs that firm under study, while the second one is input oriented and consists of choosing as the reference the efficient firm that produces the same output level than the firm under study.

6.3. Reviews on Frontier Methodologies

6.3.1. Development of Methodologies on Frontier Functions

Farrell’s original work has given rise to a host of related models known collectively as frontier methodology. Earlier studies on technical efficiency were based on the deterministic frontier model suggested by Aigner and Chu, but this model cannot account for the random factors that may move production off the frontier. Subsequently, various stochastic production frontier models were introduced to take these factors into account.

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Farrel’s\textsuperscript{14} definition of technical efficiency led to the development of methods for estimating the relative technical efficiency of farmers. The common feature of these estimation techniques is that information is extracted from extreme observations from a body of data to determine the best practice production frontier.\textsuperscript{15} From this, the relative measure of technical efficiency for the individual farmer can be derived. Despite this similarity, the approaches for estimating technical efficiency can be generally categorized under the distinctly opposing techniques of parametric and non-parametric methods.\textsuperscript{16}

Empirical studies using frontier production function methodology to measure productive efficiency can be differentiated on the basis of two criteria. The first of these relates to the use of parametric methods versus non-parametric methods. Parametric methods involve specification of a particular functional form, while non-parametric methods do not have this requirement. Production efficiency studies may also be differentiated on the basis of whether they utilize deterministic or stochastic methods (i.e., the second criterion). Deterministic methods assume that all deviations from the frontier function result from inefficiency. Stochastic methods allow for some deviation to be attributable to statistical noise.

The vast majority of empirical studies have utilized parametric approaches for measuring production efficiency. Battese\textsuperscript{17} provides a review of parametric efficiency models, both deterministic and stochastic. Deterministic frontier functions can be estimated by using two alternative approaches namely, programming models and statistical models (i.e., econometric analysis).

Stochastic frontier functions are estimated through the use of statistical models. Both deterministic and stochastic modelling approaches have received widespread use in the analysis of production efficiency for developing countries.

Given the alternative empirical tools available, the choice as to the "best" method is unclear. Little rigorous analysis has been done in assessing the sensitivity of efficiency measures to the choice of methodology. Bravo-Ureta and Rieger\textsuperscript{18} compare the results of deterministic (both programming and econometric analyses) and stochastic parametric efficiency models for a sample of the U.S. dairy farms. While the estimates from each approach differ quantitatively, the ordinal efficiency rankings of farms obtained from the different models appear to be quite similar. This would suggest that, to a certain degree, the choice between deterministic and stochastic methods is somewhat arbitrary.\textsuperscript{19}

\textbf{6.3.2. Review and Frontier Function Methodology}

Ureta and Pinheiro\textsuperscript{20} pointed out that with the many number of frontier models that have been developed based on Farrell’s work, it can be further classified into two basic types viz., parametric and nonparametric.

Parametric frontiers rely on a specific functional form while non-parametric frontiers do not. Another important distinction is between deterministic and stochastic frontiers. The deterministic model assumes that any deviation from the frontier is due to inefficiency, while the stochastic approach allows for statistical noise.\textsuperscript{21}

\textbf{6.3.2.1. Deterministic Frontiers}

The deterministic parametric approach was initiated by Aigner and Chu\textsuperscript{22} who estimated a Cobb-Douglas production frontier through linear and quadratic programming techniques. This procedure was further developed by Timmer\textsuperscript{23} who introduced the probabilistic frontier production model. Timmer estimated a series of


\textsuperscript{19} Xiaosong Xu and S.R. Jeffrey (1995) “Efficiency and Technical Progress in Traditional and Modern Agriculture: Evidence from Rice Production in China”, \textit{Staff Paper 95-02}, Department of Rural Economy Faculty of Agriculture, Forestry, and Home Economics University of Alberta, Edmonton, Canada


frontier production functions dropping at each stage the extreme observations. This process continues until the rate of change of the parameter estimates stabilizes. All these deterministic programming approaches yield estimators with undefined statistical properties.²⁴

Another class of deterministic parametric models is the statistical production frontier proposed by Afriat²⁵ in which technical efficiency is measured by a one-sided disturbance term. When explicit assumptions for the distribution of the disturbance term are introduced, the frontier is estimated by the maximum likelihood method. If no assumption is made concerning the distribution of the error term, the frontier can be estimated by the Corrected Ordinary Least Squares method (COLS) which consists of neutrally (i.e., the intercept only) shifting the frontier upwards until no positive error term remains.

6.3.2.2. Stochastic Frontiers

The stochastic frontier production model incorporates a composed error structure with a two sided symmetric and a one-sided component²⁶ and Meeusen and van den Broeck.²⁷ The one sided component reflects inefficiency, while the two-sided error captures the random effects outside the control of the production unit including measurement errors and other statistical noise typical of empirical relationships.

The estimation of a stochastic frontier function can be accomplished in two ways. First, if no explicit distribution for the efficiency component is made, then the production frontier can be estimated by a stochastic version of COLS. On the other hand, if an explicit distribution is assumed, such as exponential, half-normal or gamma, then the frontier is estimated by maximum likelihood methods.²⁸ According to Greene,²⁹ the Maximum Likelihood Estimates (MLE) make use of the specific distributions of the disturbance term and, thus, are more efficient than COLS. The

initial inability of calculating individual firm efficiency measures from the stochastic frontier model was overcome by the work of Jondrow et al.\textsuperscript{30}

6.3.3. Reviews of Frontier Function Studies in Developing Countries

Most of the available literatures on frontier function studies are confined to the measurement of technical efficiency in agriculture related production in the developing countries. In this regard, production efficiency studies can be differentiated on the basis of whether they utilize deterministic or stochastic methods. Ureta and Pinheiro\textsuperscript{31} classified the studies adopting frontier function analysis in the developing countries based on the methodology they used, into two major groups viz., Deterministic Production Frontiers; and Stochastic Production Frontiers. Deterministic methods assume that all deviations from the frontier function result from inefficiency. Stochastic methods allow for some deviation to be attributable to statistical noise.\textsuperscript{32}

Further, Ureta and Pinheiro\textsuperscript{33} sub-divided the studies adopting the deterministic models into a) parametric and b) non-parametric frontiers and the stochastic models into a) cross-sectional, b) panel data, and c) dual frontiers. Parametric methods involve specification of a particular functional form, while nonparametric methods do not have this requirement. All stochastic frontiers are basically of parametric type.\textsuperscript{34} A review of such studies has been made in the current study and presented as under.


6.3.3.1. Deterministic Production Frontiers

6.3.3.1.1. Parametric Frontiers

Shapiro and Muller\textsuperscript{35} measured technical efficiency through a deterministic Cobb-Douglas production frontier obtained by linear programming in the study to analyze the role of information and modernization in the production process of 40 cotton farms in Tanzania. Using correlation analysis, they found that technical efficiency had a high positive association with both general modernization and information.

Shapiro\textsuperscript{36} investigated technical efficiency for a sample of 37 Tanzanian cotton farmers. A Cobb-Douglas production frontier, derived by linear programming, yielded a technical efficiency of 66%.

Belbase and Grabowski\textsuperscript{37} used the COLS procedure to estimate a deterministic Cobb-Douglas production frontier model to investigate efficiency in Nepalese agriculture. A model where the dependent variable was the total value of rice, maize, millet and wheat production yielded an average technical efficiency level of 80 per cent. Separate frontiers were estimated for rice and maize which revealed average efficiency levels of 84 per cent and 67 per cent, respectively. Based on the efficiency measures obtained from the equation for all crops, correlation analysis showed that nutritional levels, income, and education were significantly related to technical efficiency, while no relationship was found for farming experience. The study suggested that technical efficiency gains could be attained through extension and education, and that the introduction of new technologies has been a key element in raising productivity in Nepalese agriculture.

Taylor \textit{et al}\textsuperscript{38} formulated a Cobb-Douglas deterministic frontier production function to analyze the impact of a World Bank sponsored credit program

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(PRODEMATA) on allocative and technical efficiencies for sample Brazilian farmers. The production frontier was estimated using both COLS and maximum likelihood (statistical frontier) assuming that, in the latter case, the non-negative farm effects had a gamma distribution. Estimates of technical efficiency for farms participating in the credit program versus non-participants revealed no major differences between the two groups. Moreover, participants exhibited allocative efficiencies slightly lower than the rest. Hence, these results imply that this credit program was not successful in improving farm level efficiency.

Chandra Reddy\textsuperscript{39} while studying the efficiency of silk cocoon production in Karnataka state of India, using the frontier production function found that a large (>82 per cent) number of sample farmers obtained at least 91 per cent of the potential output. He also examined the farmers’ category-wise input use efficiency using the Kopp measure. The quantum of excess use of inputs was comparatively higher (58.11 per cent to 60.34 per cent) on large farms than that of small counterparts (42 to 44 per cent).

Jayaram \textit{et al.}\textsuperscript{40} studied the technical efficiency in rice cultivation in Mandya district of Karnataka state in India. The results of the frontier function analysis revealed that high level of output efficiency was observed on both small (97.54 per cent) and large (97.60 per cent) sample farms. In contrast, the input use was highly inefficient. The efficiency indices obtained through the Kopp measure indicated that a majority (72 per cent) of small farms operated at an efficiency level of >75 per cent and about 46 per cent of large farms used inputs at the rate of 86 per cent and above efficiency level. Further, the actual and frontier use of input showed that all the factors were used more than frontier usage by both the category of sample farmers.

Ali and Chaudry\textsuperscript{41} examined the technical, allocative and economic efficiency for a sample of 220 farmers located in four districts of Punjab state in Pakistan.

\textsuperscript{39} Chandra Reddy, T. (1987) “Impact of Sericulture industry on income and employment in rural areas of Chittor district, Andhra Pradesh”. An Unpublished Ph.D. Thesis Submitted at University of Agricultural Sciences, Bangalore, India


Separate Cobb-Douglas probabilistic production frontiers were estimated for each district. The average technical efficiency, economic efficiency and allocative efficiency measures reported were 84 per cent, 51 per cent and 61 per cent respectively. It was found that technical inefficiency resulted in 40 per cent to 50 per cent loss in farm profits, while the loss in profits due to allocative inefficiency was only around 2 per cent.

While evaluating the technical efficiency of the subsidized credit for poverty alleviation in Anantapur district of Andhra Pradesh, Prasad et al. estimated the income relation with the credit using a frontier production functions through COLS estimates. The levels of output efficiency in relation to the maximum realizable potential averaged 35 per cent and 49 per cent under CADA and DPAP beneficiaries respectively, which contributed to the high levels of default in repayment. Hence, the low rate of repayment of loans coupled with the high incidence of technical inefficiency points to the lack of commercial viability of the projects in the area.

Panda evaluated the farm specific technical efficiency of sericulture farmers in Tamil Nadu, India, using a frontier production function. The COLS estimates revealed that the overall technical efficiency and allocative efficiency of sericulture enterprise, was to the extent of 86.28 per cent and 87.77 per cent respectively in Dharmapuri district and the same was 76.65 per cent and 74.99 per cent respectively in Dindigal Anna district.

6.3.3.1.2. Non Parametric Frontiers

Ray used a non parametric frontier methodology to farm data by applying a linear programming methodology to measure efficiency for a sample of 63 West Bengal farms in India. The efficiency measures were decomposed into output or technical efficiency and informational efficiency. The latter was defined as the ratio between optimal output given the existing technology and optimal output when

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additional technology information is available. The results revealed that although there was no significant difference in output efficiency across farm size groups, informational efficiency was very low for the small farms.

6.3.3.2. Stochastic Production Frontiers

6.3.3.2.1. Cross-Sectional Frontiers

Most of the efficiency studies conducted using stochastic methodology, have focused on Indian agriculture, a subject that has captured the attention of economists for a long time (Bhagwati and Chakravarty, and Ureta and Pinero).

Kalirajan is considered to be the first author to study the technical efficiency using stochastic frontier function for Indian data. The technical efficiency in paddy production in Tamil Nadu was studied using maximum likelihood method. A second step analysis showed that management practices and contacts with local extension agents had a significant positive impact on technical efficiency.

Kalirajan and Flinn estimated a translog stochastic production frontier by maximum likelihood to measure technical efficiency for a sample of 79 farmers in the Philippines. Several farm specific biological and socio-economic variables were regressed against technical efficiency scores. The results indicated that crop establishment by transplanting rice seedlings, fertilizer application, years of farming and extension contacts had a significant influence on the level of technical efficiency among sample farmers.

Huang and Bagi examined the technical efficiency of a sample of 151 farms in the Punjab and Haryana states of India based on a translog production frontier estimated through maximum likelihood. The study showed an average efficiency level close to 90 per cent, while the performance of small vis-a-vis large farms was almost equal.

Kalirajan\textsuperscript{50} studied how the efficient use of new technology affected production levels in 81 Philippine rice farmers, using a translog stochastic production frontier. The results revealed a wide variation in technical efficiencies across farms ranging from 42 per cent to 91 per cent, with only 30 per cent of the farmers operating close to the frontier. The results of a second step model showed that the number of farm visits by extension agents was significant in explaining the wide variation in the observed levels of technical efficiency.

Rawlins\textsuperscript{51} studied the effects of the Jamaican Second Integrated Rural Development Project (IRDPII) on the level of technical efficiency of sample farmers. The evaluation was based on the data obtained from 80 farmers participating in the IRDPII and 72 non-participants. A Cobb-Douglas stochastic production frontier was estimated for each of these two groups. The results revealed that there was relatively less variation of the frontier across IRDPII farms. However, technical efficiency for the non-participants (75 per cent) was higher than that of the participants (71 per cent). The program succeeded in shifting outward the production frontier of the participant farmers.

Kalirajan and Shand\textsuperscript{52} estimated a Cobb-Douglas production frontier by maximum likelihood for a random sample of 91 paddy farmers from the Coimbatore district in Tamil Nadu state of India. In a second step analysis, in which farm level technical efficiency was the dependent variable, they found that the level of schooling was not statistically significant in explaining differences between maximum and actual yields. However, the farmers’ non-formal education, defined as their understanding of current technology, had a significant positive role on productivity.

Phillips and Marble\textsuperscript{53} examined the influence of education on technical efficiency for Guatemala maize producers. In the analysis, a Cobb-Douglas stochastic production frontier was fitted via COLS. The analysis revealed that education, measured either in terms of literacy or years of schooling, had a positive but

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statistically insignificant effect on productivity. The authors concluded that four or more years of formal education were required before increases in productivity could be observed.

Taylor and Shonkwiler\textsuperscript{54} used both deterministic and stochastic frontiers assuming a Cobb-Douglas production model. The frontier parameters were estimated by maximum likelihood methods, assuming a gamma distribution for the former and a half normal for the latter. The results showed that for groups, participants and non-participants, the average technical efficiency estimates for the stochastic frontier (71 per cent and 70 per cent respectively) were much higher than those obtained from the deterministic frontier specification (17 per cent and 5.9 per cent respectively).

Ekanayake\textsuperscript{55} examined efficiency for a sample of 123 Sri Lankan rice farmers. The sample was divided into head and tail, according to whether the farm had good (head) or poor (tail) water access. Separate stochastic Cobb-Douglas production frontiers were estimated for each group through maximum likelihood. The results suggested that there was no significant technical inefficiency for farmers with better water access (head). However, for the poorly situated group (tail) there was significant technical inefficiency (50 per cent). In a second step analysis, Ekanayake found that literacy, experience and credit availability had significant positive impact on the technical efficiency level of the tail farmers.

Ekanayake and Jayasurya\textsuperscript{56} using the same data set as Ekanayake, compared the effects of estimating technical efficiency using a stochastic frontier versus a deterministic COLS model. The authors found that, for the ‘head’ farmers, COLS yielded an average technical efficiency of 53 per cent while the stochastic method gave an average of 100 per cent. By contrast, both procedures revealed a 50 per cent mean technical efficiency level for the ‘tail’ farmers.

Kalirajan\textsuperscript{57} set out to obtain consistent and efficient estimates of economic efficiency (EE), firm specific technical efficiency (TE) and input specific allocative efficiency (AE) for a sample of 103 Philippine rice farmers using a translog stochastic production frontier. The mean technical efficiency was estimated to be 79 per cent. Input specific AE indicated that farmers were inefficient with respect to all inputs. The results of a second step analysis, based on maximum likelihood methods, showed that non-farm income and method of crop establishment were the major factors affecting technical efficiency.

Squires and Tabor\textsuperscript{58} used a translog stochastic production frontier, estimated by maximum likelihood procedures, to measure crop-specific technical efficiency in Indonesian agriculture. The results suggest that technical efficiency (TE) estimates were higher for the production of irrigated rice compared to the other three crops. The mean TE estimates for Java rice, off-Java rice, cassava, peanuts, and mung beans were 69 per cent, 70 per cent, 57 per cent, 68 per cent and 55 per cent, respectively. A second step analysis showed that TE was not significantly related to farm size.

Pinheiro\textsuperscript{59} estimated a Cobb-Douglas total value product frontier to analyze economic efficiency (EE), technical efficiency (TE) and allocative efficiency (AE) for a sample of 60 peasant farmers located in the Dajabon region of the Dominican Republic. He found that the average EE, TE and AE for the sample were 31 per cent, 70 per cent and 44 per cent, respectively. In a second step analysis, it was found that education and experience of the farmer had a positive impact on TE. It was also found that contract farming, being an agrarian reform beneficiary, and farm size were positively associated with EE and AE, while household size exhibited a negative impact on both of these measures of performance.

Kalirajan and Shand\textsuperscript{60} using a stochastic frontier function demonstrated the method of decomposition of risks into allocative risk and technical risk and empirically measured the influence of technical and allocative risks on production, separately. The method was applied to a sample of farmers using high-yielding variety of cotton in Tamil Nadu. It was found that the farmers had not achieved their potential output on their frontiers. Their mean economic efficiency with technical and allocative risks was 68.3 per cent. The study suggested that the elimination of both these risks with better information on the best practices and market conditions has the potential of substantially raising the output in production.

Kehar Singh\textsuperscript{61} used the stochastic frontier function model to estimate the farm level TE and AE of the farmers in fish production in South Tripura district of Tripura state in India during the year 2004-05. The estimated mean TE, AE and EE were found to be lying in the range of 0.65 – 0.71, 0.51 – 0.61 and 0.35 – 0.45, respectively. The TE appeared to be more significant than AE as a source of gains in EE. The results also proved that the expansion in the use of any resource by the fish farmers would bring more than proportionate increase in their output, given the value of increasing returns to scale, obtained in production.

Employing the stochastic frontier function, Bekele et al.,\textsuperscript{62} studied the effect of farm size on efficiency of wheat production in Moretna–Jirru district in Central Ethiopia. The results revealed that the large farmers were technically more efficient than small farmers. The technical efficiencies of large farms ranged from 0.70 per cent to 0.97 per cent, while for the small farms the technical efficiency was found to range from 0.63 per cent to 0.94 per cent.

6.3.3.2.2. Panel Data Frontiers

The emerging and promising area in efficiency analysis concerns the use of panel data.\textsuperscript{63} Few of the studies which have relied on agricultural panel data to estimate stochastic frontier functions for developing countries are discussed as under:


Using the Cobb-Douglas functional form, Battese et al.\textsuperscript{64} estimated a production frontier for a sample of farmers from Aurepalle village in Andhra Pradesh state, India. The sample consisted of 289 observations encompassing 38 farm households that provided data for at least one year over the period 1975–76 to 1984-85. The analysis revealed TE measures ranging from 66.2 per cent to 91.4 per cent with a mean of 83.7 per cent.

Dawson et al.\textsuperscript{65} estimated a Cobb-Douglas stochastic production frontier by maximum likelihood procedure, using panel data for a sample of 22 rice farmers for the years 1970, 1974, 1979, 1982 and 1984 from Central Luzon in the Philippines. They assumed technical efficiency to be invariant over time. The results revealed a fairly narrow range of technical efficiency going from 84 per cent to 95 per cent with a mean of 89.3 per cent. It was however concluded that, given the relatively high efficiency levels obtained with the frontier approach, there was little room for increasing output by better use of existing resources and that future gains in rice output would have to come from additional technological progress in the study area.

Fan\textsuperscript{66} decomposed output growth in Chinese agriculture into increases in inputs, technological change, and institutional reform by assuming that improvements in technical efficiency over time are a reflection of the institutional reforms enacted in Chinese agriculture over the period of analysis. The results showed that, for the whole country, the total growth in agricultural production from 1965 to 1985 was 5.04 per cent per year. About 63 per cent of the growth in total factor productivity was found to stem from improvements in technical efficiency with the remaining 37 per cent from technological change.

Kalirajan\textsuperscript{67} used panel data for the period 1983–86 for a sample of 30 Indian rice farmers from Coimbatore district to estimate, via maximum likelihood, a translog stochastic production frontier. The analysis revealed the technical efficiency across the sample farms ranged from 53 per cent to 95 per cent with a mean of 69.3 per cent.


\textsuperscript{66} Fan, S. (1991) “Effects of Technological Change and Institutional Reform on Production Growth in Chinese Agriculture”, \textit{American Journal of Agricultural Economics}, Vol. 73, pp.266-75

Additional analyses showed that TE measures for a given firm did not change significantly over time. The results of a second step analysis indicated that access to extension services and confidence in the technology (technical advice) were the major determinants of technical efficiency at the farm level.

Battese and Coelli\textsuperscript{68} introduced a stochastic production frontier model which permits individual firm level efficiency to vary over time while allowing the data set to be unbalanced. Five alternative Cobb-Douglas models were estimated and various tests supported the notion that individual firm technical efficiency levels were time variant. The results showed that farm level TE ranged from 67.6 per cent to 88.6 per cent in 1975–76, and from 88.8 per cent to 96.2 per cent in 1984-85.

Battese and Tessema\textsuperscript{69} estimated the maximum likelihood, Cobb-Douglas stochastic production frontiers based on unbalanced panel data from a random sample of three Indian villages for the years 1975–76 to 1984-85. In this study, statistical tests were performed to discriminate between models in which both input elasticities and technical inefficiency were allowed to vary over time from time-invariant models. The hypothesis that the input elasticities were time-invariant was rejected for two of the three villages. The results also indicated that inefficiency was significant in two of the villages, and that in one case; inefficiency was significantly different over time while in the other it was time-invariant.

Rajashekar and Krishnamoorthy\textsuperscript{70} employed the unbalanced panel data while employing the stochastic frontier production function for studying the TE of natural rubber production in Kerala state of India. The farm specific technical efficiencies estimated were time invariant and it ranged from 0.546 to 0.957 with a mean technical efficiency of 0.820. Variations in the technical efficiencies of the estates between the two agro-climatic regions were not significant while they were between private and public sector estates.


\textsuperscript{69} Battese, G.E., and G.A. Tessema (1992) “Estimation of Stochastic Frontier Production Functions with Time-Varying Parameters and Technical Efficiencies Using Panel Data from Indian Villages” Revised Version of Paper Presented at the 36th Annual Conference of the Australian Agricultural Economics Society at the Australian National University, Canberra, Australia

In another study using the unbalanced panel data of 234 rice farms in Tamil Nadu state of India, Mythili and Shanmugam\textsuperscript{71} attempted to measure the farm level technical inefficiency in rice production by employing the stochastic frontier production technique. The technical efficiency ranged from 46.5 per cent to 96.7 per cent across the sample farms. The mean technical efficiency computed was 82 per cent which indicated that on an average, the realized output can be increased by 18 per cent without any additional resources.

6.3.3.2.3. Dual Frontiers

Similar to the panel data frontiers, dual based frontier methodologies are also relatively recent.\textsuperscript{72} Very few studies confining the dual frontier methodologies are studied as under:

Ali and Flinn\textsuperscript{73} used a single equation dual profit frontier model to examine farm-specific profit efficiency. A translog stochastic profit frontier was estimated via maximum likelihood for a random sample of 120 rice producers from Pakistan. The range of profit inefficiency was found to be from a low of 5 per cent to a high of 87 per cent with a mean of 31 per cent. In other words, the average farmer realized 31 per cent less in profits than what would be possible, given efficient resource use. In a second step model, where loss of profit was regressed on several household characteristics, which was found that, education had a significant role in reducing profit inefficiency. In addition, farmers reporting off-farm employment and difficulties in securing credit to purchase fertilizer exhibited higher levels of profit inefficiency.

The study by Bailey et al.,\textsuperscript{74} who analyzed the technical, allocative and size inefficiency for a sample of 68 Ecuadorian dairy farms, indicated the size inefficiency occurs when a firm fails to produce at the point where marginal cost equals output price. The analysis was accomplished by estimating a system of equations consisting

of the production frontier and the first order conditions for profit maximization assuming a Cobb-Douglas technology. The results indicated that the average loss in profits due to technical inefficiency ranged from 24.4 per cent for small farms to 22.7 per cent for the large operations. The average increase in cost due to allocative inefficiency ranged from 8.4% for small farms to 5.6 per cent for large farms. Size inefficiency measures revealed that in most cases milk price exceeded marginal cost, implying that the production level was less than optimal. The average loss in profits due to size inefficiency goes from 12.8 per cent for small farms to 11.8 per cent for large farms.

6.3.3.3. Use of combination of estimation procedures

The study conducted by Jaforullah and Premachandra\(^75\) set out to compare the empirical performance of three popular approaches to estimation of technical efficiency in production: Corrected Ordinary Least Squares regression (COLS), Stochastic Production Frontier (SPF) and Data Envelopment Analysis (DEA). The comparison focused on measuring the technical efficiency of dairy farms in New Zealand under two scale assumptions: Constant Returns to Scale (CRTS) and Variable Returns to Scale (VRTS). It was found that under the assumption of constant returns to scale, the mean TE of the industry varied from 57.3 per cent to 85.3 per cent while under the assumption of variable returns to scale it varied from 56.9 per cent to 86.9 per cent. The general findings from this study indicated the estimates of technical efficiencies of individual dairy farms, and therefore the mean technical efficiency of the New Zealand dairy industry, are sensitive to the choice of production frontier estimation method. Of the three models considered for the dairy industry, the statistical deterministic frontier, i.e., COLS produced the lowest mean technical efficiency while the SPF produces the highest mean TE in general.

6.4. Methodological Framework

Farrell’s original work has given rise to a host of related models known collectively as frontier methodology. The frontier methodologies propounded by Timmer\(^76\) and Kopp\(^77\) are the most sought ones in the earlier studies on technical efficiency.


To elucidate further, consider the case of a firm that produces an output $Y$ using one input $X$ according to the production function $Y = f(X)$. Figure 6.b, is a graphical representation of the production function. Line OF is the production frontier that defines the relationship between input and output. It is the maximum output attainable for each level of input. Hence it reflects the current state of technology in the industry. Firms in the industry operate on the frontier if they are technically/productive efficient or beneath the frontier if they are technically inefficient. Point P represents an inefficient point whereas Q and R represent efficient points. A firm operating at point P is inefficient because technically it could increase its output to the level associated with point Q without employing additional input. Alternatively, it could produce at point R on the frontier and attain the same level of output while using less input. Thus, a producer is technically efficient if, and only if, it is impossible to produce more of any output (in the case of multiple outputs) without producing less of some other output or using more of some input.78

![Figure 6.b: Measuring Input and Output efficiency](image)

Source: Subhash C. Sharma and Manoj K. Mohanty79

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6.4.1. Measurement of Technical Efficiency

As all firms located in the frontier are technically efficient, the problem lies in the selection of the reference firm. In this context, there exist two main ways to measure efficiency.

The first one is output oriented as given by Timmer\textsuperscript{80} which consists of choosing as the reference the efficient firm that uses the same amount of inputs that firm under study. In the Figure, the efficient firm is Q and output oriented technical efficiency is given by:

\[ TE_o = \frac{Y_P}{Y_Q} \quad \text{..... (6.1)} \]

The second one is input oriented (Kopp, 1981) and consists of choosing as the reference the efficient firm that produces the same output level than the firm under study. In Figure 6.b, the efficient firm is R and the input oriented technical efficiency can be expressed as follows:

\[ TE_i = \frac{X_R}{X_P} \quad \text{..... (6.2)} \]

Both measures provide the same results under the hypothesis of constant returns to scale.\textsuperscript{81}

Both the deterministic and stochastic frontier functions were adopted in the present study to ascertain the technical efficiency in silk cocoon production in the study area.

The main source of data for the current study is drawn from 240 sample farmers which included 104 bivoltine (CSR) hybrid silkworm rearers and 136 crossbreed silkworm rearers, after post classification. The sample was drawn using a multistage random sampling technique and the data collection was done during the agriculture year 2007-08. The details about the sampling methodology have been discussed in Chapter III.


6.4.2. Measurement of Technical Efficiency using Deterministic Production Frontier Functions

6.4.2.1. The Timmer Measure of Output Technical Efficiency

The idea of the production function which is built around the concept of efficiency adduced by Farrell\textsuperscript{82} and later modified by Timmer\textsuperscript{83} in number of ways. He imposed a Cobb – Douglas type specification on the frontier and computed an output based measure of efficiency. The approach adopted here is to specify a fixed parameter frontier amenable to statistical analysis. This takes the general form:

\[ Y = f(X) e^\mu \]
\[
\mu \leq 0
\]

and the Cobb – Douglas form would be

\[ \ln Y = a + \sum_{j=1}^{n} b_j \ln X_j + e \]

The production frontier in equation (6.4) is deterministic because it includes a one-sided non-negative error term e, which is assumed to be independently and identically distributed and has a non-negative mean and constant variance. There are problems in using Ordinary Least Squares (OLS) to estimate this production frontier.

In estimating the above equation, Corrected Ordinary Least Squares (COLS) regression is chosen as the most convenient means. As a first step under this procedure, the Ordinary Least Square (OLS) is applied to the above equation, yielding the Best Linear Unbiased Estimates (BLUE) of bj coefficients. The intercept estimate is then corrected by shifting the function until no residual is positive and one is zero. This is done by adding the largest error term of the fitted model to the intercept.

According to Greene\textsuperscript{84}, while OLS provides the best linear unbiased estimates of the slope parameters and appropriately computed standard errors, it does not provide an unbiased estimate of the intercept parameter ‘a’. The OLS estimator of ‘a’ is biased downward. Due to this problem, it is possible for the estimated OLS

residuals of the model to have the incorrect signs. Since the calculation of technical efficiency relies on these residuals being non-positive, he suggests a correction for this biasedness by shifting, the OLS estimator of ‘a’, upward by the largest positive OLS residual (e*). This correction makes all the OLS residuals non-positive, implying that the estimates of ε_i are non-negative and none of the farms is more than 100 per cent efficient.

The Timmer measure of technical efficiency of a farm is the ratio of the actual output to the potential output, given the level of input use on farm ‘i’. It thus indicates how much extra output could be obtained if farm ‘i’ were on the frontier.

\[
\text{Timmer measure of technical efficiency} = \frac{Y}{Y^*} \leq 1 \quad \ldots (6.5)
\]

Where \(Y^*\) is the maximum value of output obtainable for given levels of the inputs.

6.4.2.2. The Kopp Measure of Input Technical Efficiency

Kopp suggests a different approach within the Farrell frame work. This involves the econometric estimation of a parametric frontier function, followed by the algebraic identification of the efficiency standard for each data point.

The Kopp measure of technical efficiency compares the actual level of input use to the level which would be used if farm ‘i’ was located on the frontier, given the actual output of farm ‘i’ and given the same ratios of input usage.

If, \(\ln Y = a + b_1 \ln X_1 + b_2 \ln X_2 + \ldots + b_n \ln X_n + e \quad \ldots (6.6)\)

Let \(R_1 = \frac{X_1}{X_2}, R_2 = \frac{X_3}{X_2}, \ldots, R_3 = \frac{X_n}{X_2} \quad \ldots (6.7)\)

And \(X_1^*, X_2^*, \ldots, X_n^*\) denotes the optimum use of inputs.

Then, \(\ln X_2^* = \left( \ln Y - a^* - b_1 \ln R_1 - b_2 \ln R_2 - \ldots - b_n \ln R_n \right) / \sum b_i \quad \ldots (6.8)\)

\(\ln X_1^*, \ln X_3^*, \ldots, \ln X_n^*\) are calculated in a similar fashion. Then we may compute;

\[
\text{TE}_i = \frac{X_2^*}{X_2} = \frac{X_1^*}{X_1} = \frac{X_3^*}{X_3} = \ldots = \frac{X_n^*}{X_n} \quad \ldots (6.9)
\]

The frontier usage of inputs is compared with the actual usage of inputs by the respondent farmers.
6.4.2.3. Specification of the Models Used in the Current Study

The frontier production functions were estimated in the present analysis by using a Cobb-Douglas type of production function, adopting the method of Corrected Ordinary Least Squares (COLS).

The Cobb-Douglas function has been the most commonly used function in the specification and estimation of production frontiers in empirical studies. It is attractive due to its simplicity and because of the logarithmic nature of the production function that makes econometric estimation of the parameters a very simple matter. It is true, as Yin\textsuperscript{85} points out, that this function may be criticized for its restrictive assumptions such as unitary elasticity of substitution and constant returns to scale and input elasticities, but alternatives such as translog production functions also have their own limitations such as being susceptible to multicollinearity and degrees of freedom problems. A study done by Kopp and Smith\textsuperscript{86} suggests that functional specification has only a small impact on measured efficiency.

The model used in the present analysis of both the deterministic models of frontier functions\textsuperscript{87,88} is as follows:

\[ Y = f (X_1, X_2, X_3, X_4, X_5, X_6) \quad \ldots \quad (6.10) \]

Where,

- \( Y \) = Silk Cocoon Production (Kg/acre/year)
- \( X_1 \) = Farmyard Manure (Rs./acre/year)
- \( X_2 \) = Chemical Fertilisers (Rs./acre/year)
- \( X_3 \) = Human Labour (Mandays/acre/year)
- \( X_4 \) = Depreciation Cost (Rs./acre/year)
- \( X_5 \) = No of Disease Free Layings (DFLs/acre/year)
- \( X_6 \) = Disinfectants (Rs./acre/year)

The source of data on these inputs is discussed in the Chapter IV. Two models are separately fitted for the type of the silk worm reaper, i.e. crossbreed silkworm reaper and bivoltine (CSR) hybrid silkworm reaper. The estimated frontier functions are presented in the Table 6.1.

6.4.2.4. Timmer and Kopp Measure of Technical Efficiency

It is seen that in the case of crossbreed silkworm rearers were in the region of constant returns to scale, as the sum of the regression coefficients were not significantly different from one. The regression coefficients for chemical fertilisers (at 5 per cent) and number of disease free layings brushed per acre (at 1 per cent) were found to be positive and significant. The percentage of variation in ‘Y’ has been explained up to 61 per cent by the variables included in the model.

In the case of Bivoltine (CSR) hybrid silkworm rearers, the sum of the regression coefficients were also found to be not significantly different from one, thus indicating these rearers too operated in the region of constant returns to scale. The variables such as farmyard manure (at 5 per cent), chemical fertilisers (at 1 per cent), human labour (at 5 per cent) and number of Disease Free Layings (at 1 per cent) were found to be positive and significant. The percentage of variation in ‘Y’ was explained up to 96 per cent through the coefficient of determination (adjusted R²) by the variables included in the model.

Table 6.1: Cobb-Douglas Production Functions for Crossbreed and Bivoltine (CSR) Hybrid Silkworm Rearers

<table>
<thead>
<tr>
<th>Sl. No.</th>
<th>Independent Variable</th>
<th>Crossbreed</th>
<th>Bivoltine (CSR) Hybrid</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>b&lt;sub&gt;i&lt;/sub&gt; t-value Significance level</td>
<td>b&lt;sub&gt;i&lt;/sub&gt; t-value Significance level</td>
</tr>
<tr>
<td>1</td>
<td>Intercept</td>
<td>0.109</td>
<td>-1.720</td>
</tr>
<tr>
<td>2</td>
<td>Farm Yard Manure (Rs./acre/year)</td>
<td>0.113</td>
<td>1.771 0.079 0.045 2.005 0.048</td>
</tr>
<tr>
<td>3</td>
<td>Chemical Fertilisers (Rs./acre/year)</td>
<td>0.177</td>
<td>2.330 0.022 0.154 5.887 0.000</td>
</tr>
<tr>
<td>4</td>
<td>Human Labour (Mandays/acre/year)</td>
<td>-0.134</td>
<td>-1.716 0.089 -0.079 -2.222 0.029</td>
</tr>
<tr>
<td>5</td>
<td>Depreciation Cost (Rs./acre/year)</td>
<td>-0.020</td>
<td>-0.623 0.535 0.015 1.431 0.156</td>
</tr>
<tr>
<td>6</td>
<td>No of Disease Free Layings (DFLs/acre/year)</td>
<td>0.806</td>
<td>9.369 0.000 0.997 24.715 0.000</td>
</tr>
<tr>
<td>7</td>
<td>Disinfectants (Rs./acre/year)</td>
<td>-0.086</td>
<td>-1.713 0.090 -0.010 -0.373 0.710</td>
</tr>
<tr>
<td>8</td>
<td>Sum bi</td>
<td>0.86</td>
<td>1.12</td>
</tr>
<tr>
<td>9</td>
<td>Adjusted R²</td>
<td>0.61</td>
<td>0.96</td>
</tr>
<tr>
<td>10</td>
<td>Highest error term</td>
<td>0.59</td>
<td>0.133</td>
</tr>
</tbody>
</table>
As a next step, based on the COLS estimates, the efficiency of production was measured in terms of the physical maximum attainable by each farmer, based on the Timmer’s measure of technical efficiency (Table 6.2) as well as input use technical efficiency based on Kopp’s measure of technical efficiency (Table 6.3).

The level of output technical efficiency was in general, higher in case of bivoltine (CSR) hybrid silkworm rearers with 87.67 per cent, while the same was 56.35 per cent in case of crossbreed silkworm rearers. Based on the decile classification the rate of participants who had efficiency at the rate of 40 – 50 per cent was about 16.18 per cent, and similarly the rate of efficiency was 50 – 60 per cent in case of 55.88 per cent, 60 – 70 per cent in case of 19.85 per cent and 70 – 80 per cent in case of only 1.47 per cent, among the cross breed silkworm rearers. Among the bivoltine (CSR) silkworm hybrid rearers, the rate of efficiency was in the range of 70 – 80 per cent in case of 2.88 per cent, while it was in the range of 80 – 90 per cent in case of 76.92 per cent and 90 – 100 per cent in case of 20.19 per cent of the farmers. The average output efficiency was highest among the bivoltine (CSR) hybrid silkworm rearers at 87.67 per cent followed by crossbreed silkworm rearers at the rate of 56.35 per cent ((Table 6.2).

<table>
<thead>
<tr>
<th>Output Technical Efficiency Rating (%)</th>
<th>Silkworm Rearer</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Crossbreed</td>
</tr>
<tr>
<td></td>
<td>No. of rearers</td>
</tr>
<tr>
<td>0-10</td>
<td>0</td>
</tr>
<tr>
<td>10-20</td>
<td>0</td>
</tr>
<tr>
<td>20-30</td>
<td>1</td>
</tr>
<tr>
<td>30-40</td>
<td>4</td>
</tr>
<tr>
<td>40-50</td>
<td>22</td>
</tr>
<tr>
<td>50-60</td>
<td>76</td>
</tr>
<tr>
<td>60-70</td>
<td>27</td>
</tr>
<tr>
<td>70-80</td>
<td>2</td>
</tr>
<tr>
<td>80-90</td>
<td>3</td>
</tr>
<tr>
<td>90-100</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td>136.00</td>
</tr>
<tr>
<td>Average rate of Technical Efficiency (%)</td>
<td>56.35</td>
</tr>
</tbody>
</table>
Similar to the Timmer’s measure of output technical efficiency, the Kopp’s measure of input technical efficiency was worked out for both the categories of crossbreed and bivoltine (CSR) hybrid rearers in the study area (Table 6.3). The average rate of input technical efficiency was highest at the rate of 88.93 per cent in case of bivoltine (CSR) hybrid rearers followed by 51.33 per cent in case of crossbreed rearers. Based on the decile classification, the proportion of the silkworm rearers under each classification was worked out. It was seen that in case of crossbreed silkworm rearers, rate of input efficiency was 30 – 40 per cent in case of 5.15 per cent farmers, 40 – 50 per cent in case of 37.50 per cent farmers, 50 – 60 per cent in case of 44.85 per cent farmers, 60 – 70 per cent in case of 6.62 per cent farmers and 70 – 80 per cent in case of only 2.21 per cent farmers. However, the rate of input technical efficiency among the bivoltine (CSR) hybrids was highest at the rate of 80 – 90 per cent among 71.15 per cent of the farmers followed by 90 – 100 per cent among 28.85 per cent of the farmers.

In the above analysis it is revealed that the bivoltine (CSR) hybrid silkworm rearers were highly efficient than the crossbreed silkworm rearers in terms of output production and input usage.

**Table 6.3: Kopp’s Input Technical Efficiency Rating (%) based on COLS estimates**

<table>
<thead>
<tr>
<th>Input Technical Efficiency Rating (%)</th>
<th>Silkworm Rearer</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Crossbreed</td>
<td>Bivoltine (CSR) Hybrid</td>
</tr>
<tr>
<td></td>
<td>No. of rearers</td>
<td>Percentage</td>
</tr>
<tr>
<td>0-10</td>
<td>0</td>
<td>0.00</td>
</tr>
<tr>
<td>10-20</td>
<td>0</td>
<td>0.00</td>
</tr>
<tr>
<td>20-30</td>
<td>2</td>
<td>1.47</td>
</tr>
<tr>
<td>30-40</td>
<td>7</td>
<td>5.15</td>
</tr>
<tr>
<td>40-50</td>
<td>51</td>
<td>37.50</td>
</tr>
<tr>
<td>50-60</td>
<td>61</td>
<td>44.85</td>
</tr>
<tr>
<td>60-70</td>
<td>9</td>
<td>6.62</td>
</tr>
<tr>
<td>70-80</td>
<td>3</td>
<td>2.21</td>
</tr>
<tr>
<td>80-90</td>
<td>2</td>
<td>1.47</td>
</tr>
<tr>
<td>90-100</td>
<td>1</td>
<td>0.74</td>
</tr>
<tr>
<td>Total</td>
<td>136</td>
<td>100.00</td>
</tr>
</tbody>
</table>

Average rate of Technical Efficiency (%)

<table>
<thead>
<tr>
<th>Crossbreed</th>
<th>51.33</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bivoltine (CSR) Hybrid</td>
<td>88.93</td>
</tr>
</tbody>
</table>
To ascertain the quantum of excess use of inputs in production was made based on the Kopp’s measure of input technical efficiency. It was found that there was an excess use of inputs included in the function (Table 6.4). In case cross breed silkworm rearers, the quantum of excess inputs used was to the extent of Rs. 2083.73 per acre per year of farmyard manure, Rs.1597.41 per acre per year of chemical fertilizer, 192 mandays of human labour, Rs. 3981.58 per acre per year of depreciation on equipments and buildings and 532 number of dfls per acre per year and Rs. 1348.95 per acre per year of disinfectants used in silk worm crop care. This evidences that the crossbreed silkworm rearers in the study area were highly inefficient in handling their resources, due to which the cost of production tended to be high, making the profit margins very marginal.

In case bivoltine silkworm rearers, the quantum of excess inputs used was to the extent of Rs. 448.20 per acre per year of farmyard manure, Rs.534.99 per acre per year of chemical fertilizer, 41 mandays of human labour, Rs. 834.29 per acre per year of depreciation on equipments and buildings and 108 number of dfls per acre per year and Rs. 303.89 per acre per year of disinfectants used in silk worm crop care. However, the extent of wastage of inputs was minimum in case of bivoltine (CSR) hybrid silkworm rearers. Thus, with the new technologies being introduced in the field like new silkworm races, the wastage in the input usage was systematically reduced in the study area. This clearly indicates that, the new technologies of sericulture are mainly cost effective, thus improving the efficiency of the farmers in the region.

Table 6.4: Actual and Frontier Usage of Inputs in Sericulture - Estimated Based on Input Technical Efficiency Ratings

<table>
<thead>
<tr>
<th>Sl. No.</th>
<th>Input</th>
<th>Cross Breed</th>
<th>Bivoltine (CSR) Hybrid</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Actual input</td>
<td>Frontier input</td>
<td>Quantum of excess input used</td>
</tr>
<tr>
<td>1</td>
<td>Farm Yard Manure (Rs./acre/year)</td>
<td>4331.78</td>
<td>2248.05</td>
</tr>
<tr>
<td>2</td>
<td>Chemical Fertilisers (Rs./acre/year)</td>
<td>3302.83</td>
<td>1705.42</td>
</tr>
<tr>
<td>3</td>
<td>Human Labour (Mandays/acre/year)</td>
<td>394</td>
<td>202</td>
</tr>
<tr>
<td>4</td>
<td>Depreciation Cost (Rs./acre/year)</td>
<td>8148.76</td>
<td>4167.18</td>
</tr>
<tr>
<td>5</td>
<td>No of Disease Free Layings (DFLs/acre/year)</td>
<td>1093</td>
<td>561</td>
</tr>
<tr>
<td>6</td>
<td>Disinfectants (Rs./acre/year)</td>
<td>2767.85</td>
<td>1418.89</td>
</tr>
</tbody>
</table>
The results of Timmer and Kopp measures of technical efficiency revealed that the farmers particularly the bivoltine (CSR) hybrid silkworm rearers were comparatively more efficient than the crossbreed silkworm rearers. With the average output and input technical efficiency of 87.67 per cent and 88.93 per cent respectively, the bivoltine (CSR) hybrid silk cocoon producers had higher levels of efficiency in production, which also means that these farmers had imparted necessary skills in the production of silk cocoon. Contrary to this, the crossbreed silkworm rearers had the output and input technical efficiency ratings of 56.35 per cent and 51.33 per cent respectively, which indicated that, these farmers were relatively inefficient in using their resources in production of silk cocoon. In other words, the crossbreed silkworm rearers could have achieved the current level of silk cocoon production with 48.77 per cent lesser than the current level of use of inputs.

6.4.3. Measurement of Technical Efficiency using Stochastic Production Frontier Functions

6.4.3.1. The Stochastic Frontier Production Function (SFPF)

The stochastic frontier modelling is becoming increasingly popular because of its flexibility and ability to closely combine the economic concepts with modelling reality.\(^8^9\) The modeling, estimation and application of stochastic frontier production function to economic analysis assumed prominence in econometrics and applied economic analysis following Farrel’s\(^9^0\) seminal paper. Farell’s methodology had been applied widely, while undergoing refinement and improvement. And of such improvement is the development of stochastic frontier model which enables one to measure firm level technical and economic efficiency using maximum likelihood estimate (a corrected form of ordinary least square – COLS). Aigner et al.,\(^9^1\) and Meeusen and Van de Broeck\(^9^2\) were the first to propose stochastic frontier production function and since then many modifications had been made to stochastic frontier analysis. The use of this methodology is consistent with recent agricultural production

efficiency studies. There are also some conceptual advantages to using a stochastic approach, as it allows for statistical noise rather than attributing all deviations to efficiency differences. Finally, it is relatively straightforward to implement and interpret.

The Stochastic Production Frontier (SPF) function model of Cobb-Douglas functional form which is as follows:

\[ Y_i = f(X_i, \beta) \exp v_i - u_i \]  

Where \( Y_i \) represents the production of the \( i \)-th farm, \( X_i \) represents the actual input vector, \( \beta \) is the vector of production function. Parameters, \( 'v_i \) s' are assumed to be independent and identically distributed random errors, having normal \( N(0, \sigma_v^2) \) distributional and independent of \( U_i \) s. The \( 'u_i \) s' are technical inefficiency effects, which are assumed to be non-negative truncation of the half-normal distribution \( N(\mu, \sigma_u^2) \).

One of the disadvantages of the SPF method is that its estimation requires explicit specification of the distribution of the inefficiency term. There is no consensus among econometricians as to what specific distribution ‘U’ should have. In previous empirical studies a variety of distributions, ranging from the single-parameter half-normal, exponential and truncated normal distributions to the two-parameter gamma distribution, has been used.

---

The Technical Efficiency (TE) of individual farmer is defined in terms of the ratio of the observed output to the corresponding frontier’s output, conditional on the level of input used by the farmers. Hence the TE of the farmer is expressed as:

\[
\text{TE}_i = \frac{Y_i}{Y_i^*} = \frac{f(X_i; \beta) \exp V_i - U_i / f(X_i; \beta) \exp V_i}{f(X_i; \beta) \exp V_i} \quad \ldots (6.12)
\]

\[
= \exp (-U_i) \quad \ldots (6.13)
\]

Where, \( Y_i \) is the observed output and \( Y_i^* \) is the frontier’s output.

Given the assumptions of the above stochastic frontier models, the inference about the parameters of the model can be based on the Maximum Likelihood (ML) estimation because the standard regularity conditions hold. Aigner et al.,\(^{102}\) suggested that ML estimates of the parameters of the model can be obtained in terms of parameterisation \( \sigma_u^2 + \sigma_v^2 = \sigma^2 s \) and \( \lambda = \sqrt{\frac{\sigma_u^2}{\sigma_v^2}} \). Battese and Corra\(^{103}\) replaced \( \sigma_u^2 \) and \( \sigma_v^2 \) with \( \sigma^2 \) (variance of composite term) = \( \sigma_u^2 + \sigma_v^2 \) and \( \gamma = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2} \), so that \( 0 < \gamma < 1 \). In the case of \( \sigma_v^2 = 0 \), \( \gamma \) would be equal to 1 and all the differences in error terms of the frontier production function are the results of management factors under the control of the producer.\(^{104}\) When \( \sigma_u^2 = 0 \), \( \gamma \) would be equal to zero, which means all the differences in error terms of the frontier production function are the results of the factors that the producer has no control over, i.e., random factors. This also implies the existence of stochastic frontier. \( \gamma \) close to 1 indicates that the random component of the inefficiency effects makes a significant contribution to the analysis of production system.

\( \gamma \) statistic is used for hypothesis testing concerning the existence of the inefficiencies. If \( H_0 (\gamma = 0) \) is rejected, it means that there are inefficiencies and the function could be estimated using ML estimation method. If \( H_0 \) is not rejected, ordinary least squares method gives the best estimation of the production function.


6.4.3.2. Specification of the Stochastic Frontier Function Used in the Study

The model used in this study is based on the one proposed by Battese and Coelli\textsuperscript{105} and Battese \textit{et al.},\textsuperscript{106} in which, the stochastic frontier specification incorporates models for the inefficiencies effects and simultaneously estimate all the parameters involved in the production function models.

6.4.3.2.1. Model Specification

The empirical model of the stochastic production frontier is specified as:

\[ \ln Y_{ij} = \alpha_0 + \alpha_1 \ln X_{1ij} + \alpha_2 \ln X_{2ij} + \alpha_3 \ln X_{3ij} + \alpha_4 X_{4ij} + \alpha_5 X_{5ij} + \alpha_6 X_{6ij} + V_{ij} - U_{ij} \] .... (6.14)

The subscripts \( i \) and \( j \) refer to the \( i^{th} \) farmers and \( j^{th} \) observation respectively.

Where:

- \( Y \) = Total farm output of silk cocoon (kg)
- \( X_1 \) = Farmyard manure (Rs./acre/year)
- \( X_2 \) = Chemical Fertilisers (Rs./acre/year)
- \( X_3 \) = Human Labour (Mandays/acre/year)
- \( X_4 \) = Depreciation Cost (Rs./acre/year)
- \( X_5 \) = No of Disease Free Layings (DFLs/acre/year)
- \( X_6 \) = Disinfectants (Rs./acre/year)
- \( V_{it} \) = a random error term with normal distribution \( N(0, \delta^2) \)
- \( U_{ij} \) = a non-negative random variables called technical inefficiency effects associated with the technical inefficiency of production of farmers involved.
- \( \ln \) = the natural logarithm (i.e. to base e).
- \( \alpha_0 - \alpha_8 \) = parameters to be estimated.

This model is estimated for the two technology groups viz., Crossbreed silkworm rearers and Bivoltine (CSR) hybrid silkworm rearers, through maximum likelihood method by using Limdep 7.0 software, which gives the estimates of parameters \( \lambda = \sqrt{\left(\sigma_u^2 / \sigma_v^2\right)}, \sigma_u^2, \sigma_v^2 \) and \( \sigma \). \( \gamma \) is estimated from the estimates of \( \sigma_u^2 \) and \( \sigma_v^2 \) as \( \gamma = \sigma^2 / (\sigma_u^2 + \sigma_v^2) \).


6.4.3.3. Results of Stochastic Frontier Function

The inputs that are important in the production of silk cocoon are taken to include Farm Yard Manure, Chemical Fertilisers, Human Labour, Depreciation Cost, Number of Disease Free Layings (DFLs) and Disinfectants. The labour is measured by the total number of worker-days per week including paid and unpaid labour. Capital is measured by the depreciation value of fixed assets, including the value of equipments, land and buildings. Inputs such as farmyard manure, chemical fertilizer, disease free layings (DFLs) and disinfectants are measured in terms of expenditures on them.

The maximum likelihood estimates of the stochastic frontier production model for both crossbreed silkworm rearers and bivoltine hybrid (CSR) silkworm rearers was worked out and the estimates of the parameters of the stochastic production frontier (SPF) as specified by equation (6.14) are presented below in Table 6.5. It can be seen from the table that the estimated parameters such as value of farmyard manure, chemical fertilizers and number of disease free layings are statistically significant at 1 per cent, while the coefficient of human labour was negative and significant at 5 per cent in case of crossbreed silkworm rearers. Similarly, the parameters such as farmyard manure, chemical fertilizer and number of disease free layings are statistically significant at 1 per cent, while the parameters such as human labour, depreciation cost and disinfectants were non significant in case of hybrid (CSR) silkworm rearers.

The estimated values of $\sigma^2_u$ and $\sigma^2_v$ indicate that the difference between the observed output and frontier output is not due to the statistical variability alone, but also due to the technical inefficiencies (Table 6.5). $\gamma$ is the ratio of the variance of ‘u’ to the sum of the variance of ‘u’ and ‘v’. The estimates of $\gamma$ indicates the presence as well as the dominance of inefficiency effect over random error in both the categories of farmers. The fact that $\gamma$ is statistically significantly different from zero implies that the effect of technical inefficiency plays an important role in the variation of observed silk cocoon output. The estimated value of $\gamma$ in the SPF model, which is 0.57 and 0.60 among the cross breed rearers and bivoltine (CSR) hybrid rearers respectively, imply that 57.0 % and 60.0 % of the total variation in silk cocoon output is due to technical inefficiencies.
Table 6.5: Stochastic Frontier Function for Crossbreed and Bivoltine (CSR) Hybrid Silkworm Rearer

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Cross Breed</th>
<th></th>
<th></th>
<th>Bivoltine (CSR Hybrid)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>t-value</td>
<td>Significance</td>
<td>Coefficient</td>
<td>t-value</td>
<td>Significance</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.04</td>
<td>-1.67</td>
<td></td>
<td>-1.67</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Farm Yard Manure</td>
<td>0.15</td>
<td>2.49</td>
<td>0.01</td>
<td>0.18</td>
<td>2.58</td>
<td>0.01</td>
</tr>
<tr>
<td>Chemical fertilizer</td>
<td>0.17</td>
<td>2.65</td>
<td>0.01</td>
<td>0.22</td>
<td>3.70</td>
<td>0.00</td>
</tr>
<tr>
<td>Human Labour</td>
<td>-0.11</td>
<td>-1.47</td>
<td>0.14</td>
<td>0.01</td>
<td>0.19</td>
<td>0.85</td>
</tr>
<tr>
<td>Depreciation cost</td>
<td>-0.02</td>
<td>-0.47</td>
<td>0.64</td>
<td>-0.00</td>
<td>-0.09</td>
<td>0.93</td>
</tr>
<tr>
<td>No of Disease Free Layings</td>
<td>0.79</td>
<td>7.59</td>
<td>0.00</td>
<td>0.76</td>
<td>7.77</td>
<td>0.00</td>
</tr>
<tr>
<td>Disinfectants</td>
<td>-0.09</td>
<td>-2.11</td>
<td>0.04</td>
<td>-0.04</td>
<td>-0.79</td>
<td>0.43</td>
</tr>
</tbody>
</table>

Variance parameters for compound error

<p>| | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Lambda (λ)</td>
<td>1.160</td>
<td>1.907</td>
<td>0.057</td>
<td>1.229</td>
<td>2.028</td>
</tr>
<tr>
<td>Sigma (σ)</td>
<td>0.209</td>
<td>6.621</td>
<td>0.000</td>
<td>0.169</td>
<td>7.348</td>
</tr>
<tr>
<td>Sigma-squared (v)</td>
<td>σ_v^2</td>
<td>-</td>
<td>-</td>
<td>0.01</td>
<td>-</td>
</tr>
<tr>
<td>Sigma-squared (u)</td>
<td>σ_u^2</td>
<td>-</td>
<td>-</td>
<td>0.02</td>
<td>-</td>
</tr>
<tr>
<td>Log likelihood function</td>
<td>44.28</td>
<td>-</td>
<td>-</td>
<td>53.70</td>
<td>-</td>
</tr>
<tr>
<td>Gamma (γ)</td>
<td>0.57</td>
<td>-</td>
<td>-</td>
<td>0.60</td>
<td>-</td>
</tr>
</tbody>
</table>

The per cent distribution of farms in decile ranges of farm specific technical efficiency has been worked out and presented in the Table 6. The frequencies of occurrence in the decile range (Table 6.6) indicate that the highest number of crossbreed silkworm rearers and bivoltine (CSR) hybrid silkworm rearers have technical efficiency between 90 and 100 per cent. The average rate of technical efficiency among these farms was found to be 66 per cent and 89 per cent respectively.
Table 6.6: Output Technical Efficiency Rating (%) Based on Stochastic Frontier Production Function (SFPF)

<table>
<thead>
<tr>
<th>Output Technical Efficiency Rating (%)</th>
<th>Cross Breed</th>
<th>Bivoltine (CSR) Hybrid</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No of rearers</td>
<td>Percentage</td>
</tr>
<tr>
<td>0-10</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>10-20</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>20-30</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>30-40</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>40-50</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>50-60</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>60-70</td>
<td>6</td>
<td>4</td>
</tr>
<tr>
<td>70-80</td>
<td>17</td>
<td>13</td>
</tr>
<tr>
<td>80-90</td>
<td>50</td>
<td>37</td>
</tr>
<tr>
<td>90-100</td>
<td>60</td>
<td>44</td>
</tr>
<tr>
<td>Total</td>
<td>136</td>
<td>100</td>
</tr>
</tbody>
</table>

Average rate of Technical Efficiency (%)  
Cross Breed: 0.66  
Bivoltine (CSR) Hybrid: 0.89

6.4.3.4. Comparison of TE Estimates Obtained Under both COLS and SFPF Procedure

A comparison of the distributions of TE estimates from both the COLS and SFPF models shows that the distribution is relatively symmetric in the COLS model, while it is skewed in the SFPF model, in both the categories of the farmers (Table 6.7 & 6.8). However with the very high rate of technical efficiency among the bivoltine (CSR) hybrid rearers, it was found that again the observations were again skewed.
Table 6.7: A Comparative account of Technical Efficiency Ratings based on COLS and SFPF estimates for Cross Breed Silkworm Rearers

<table>
<thead>
<tr>
<th>Technical Efficiency Rating (%)</th>
<th>Estimate procedure of Technical Efficiency</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>COLS</td>
<td>SFPF</td>
<td></td>
</tr>
<tr>
<td></td>
<td>No. of rearers</td>
<td>Percentage</td>
<td>No. of rearers</td>
</tr>
<tr>
<td>10-20</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>20-30</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>30-40</td>
<td>4</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>40-50</td>
<td>22</td>
<td>16</td>
<td>1</td>
</tr>
<tr>
<td>50-60</td>
<td>76</td>
<td>56</td>
<td>2</td>
</tr>
<tr>
<td>60-70</td>
<td>27</td>
<td>20</td>
<td>6</td>
</tr>
<tr>
<td>70-80</td>
<td>2</td>
<td>1</td>
<td>17</td>
</tr>
<tr>
<td>80-90</td>
<td>3</td>
<td>2</td>
<td>50</td>
</tr>
<tr>
<td>90-100</td>
<td>1</td>
<td>1</td>
<td>60</td>
</tr>
<tr>
<td>Total</td>
<td>136</td>
<td>100</td>
<td>136</td>
</tr>
</tbody>
</table>

Table 6.8: A Comparative account of Technical Efficiency Ratings Based on COLS and SFPF estimates for Bivoltine (CSR) Hybrid Silkworm Rearers

<table>
<thead>
<tr>
<th>Technical Efficiency Rating (%)</th>
<th>Estimate procedure of Technical Efficiency</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>COLS</td>
<td>SFPF</td>
<td></td>
</tr>
<tr>
<td></td>
<td>No. of rearers</td>
<td>Percentage</td>
<td>No. of rearers</td>
</tr>
<tr>
<td>0-10</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>10-20</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>20-30</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>30-40</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>40-50</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>50-60</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>60-70</td>
<td>0</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>70-80</td>
<td>0</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>80-90</td>
<td>80</td>
<td>77</td>
<td>35</td>
</tr>
<tr>
<td>90-100</td>
<td>21</td>
<td>20</td>
<td>57</td>
</tr>
<tr>
<td>Total</td>
<td>104</td>
<td>100</td>
<td>104</td>
</tr>
</tbody>
</table>
6.5. Summary and Inference

There existed clear inefficiencies in the production of silk cocoon in the study area. However, these inefficiencies have attributed to wastage of resources in production. Hence, a major gap exists in the resource usage in the production of silk cocoon, particularly while producing crossbreed cocoons. However, the bivoltine silk cocoon producers exhibited comparatively higher rate of discipline in the organization of resources in production. The inefficiencies exhibited in crossbreed silk cocoon production indicate that majority of these farmers combine their resources with the non cash inputs, which might have resulted in high level of inefficiencies. Extension efforts, therefore, should be strengthened to educate the farmers to take up bivoltine production which can hasten discipline in production. Better resource management is therefore, the primary concern for the extension experts and farm management specialists, as these farmers are utilizing the irrigated lands for the cultivation of mulberry.

This analysis is also set out to compare the empirical performance of two popular approaches to estimation of technical efficiency in production: Corrected Ordinary Least Squares Regression (COLS) and Stochastic Production Frontier (SPF). The comparison has focused on measuring the technical efficiency of sample sericulture farms in Karnataka state. The general findings from this study indicate that estimates of technical efficiencies of individual sericulture farms, and therefore the mean technical efficiency of the sericulture, are sensitive to the choice of production frontier estimation method. Of the two models considered, the statistical deterministic frontier, i.e., COLS, produces the lowest mean technical efficiency while the SPF produces the highest mean TE in general. However, in many of the studies it is revealed that, it is not always the case that the SPF models produce a larger mean technical efficiency than COLS models. The mean TE estimates from the SPF model show that the sericulture farms are operating near to or at the efficient frontier. Individual farm TE estimates exhibit greater variability under both COLS and SPF models.
The findings above are consistent with those of comparable studies done in the past. Jaforullah\textsuperscript{107} found the mean TE from the deterministic frontier to be lower than from the stochastic frontier. Neff, Garcia and Nelson\textsuperscript{108} also found the stochastic frontier to yield higher mean TE estimates compared to the deterministic models. They also found the correlation between the parametric measures to be very high, but the correlation between parametric and non-parametric models to be fairly low.

The above findings lead to the conclusion that if one aims at estimating mean technical efficiency of an industry, it is advisable that one uses different methods of efficiency estimation as opposed to a single method, as the measurement of technical efficiency is sensitive to the choice of estimation method. Such an approach will produce better information on the technical efficiency of the industry by producing a range within which the true technical efficiency may lie. The narrower the range, the more confident a researcher can be about the technical efficiency of the industry. However, if one is keen to use only one estimation method then, in choosing the method, one must consider the type of the industry under study, the type of data in hand, the strengths and weaknesses of estimation methods and the objectives of the study.